Hacettepe University Graduate School of Social Sciences

Department of Economics

PRODUCT DIVERSIFICATION AND RELATEDNESS: EVIDENCE FROM TURKISH MANUFACTURING FIRMS

Leventcan GÜLTEKİN

Ph.D. Dissertation

Ankara, 2024

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The jury finds that Leventcan Gültekin has on the date of 19/01/2024 successfully passed the defense examination and approves his Ph.D. Dissertation titled “Product Diversification and Relatedness: Evidence From Turkish Manufacturing Firms”.

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ABSTRACT

GÜLTEKİN, Leventcan. *Product Diversification and Relatedness: Evidence From Turkish Manufacturing Firms*, Ph.D. Dissertation, Ankara, 2024.

Economic diversification is a critical issue for the sustainability of growth due to its dynamic learning effect and risk-spreading dimension. To understand how the productive structure evolves in the economy, it is important to examine the product diversification behavior of firms in depth. The recent research in product diversification has also paid attention to the relatedness concept that is emerged from the Product Space framework. Principle of relatedness suggest that economic actors tend to diversify towards related products that require capabilities similar to their own.

This thesis emphasizes the role of relatedness and examines the impact of proximity to firm- and place-based capabilities on the product diversification process of firms in Türkiye. Using a large firm-level data between 2012-2017 and logistic regression methodology, this thesis analyze the extent to which a firm's choice of a new product is influenced by (1) the firm's existing export portfolio, (2) the firm's existing import portfolio, (3) the competitive export portfolio of the region in which the firm is located, and (4) the competitive export portfolio of its neighboring regions.

Empirical findings suggest that firms diversify into related products that are aligned with firm- and location-based capabilities when choosing new products. In particular, firm-level capabilities appear to play a more important role in driving new product choices than existing capabilities at the regional level. Regarding the spillover effect across regions, there is no significant effect of capabilities available in neighboring regions on firms' choice of new products. The empirical findings are robust when agglomeration externalities, firm-level control variables and different subsamples are considered. The subsample estimates reveal that the effect of relatedness on product choice varies across different firm size groups and product complexity levels.

Key Words: Relatedness, Product Diversification, Capabilities, Agglomeration Economies, Logistic Regression

ÖZET

GÜLTEKİN, Leventcan. *Product Diversification and Relatedness: Evidence From Turkish Manufacturing Firms*, Doktora Tezi, Ankara, 2024.

Ekonomik çeşitlenme, yarattığı dinamik öğrenme etkisi ve risk azaltma yönüyle büyümenin sürdürülebilirliği açısından kritik bir konudur. Ekonomide üretim yapısının nasıl evrildiğini anlamak açısından da firmaların ürün çeşitlendirme davranışlarının derinlemesine incelenmesi önem arz etmektedir. Ürün çeşitlendirmesi üzerine yapılan son araştırmalar, Ürün Uzayı çerçevesinden ortaya çıkan ilişkililik kavramına da dikkat çekmiştir. İlişkililik ilkesi, ekonomik aktörlerin sahip olduğu kabiliyetlere benzer kabiliyetler gerektiren ilişkili ürünlere doğru çeşitlenme eğiliminde olduğunu öne sürmektedir.

Bu tez kapsamında ilişkililiğin rolü vurgulanarak Türkiye'de firmaların ürün çeşitlenme sürecinde firma ve mekân bazlı kabiliyetlere yakınlığın etkisi incelenmektedir. Spesifik olarak bir firmanın yeni ürün seçiminde; (1) firmanın mevcut ihracat portfoyü, (2) firmanın mevcut ithalat portfoyü, (3) firmanın içerisinde bulunduğu bölgenin rekabetçi ihracat portfoyü ve (4) komşu bölgelerinin rekabetçi ihracat portfoyü ile ilişkililiğin ne ölçüde etkisi olduğu 2012-2017 yılları arasını kapsayan firma bazında veri ve lojistik regresyon metodolojisi kullanılarak analiz edilmektedir.

Ampirik bulgular; firmaların yeni ürün seçiminde, firma ve mekân bazlı kabiliyetlerle uyumlu olan ilişkili ürünlere çeşitlenme gerçekleştirdiğini göstermektedir. Özellikle, firma düzeyindeki kabiliyetlerin, bölgesel düzeydeki mevcut kabiliyetlere kıyasla yeni ürün tercihlerini yönlendirmede daha önemli bir rol oynadığı görülmektedir. Bölgeler arası yayılma etkisiyle ilgili olarak; komşu bölgelerde mevcut olan kabiliyetlerin firmaların yeni ürün seçiminde anlamlı bir etkisi gözlemlenememiştir. Ampirik bulgular; farklı alt örneklemler, yığılma dışsallıkları ve firma bazlı kontrol değişkenleri de dikkate alındığında tutarlıdır. Alt örneklem tahminleri, ilişkililiğin ürün seçimi üzerindeki etkisinin farklı firma büyüklük grupları ve ürün kompleksite seviyesine göre farklılaşma gösterdiğini ortaya koymaktadır.

Anahtar Kelimeler: İlişkililik, Ürün Çeşitlendirmesi, Kabiliyetler, Yığınlaşma Ekonomileri, Lojistik Regresyon

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ABBREVIATIONS

EIS:	Entrepreneurship Information System
HS:	Harmonized System
NACE	Statistical classification of economic activities in the European Community
OECD:	Organisation for Economic Co-operation and Developmen
PCI:	Product Complexity Index
RBV:	Resource Based View
RCA:	Revealed Comparative Advantage
R&D:	Research and Development
SEDI:	Socioeconomic Development Index
UNCOMTRADE:	United Nations Commodity Trade

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INTRODUCTION

Economic diversification has been a crucial topic in the debate on how countries can enhance economic performance and attain higher income levels. It is often argued that structural change and diversification plays an important role in the process of economic growth and development. Economic growth does not just involve producing more of the same thing. But rather, it includes expanding the range of the products and activities, introducing new ones that are technologically advanced and sophisticated. Economic diversification is regarded a crucial issue based on the two main arguments: (1) dynamic learning effect and (2) strategy of risk spreading.

In terms of the dynamic learning effect, long-run economic growth is linked to the process of acquiring the knowledge and capability to manufacture a wider variety of products. Economic diversification fosters a dynamic learning effect by encouraging the development and accumulation of diverse skills, technologies, and knowledge across different sectors of the economy. This concept is grounded in the idea that the existence of variety of industries and activities stimulates innovation, knowledge transfer, and the acquisition of new skills.

Romer (1990) argues that diversification has an amplifying effect on other factors of production. Especially in countries which have insufficient sources of economic growth, most improvement in productivity arise from the investment process itself (Agosin, 2009). Newly introduced goods bring new knowledge that can lead to the creation of new economic products and services that have greater value-added as compared to existing ones.

In terms of risk spreading strategies, a high level of concentration in a limited number of areas may increase the vulnerabilities of the economy to various external shocks, such as sudden changes in demand and supply, and fluctuations in exchange rates. (Agosin et al. 2012; Cadot et al. 2013). Thus, diversification contributes to an economy's capacity to stabilize its export revenues in case of trade shocks. For instance, countries whose exports exhibit significant dependence on a limited range of products are more exposed to real exchange rate fluctuations. Moreover, if external demand for one sector decreases, the presence of a diversified sectoral structure mitigates the overall negative impact.

In this regard, what determines diversification and how new products and industries emerge are essential questions in academic and policy agendas (Boschma and Gianelle, 2014; Hidalgo, 2023). Having a better understanding on the dynamics of product diversification and identifying mechanisms to facilitate it is crucial in formulating strategies for development. In literature, various theoretical frameworks has been developed to understand and explain product diversification process within the firms (Teece, 1982; Bernard et al., 2010, 2011, Dosi et al., 2020). Theoretical and empirical studies on product diversification have benefited from various streams of literature including industrial organization, international trade, evolutionary economics and economic complexity (Wernerfelt, 1984; Hidalgo et al., 2007; Iacovone and Javorcik, 2010).Recent developments in the economic complexity and evolutionary economic geography literature suggest that the emergence of new products and industries is not a random occurrence but significantly shaped by the existing capabilities of countries or regions. Each product demands diverse set of distinct complementary and non-tradable inputs. These are called capabilities (Haussman and Hidalgo, 2010). Countries vary in the quantity and specific mix of capabilities they possess, and products differ in the combination of capabilities they demand. It is argued that the concept of ***relatedness*** has significant potential to explain the diversification trajectory of economies.

In their seminal paper, Hidalgo et al. (2007) introduce the concept of the Product Space, which is a network representation of the relatedness of different products. Product Space approach implicitly assume that products can be related due to their need for similar production resources, such as knowledge bases, organizational culture, human capital, and supporting institutions. Empirically, they show that countries predominantly expand their product portfolios by entering products related to their existing portfolios (Hausmann and Hidalgo, 2010; Boschma and Capone, 2016). The evolutionary economic geography literature confirms the same phenomenon at the regional level, suggesting that the presence of locally related activities plays a facilitating role in the emergence of new products and industries (Neffke et al., 2011; Boschma et al., 2013; Boschma et al., 2017a).

In the lens of relatedness, this thesis aims to analyze the effect of firm and region specific capabilities and resources on a firm’s new product choice. We exploit rich firm level data to analyze Turkish manufacturing firm’s new export product choices conditional on its relatedness with internal and local capabilities for the cross-section period of 2012-2017.

The Turkish economy presents an important case for analyzing export diversification, as it is ranked 23rd in the world in terms of total exports with a rapidly growing manufacturing sector. With its diverse export portfolio, Turkey ranks as the 42nd most complex economy, as indicated by the Economic Complexity Index (OEC, 2023). Exporting a variety of products often involves the acquisition and application of diverse technologies. In the developing country like Türkiye, this process can contribute to technological upgrading within firms, fostering innovation and increasing their competitiveness on a global scale. Understanding the product space allows these economies to explore new, related products that they can enter, promoting diversification and reducing dependence on a few activities.

Available product specific capabilities in the firm can serve as a significant knowledge base during the exploration stage. The presence of related knowledge sources and agglomeration can reduce the entry costs for new products (Hazir et al., 2019). Specifically, we investigate the extent to which a firm's entry into new products is influenced by its relatedness with (1) the firm's existing export basket, (2) the firm's existing import basket, (3) the region's competitive export basket, and (4) the competitive export basket of neighboring regions. The utilitization of firm-level microdata allows for the analysis of the role of different knowledge sources separately in product innovation. Given previous literature on economic complexity and relatedness, we expect that the likelihood of a firm developing a new product is a function of related capabilities present at firm and local level.

In the empirical analysis, we also consider the role of specific heterogeneities at both the firm and product levels. Small and large firms may exhibit differences in their level of connection with the local economy, leading to differences in their reliance on internal and local resources. Larger firms, with their extensive outreach capacity and network, may depend less on existing internal and local capabilities This circumstance could enhance their ability to diversify into unrelated areas and break free from historical path dependencies. Moreover, depending on the complexity of the product effect of firm and local factors might change. Highly complex knowledge may disperse slowly due to its tacit dimension. Therefore, we conduct subsample estimations to examine the influence of firm size and product complexity on the role of firm and place based capabilities.

Our findings indicate that firm and local-specific capabilities are significant drivers of a firm's entry into new export products. Specifically, we find that capabilities at the firm level play a more significant role in driving new product choices compared to capabilities present at the region level. These findings remain consistent even when accounting for different subsamples, the effects of agglomeration economies, and other firm-specific controls. Moreover, subsample estimations show that the magnitude of relatedness shows significant variations among different firm size groups and products with different complexity levels.

This thesis, makes three significant contributions to the literature. Firstly, although there are quite a number of empirical studies on relatednes and diversification relationship at the country/regional level (Boschma et al., 2013; Bahar et al., 2014; Essletzbichler, 2015; Xiao et al., 2018; Jun et al., 2020), only a few studies examine it at the firm level (Neffke and Henning, 2013; Lo Turco and Maggioni, 2016; Hazir et al., 2019). Firm level evidence on relatedness and product diversification is scarce. Thus, this study contributes to the literature by examining the role of relatedness in the choice of new products by focusing on the case of Turkish manufacturing firms.

Secondly, by adopting a spatially multi-scaled perspective, this study contributes to the literature by simultaneously considering firm-, region-, and neighbor region-level capabilities. A majority of studies in the literature primarily investigate the endogenous product selection of firms based on firm and product-level characteristics (Breschi et al., 2003; Bernard et al., 2010; Mayer et al., 2014; Dosi et al., 2020). However, these studies often neglect the importance of local learning and agglomeration economies. The economic geography literature often highlight that knowledge externalities at the regional level play a pivotal role in shaping a firm's product diversification and innovative activity (Lo Turco and Maggioni, 2016; Hazir et al., 2019). In this regard, findings of this thesis offer a significant contribution to the ongoing discussion regarding the measurement of the relative impact of regional environment compared to firm-specific factors on the product innovation performance of firms. Thirdly, to our knowledge, there is no study that incorporates the role of capabilities originating from neighboring regions and importing activities in influencing firms' choices of new products. Even though, some scholars (Boschma et al., 2017b; He at al., 2019; Balland et al. 2021) explored the effect of inter-regional spillovers on diversification patterns of regions, firm-level analysis in this context is scarce. We expect that these extra-territorial connections may allow firms to access information across distance and reduce their reliance on existing firm and local level capabilities. Therefore, this study will be the first to investigate this dimensions as well.

The structure of the thesis is organized into four sections. The first section explores a theoretical and empirical literature on the drivers of product diversification of firms. Second section focuses on the concept of relatedness and its role in product diversification. The third section provides information on data and methodology adopted in the study. Fourth section reports the results of econometric estimations. Lastly, the conclusion summarizes the findings of the study, and discusses policy implications.

CHAPTER 1: OVERVIEW OF THEORETICAL BACKGROUND AND EMPIRICAL LITERATURE

Why and how firms diversify? These questions have been the interest point of many disciplines including economics, managerial sciences, innovation studies and economic geography. This section gives an overview of theoretical and empirical literature on firm diversification and its determinants. In particular, we focus on on three streams of literature: (1) industrial organization, (2) international trade, and (3) economic complexity and relatedness literature. Each of these literature streams sheds light on different dimensions of the topic.

1.1. INDUSTRIAL ORGANIZATION LITERATURE

Topic of the product diversification within the firms has been a crucial point of interest in the industrial organization literature. Studies in the industrial organization literature elaborates the issue of diversification in the scope of internal organization of firms and their market strategy. Earlier works in the neoclassical perspective attempted to explain economic rationale of the existence of multiproduct firms (Panzar and Willig, 1981; Teece, 1982). A fundamental issue of the theory of the multiproduct firm is explaining why firms diversify their portfolio rather than reinvesting in their existing business or distributing their profits/assets directly to shareholders. In the literature, firm’s motivation to diversify is explained with two dimensions; (1) production efficiency and (2) demand-side effects.

On the production efficiency side, motivation to diversify arises from the cost advantages. Panzar and Willig (1977) introduce the concept of economies of scope to analyze the existence of multi-product firms. According to *economies of scope*, the average cost falls whenever firms combine two or more product in the product line. Source of the scope economies explained by sharable inputs among products. These shareable inputs might be human capital or productive capacity such as machinery to produce certain types of products. For example, a firm that produces both motorcycles and bicycles can save money by using the same manufacturing facilities to produce both products. The firm can also save money by sharing research and development costs, marketing costs, and administrative costs.

Panzar and Willig (1977) argue that *economies of scope* may explain the economic base for existing multiple product lines in companies. For example, if joint production of x_1 and x_2 involves scope economies, then $c(x_1, x_2) < c_1(x_1,\ 0) + c_2(0, x_2)$. Taking this inequality into account, under the presence of economies of scope, the co-production of two goods will cost less than producing them separately which in turn leads to the emergence of multiproduct firms (Panzar and Willig, 1977: 483). Bailey and Friedlander (1982) explain the channels that lead to cost reduction due to joint production. These channels include: (1) separating products from shared inputs; (2) the presence of underutilized fixed factors; (3) economies of networking; (4) reuse of inputs in multiple products; (5) intangible asset sharing.

Teece (1980) argues that the analysis and conclusion of Panzar and Willig (1977) is too strong for reaching a conclusion that scope economies will create cost decreasing conditions. Because, scope economies are neither necessary nor a sufficient condition for saving costs through multi-production activities. Scope economies are obtained through the utilization of inputs among different activities without complete congestion. Shared inputs may be imperfectly divisible or it may be public input such as human capital when its attained many product lines may benefit from it. Teece (1980) put forwards that the effective tradability potential of input and services on markets will determine whether scope economies will be gained through multiproduct activity. When tradability of particular inputs are problematic, then intrafirm arrangements will be more rational.

Transaction Cost Economics (TCE) approach based on the studies of Ronald Coase (1960) and Oliver Williamson (1975) address this issue by providing insights into how firms make decisions regarding product diversification based on the analysis of transaction costs. In neoclassical theory, it is presumed that profit-maximizing firms operate in a competitive market where transaction costs are zero (Teece, 1982). However, under these conditions, there is no way to build a theory of multi-product firms. In the absence of transaction costs there will not be any incentive for firms to undertake multiple product structures since market contracts will yield scope economies.

TCE focuses on the costs associated with transactions in economic activities and how these costs influence the organizational structure of firms. In the context of product diversification, TCE suggests that firms may choose to diversify their product offerings to internalize certain transactions and economize on transaction costs (Klein and Lien, 2009). It is argued that, in order to gain efficient advantages, a multiproduct firm's portfolio of businesses should be either *substitutable or complementary.*

In the case of substitutability, a resource used for product X can also be used in product Y without productivity loss. Especially when resources are indivisible, excess capacity in one resource might be used in more than one production line. Even though the existence of these indivisibilities explains joint production, it still cannot explain the existence of multi-product firms. Under zero transaction costs, single-product firms could obtain scope economies simply through contracting for sharing inputs. Therefore, the choice between contracting or integration depends on transaction costs rather than the production technology.

In the case of complementarity, value of one resource in an industry increases as a result of investment in another industry. Indeed, within value chains, there are always complementarities, but not all of them are integrated. Firm diversification is rational if firms cannot take advantage of complementarities through contracting due to high transaction costs. In this case, the main problem related to contracting is not indivisibilities, but rather difficulties in specifying contingencies and contractual incompleteness (Klein and Lien, 2009).

Teece (1980) investigates the US petroleum industry firms' participation in other energy industries. He reports that firms' diversification into alternative energy industries is driven by the scope economies generated by the sharing of industrial know-how across related sectors. The petroleum industry, traditionally focused on oil and gas, found opportunities for synergies by leveraging its expertise in technology, engineering, and resource management across a broader spectrum of energy-related activities.

Jovanovic (1982) suggests that main forces behind the diversification are slack management resources and shareable R&D inputs. As industries mature, R&D capacity within the firm becomes increasingly crucial and R&D outcomes can be shared among similar product categories. Due to R&D activity a firm may discover new ways to decrease cost that many product lines can benefit from. Since R&D costs are fixed, the more diversified a firm is, the more likely it is to take advantage of these new discoveries. In addition to R&D processes, a manager may be able to manage more than a single firm. When a manager is only responsible for one firm, slack managerial resources go to waste, which is not an optimal allocation of resources. Therefore, slack managerial resources are one of the reasons why firms choose to diversify in order to allocate resources effectively.

The logic of scope economies explain the advantages in terms of cost efficiencies. These advantages can be conceptualized not only in relation to cost benefits but also with respect to demand-side advantages linked to outputs (products and services). When firms diversify into another market by utilizing excess resources, they generate increased revenues per unit of input. On the demand side, a firm's incentive to diversify can also be explained by the potential to increase demand for its products. When a firm diversifies by utilizing excess resources, it can reach new markets and attract new customers. For example, a firm that produces both cars and trucks can reach new customers by selling its cars to people who do not need trucks and by selling its trucks to people who do not need cars. In this way, firms can generate increased revenues per unit of input (Helfat and Eisenhardt 2004). In addition, diversification can help a firm to reduce its risk. When a firm has multiple products, it is less likely to be harmed by a decline in demand for one of its products. For example, a firm that produces both cars and trucks is less likely to be harmed by a decline in the demand for cars if it also has a strong business in trucks.

Brander and Eaton (1984) develops a model where firms can produce product pairs that are distant substitutes or close substitutes. According to the model, the firm’s product choice is affected by demands for different products (elasticity of substitution). Firms should produce distant substitutes in order to maximize profits through product diversification. Shaked and Sutton (1990) consider the case of horizontal differentiation and demonstrates that large expansion or little competition induces firms to diversify their products. The rationale behind this behavior is that intense competition among firms leads to decreased profits, triggering firms to offer new unique products to preserve their monopoly power and increase their overall profitability.

1.2. INTERNATIONAL TRADE LITERATURE

Product diversificiation and extensive margin of the trade issues are addressed in different ways in international trade literature. Traditional Comparative Advantage (Ricardian model or the Heckscher-Ohlin model) theory primarily focuses on explaining the gains from trade at the intensive margin rather than the extensive margin. Ricardian model is concerned with explaining the pattern of specialization and trade in terms of relative opportunity costs and how it leads to increased efficiency and gains from trade.

It assumes that countries will recognize their comparative advantages and engage in trade accordingly (Feenstra, 2004:3).

In the Heckscher-Ohlin (H-O) model, gains from trade arise from comparative advantage based on variations in factor endowments between countries. The primary factors of production considered in this model are capital and labor. The fundamental idea is that countries will specialize in the production of goods that intensively use their abundant factor and trade with countries that have a different factor endowment. The model does not explicitly focus on the extensive margin of trade—the decision of whether or not to trade or the determination of the range of goods that are traded (Feenstra, 2004: 34).

The New Trade Theory (NTT) emphasizes scale economies, imperfect competition, and product differentiation as key factors influencing international trade patterns (Krugman, 1979). In NTT, products are often assumed to be differentiated, and consumers have preferences for variety. The gains from trade in NTT arise from the expansion of the market. As countries engage in trade, the overall market size increases, enabling firms to produce more, achieve economies of scale, and reduce average costs. This dynamic benefits consumers through lower prices and increased product variety. Moreover, it allows firms to specialize in the production of specific goods, leading to a more efficient allocation of resources. (Krugman, 1980).

Until the early 2000s, international trade literature has not paid much attention to firm-level analysis. Previously in Comparative Advantage and New Trade Theory literature, the identical representative firm assumption was adopted for the sake of simplification and tractability. The growing availability of firm-level datasets has led to increased interest among researchers in conducting analyses at the firm level. (Pavcnik, 2002; Trefler, 2004; Bernard et al., 2007; 2012; Timoshenko, 2015). Information obtained from firm level data sources shows that there exists a considerable degree of heterogeneity among firms which in turn affects the aggregate outcome (Bernard et al., 2007).

In this regard, economists attempted to develop different micro-founded trade models with a particular focus on firm heterogeneity. As compared to traditional comparative advantage theories, micro-founded trade models provided alternative explanations for the gains from trade (Melitz, 2003; Bernard et al., 2007). Studies investigate how trade liberalization can generate welfare gains by expanding product variety and increasing productivity within industries.

In his seminal paper, Melitz (2003) introduced the notion of firm heterogeneity into model of intra-industry trade model of Krugman (1980). In Melitz’s (2003) model, firms are heterogeneous in terms of their productivity levels and face sunk entry costs in exporting their goods. The model assumes that each firm operates in a monopolistic competition market and produces differentiated products. Due to the existence of sunk entry costs, some firms make negative profits, since levels of their productivity are below the zero-profit productivity cut-off. In the literature, Melitz (2003) model is used to analyze the impact of trade liberalization on the distribution of firm-level outcomes such as exports, output, and profits (Trefler, 2004; Mayer and Ottaviano, 2008).

In Melitz (2003) type models, heterogeneity and productivity differences among firms, imperfectly competitive structure of the market and fixed market entry costs are the main driver of consequences of trade. Following trade liberalization, trade costs show decline. However, because of fixed trade costs, only the most productive firms survive in the export market. With the fall in prices, relatively less productive firms are forced to exit the market, thus due to allocation in industries, high productivity non-exporters expand their market and increase total sales through export. Eventually, average productivity in the industry increases with the increasing weight of more productive firms in the economy.

Firm Heterogeneity models generally assume that differences in the capacity of firms to enter export markets or new foreign markets are primarily determined by heterogeneous productivity levels. Plenty of studies in international economics literature find evidence supporting the hypothesis of Melitz (2003). Pavcnik (2002) investigates the trade liberalization experience of Chile during the 1970s. She provides empirical evidence regarding productivity improvements among firms through shuffling resources among plants in the same industry following trade liberalization. Trefler (2004) focuses on the Canadian-US Free Trade Agreement case and reports that the productivity of industries in Canada increased significantly as a result of tariff reductions, with the reduced employment in low productivity plants. Bernard et al. (2006) use a long panel of US manufacturing industries from 1987 to 1997 and find that lower trade costs have a positive impact on aggregate industry productivity growth.

Earlier studies within the firm heterogeneity framework explain how trade liberalization promotes process innovation through enhancing firm productivity. However, these studies have not explicitly tackled the aspect of product innovation and the extensive margin specific to products. In subsequent studies, firm heterogeneity models has been extended in various ways to incorporate characteristics of multi-product firms, such as endogenous product selection and extensive margin of the trade (Bernard et al., 2007; Eckel and Neary, 2010; Bernard et al., 2010; Dhingra, 2013; Hazir et al., 2019). These extended models have potential to explain the previously overlooked fact that trade liberalization not only affects the size of existing trading relationships through intensive margin, but also affects extensive margins of firms.

These models essentially aimed to capture endogenous dynamics between firms as well as within firms. Particularly, how multi-product firms respond to sudden changes in economic environment such as trade liberalization. The aggregate response to policy shocks emerges as a mixture of these distinct dynamics. Empirical results from the study support the predictions of the theoretical models highlighting that product switching and diversification within the firm is one of extensive margin adjustment in reaction to globalization (Nocke and Yeaple, 2006; Bernard et al., 2007; Eckel and Neary, 2010).

Modeling multiple-product firms is beneficial in various respects. Firm-level disaggregated data allows us to detect some features that standard models cannot explain such as concentration and skewness of export volume products within firms, or the relationship between product and export destination characteristics. Studies documented a striking fact that in many countries, the volume of international trade is concentrated in the operations of few firms. For example, Bernard et al. (2009) report that 1 percent of the total firms in the US, controls almost 90 percent of foreign trade in the US. Also, OECD (2017) emphasizes that a substantial portion of exports in all OECD countries can be attributed to the top 100 exporting companies. It ranges from 25 percent to 90 percent among countries. Particularly in Turkey, top 100 exporters account for 35 percent of total exports (OECD, 2017).

Nocke and Yeaple (2006) develop a model of multi-product firm with endogenous product selection where firms have fixed marginal costs for each product line. Firms vary in their ability to organize and manage their operations, and those with greater organizational capability are less affected by marginal cost increases as they expand their product lines.

Eckel and Neary (2010) present a general equilibrium model of multi-product firms with supply and demand linkages. In their model, firms change their product scope by reacting to globalization shocks that reveal themselves in two form: (1) competition effect, (2) market size effect. The model predicts that increasing competition induces firms to focus on its core competence products and exit high-cost products. Moreover, the model highlights that one of the potential losses from the trade is falling product diversity.

Bernard et al. (2010) develop a model in which a firm's product scope is an endogenously function of characteristics of firm and products. Particularly, at the firm level its productivity and at the product level its attractiveness to consumers are the main determinants of the firm's profitability. Their model predicts that in equilibrium most productive firms have a wider scope of product compared to less productive firms because due to their higher revenues stemming from productivity, they can cover the fixed cost of each product.

Iacovone and Javorcik (2010) use Mexican firm-level data to examine product-level dynamics following the implementation of the North American Free Trade Agreement (NAFTA). They document that, in the presence of uncertainty, exporters enter into new markets with a product already being sold at home market and new product discoveries are generally a small share of overall varieties. Nonetheless, when exporters introduce new products it is followed by other firms within a short period of time.

Bernard et al. (2011) develop a general equilibrium model of multiple-product, multiple-destination firms that is an extension of Melitz's (2003) heterogeneous firms framework. In their model, firms are subject to sunk entry costs for each market and product which affects their profit level and choice among a variety of products and export markets. Firm's profitability is a function of its productivity and consumer taste for its products. Declining trade costs force firms to drop their least attractive products and increase firm productivity. One of the most important facets of their model is that the firm component (productivity) leads to selection across firms and the product component (consumer taste) leads to selection within firms. Higher productivity firms can yield enough profit to cover the fixed cost of a product given its attributes for the destination market. Therefore, higher productivity firms can provide a wider range of products to each market because they can achieve a sufficient level of profit to cover the fixed cost of products with lower attributes.

Dhingra (2013) suggests that when firms become engaged in international markets, to cope with external competition they decrease product scope due to *cannibalization effect* and increase process innovation through scale economies stemming from market-size effect.

Timoshenko (2015) finds that maturity of exporters significantly affects their product switching behaviour that new exporters add and drop products more frequently. She develops a model in which firm-product efficiency affects supply side, and firm-destination appeal affects demand for the firm's products. The model implies that firms learn about the appeal and preference for its products thus new firms respond to changes in demand by switching its products. Using micro data on Brazilian exporters, she demonstrates that the model model can capture two-thirds of observed product switching patterns.

Şeker et al (2015) develop a structural model of multi-product firms to show how imported intermediaries play a pivotal role in fostering product innovation. In their model, imported intermediate goods diminish the cost of innovation. Firms can increase the likelihood of product innovation as they gain insight from the knowledge embodied in foreign intermediaries. Using firm level data on Indian firms, they demonstrate that knowledge externalities derived from imported goods have a positive effect on product innovation rate of the firms.

Arkolakis et al. (2021) show that new export products that are distant from firm's core competencies are associated with higher unit costs. Additionally, there are economies of scope concerning market-access costs for additional products intended for a specific market destination.

Studies within the multi-product firms literature highlights that competition in the global market forces firms optimize therir product scope by focusing on top performing products. Another channel that can affect firm's product scope is the potential to access to cheaper and superior intermediate inputs through importing. Literature gives theoretical basis on on how imported inputs can affect firm performance and product scope. Firstly, complementary gains can be achieved when incorporating imported inputs into the production process (Ethier, 1982; Kasahara and Lapham, 2013). Secondly, international trade may enable the technology transfer by the diffusion of technologies embedded in intermediate import products. (Keller, 2002b; Goldberg et al., 2010).

Goldberg et al. (2010) focus on India's trade liberalization experience to explore the effect of trade liberalization on the product scope of firms. In their theoretical framework, they have separated the effect of trade liberalization into *price* channel and *variety* channel. Using firm level data on Indian firms they found that lower tariffs contribute to a higher abundance of new imported inputs, subsequently resulting in an expansion of the firm's product scope

Bas and Strauss-Kahn (2014) explore the role of imported intermediaries on export scope of firms using French firm-level database. They find that that percent increase in imported input varieties expand extensive product margin of firms 10.5 percent. Kasahara and Lapham (2013) analyze Chiliean plant level data and find that policies that prohibit importing activity have negative effect on export product scope of the firms. Using Turkish firm level data and Propensity Score Matching technique, Lo Turco and Maggioni (2015) shows that participation into importing activity positively affects the extensive product margins of the firms.

1.3. ECONOMIC COMPLEXITY AND RELATEDNESS LITERATURE

Most of the studies in the industrial organization and international trade literature adopting a mainstream neoclassical framework provides significant insights on how product switching occurs endogenously within firms. (Bernard et al., 2010; Eckel and Neary, 2010).

In neoclassical growth models, growth is defined as a function of capital and labour inputs. However technological progress is treated as an exogenous factor and it is assumed that technological development occurs outside of the economy (Solow, 1956). In contrast, endogenous growth theory argues that technological progress is essentially an endogenous process within the system. Human capital and knowledge accumulation are regarded as the most critical elements of technological progress which eventually affect the growth path of economies (Romer, 1990) There are numerous channels through that societies can gather knowledge, including formal education, on-the-job training, fundamental scientific research, experiential learning, process, and product innovation. Aghion and Howitt (1992) argues that one of the most crucial important determinants in endogenous growth is product innovation and diversification.

The evolutionary economics literature argue that knowledge stock within the firm accumulates through learning-by-doing (Nelson and Winter, 1982; Dosi et al., 2020). This accumulated knowledge is expressed through the development of cognitive capabilities in both individuals (in the form of skills) and firms (in the form of routines) (Nelson and Winter, 1982). In this sense, knowledge production is generally seen as a process of recombination of existent ideas. Because of the tacit and cumulative features of the knowledge, it is very difficult for other actors to imitate. Knowledge is generally specific to particular actors and variety of economic activities are representation of knowledge accumulation among different actors (Howells, 2002). Firms possess firm-wide capabilities that are relevant for all products and also product specific capabilites that are specific to a particular product.

Nevertheless, the capabilites specific to products within firms are often related. Therefore, firms tend to expand into products that exhibit technological similarities to their existing products (Boschma and Frenken, 2011). The cost of diversification diminishes as the degree of activity similarity increases because businesses typically have limited access to information and imperfect capabilities to absorb, process, and respond to new information, as highlighted by Cohen and Levinthal (1990).

Recent studies in economic complexity literature indicate that relatedness between products has significant implications to explain economic diversification (Hazir et al. 2019; Frigon and Rigby, 2022, Balland et al., 2022). In essence, we assert that two product/industry are related when they necessitate similar capabilites and knowledge. Products and industries may be related due to their need for similar production resources, such as knowledge bases, organizational culture, human capital, and supporting institutions (Hidalgo et al., 2007). It is argued that firms tend to diversify into *related* products in order to leverage their existing knowledge, resources, and capabilities to explore new opportunities (Boschma and Frenken, 2011). In diversification process, available pool of capabilities and knowledge play a crucial role in moving into new production areas by providing the firm with a foundation of existing knowledge, skills, and expertise. With the help of this knowledge base, firms can find and seize new market opportunities and create novel goods and services (Grant, 1996).

The role of relatedness in product diversification gained much more popularity after the pioneering work of Hidalgo et al. (2007) on *Product Space*. The concept of Product Space uses network analysis to model the structure of economic complexity and diversification at the country level. The Product Space is a graphical representation of the relationships between products based on their co-occurrence in countries' export baskets. Products that are commonly co-exported tend to be close to each other in the Product Space (more related products), while products that are not frequently co-exported are farther apart (less related products). In the market, goods and services differ in terms of what kind of capabilities they require. Each product needs its own tools, codes, and know-how that make it possible to produce it. For example, producing an electric car requires the availability of electric engineers, designers, battery suppliers and software connected industries etc. Products close to each other in the product space have similar capability and input requirements. Diversification is a naturally uncertain process. This uncertainty can be mitigated by leveraging existing local capabilities in the process.

The Product Space framework suggests that countries or firms may face path dependence and diversification constraints in their efforts to diversify into new products market (Hausmann and Hidalgo, 2010, Kharel, 2019; Hidalgo, 2021). Since the seminal work on the product space by Hidalgo et al. (2007), it has been applied into different domains such as the technology space (Kogler et al., 2013; Rigby, 2015; Balland et al., 2019), the industry space (Neffke et al., 2011; Essletzbichler, 2015), the occupation space (Muneepeerakul et al., 2013, Jara-Figueroa et al., 2018).

Using the product space framework, many studies have examined the impact of relatedness on product diversification and the emergence of new industries. Haussman and Klinger (2007), Hausmann and Hidalgo (2010) and Boschma and Capone (2016) empirically demonstrate that the existing industrial structure of countries has a significant effect on the future state of industrial structure. They argue that countries' industrial structure is governed by a path-dependent evolution process and countries predominantly expand their export product portfolios by entering products related to their existing portfolios. The economic geography literature confirms the same phenomenon at the regional level, suggesting that the presence of locally related activities plays a facilitating role in the emergence of new products and industries (Neffke et al., 2011; Boschma et al., 2013; Boschma et al., 2017a). Most of the studies find related diversification more frequent as compared to unrelated diversification (Kogler et al., 2013; Essletzbichler, 2015, Boschma et al., 2017b).

The traditional approach to relatedness traces its roots back to the Resource-Based View of the Firm (Penrose, 1959; Wernerfeld, 1984) in the strategic management literature. In Resource Based Theory of the Firm (RBV) framework, Penrose (1959) evaluates the growth of firms as simply exploitation of productive opportunities. According to RBV, firms are regarded as a bundle of tangible or intangible assets such as physical assets, human capital, organizational culture, reputation, and technology (Wernerfelt, 1984).

Depending on these assets, firms have product-specific competencies to produce particular products. Therefore, firms often diversify into technologically related products instead of unrelated products. Since firms have accumulated both firm and product specific routines and capabilities over time, it would be a much more effective choice to diversify into *related* products that require similar capabilities. It’s more likely easier to shift from producing tables to chairs than it is to move from tables to computers.

Economic geography literature provides additional insights and empirical evidence suggesting that relatedness can extend beyond the scale of the firm. In fact, local economic structure can influence the firm-level dynamics of diversification (Hazir et al., 2019, Frigon and Rigby, 2022). Since capabilities are developed as a consequence of local interaction of firms and other economic actors, they tend to be place specific (Storper and Venables, 2004). Due to tacit dimension of the complex knowledge it also have tendency to lock-in a place (Maskell and Malmberg, 1999). Literature has produced robust empirical that diversification pathway of the regions are not random. But rather, they build new capabilities by leveraging their existing capabilties (Boschma et al., 2013; Essletzbichler, 2015; Boschma et al., 2017a).

Recent studies in the literature investigate how a firm’s product diversification choices are influenced by the capabilities present at firm and local levels (Lo Turco and Maggioni, 2016; Hazir et al., 2019; Frigon and Rigby, 2022). Thus, exploitation of capabilities is not only an internal process but also a result of interactions with the external environment. This highlights the importance of understanding and leveraging the unique capabilities and resources of a specific location to drive innovation and competitiveness in firms operating within that region. Empirical works obtain similar results, showing that the beside of internal resources, local product space matters for a firm’s product entry decision, and firms tend to diversify into products that require similar capabilities available at the firm and local levels (Poncet and Waldemar, 2015; Frigon and Rigby, 2022).

CHAPTER 2: PRODUCT DIVERSIFICATION AND RELATEDNESS

2.1. ROLE OF FIRM AND PLACE BASED CAPABILITIES

In this thesis, we adopt multi-level perspective by addressing role of both firm and local level capabilities. This section delves into two subsection with more detailed focus on role of relatedness on product diversification of firms. The first subsection explores role of firm based factors that shape a firm's product diversification strategy. It unfolds the Resource-Based View (RBV) of the firm, emphasizing the distinctive nature of resources possessed by firms and the immobility of these resources as crucial factors in gaining sustainable competitive advantages. The second sucsection shifts the focus to the role of local capabilities and aglomerations. It highlights the importance of local knowledge sourcing and embedded socio-economic relations in fostering knowledge spillovers.

2.1.1. Firm Level Capabilities

Productive structure at the firm level can indeed have a significant impact on its product diversification strategy. The productive structure, which includes factors such as resources, capabilities, organizational structure, technology, and processes, plays a crucial role in shaping a firm's ability to successfully implement and manage product diversification (Barney, 1991; Wan et al., 2011; Neffke and Henning, 2013).

In her pioneering work named *The Theory of the Growth of the Firm,* Edith Penrose (1959) laid the foundations of the Resource-Based View (RBV) of the firm. Later, with the works of Wernerfelt (1984) and Barney (1991), it became the dominant framework in strategic management field. RBV offers a framework to understand the foundational elements of organizational performance and competitive advantage. RBV is based on two underlying assumptions that explain how firm-based resources create long-term competitive advantage and why some firms are more competent than the others.

First assumption highlights that resources possessed by the firms are distinct from one another. Not all firms are equal in terms of resources, and those with distinct and difficult-to-replicate resources are more likely to achieve sustainable competitive advantages (Penrose, 1959; Wernerfelt, 1984). In essence, firms are unique combinations of resources where internal capacities and organizational procedures come together with product-specific capabilities related to the production of a specific commodity. These product-specific capabilities create a crucial foundation of knowledge that firms can leverage while exploring new diversification areas (Penrose, 1959).

Second assumption is about resource immobility which emphasizes that difficulties in trading resources may lead to persistent differences in resources. Immobility of resources inhibits other firms from quickly obtaining or imitating a firm’s resources. It also suggests that firms might encounter challenges in selling their excess unique resources within the market (Nelson and Winter, 1982). Adapting these productive resources across several business areas in the firm is regarded as an optimum strategy since marginal costs of employing those resources in the same firm are generally minimal. Potential benefits of utilizing them in a different business segment can be substantial (Rumelt, 1974; Barney, 1991).

In RBV, resources can be seperated into two types: tangible and intangible. Tangible resources are those that are easily visible, touchable, and quantifiable. It includes; firm’s pyhsical assets, properties and cash. On the other hand, intangible resources are difficult to observe and quantify. It includes; employee skills, brand, intellectual rights etc. Capabilities are another fundamental concept within RBV. Particularly, capabilities refer to the ability of the firm in managing and exploiting resources to generate value added and gain an advantage over competitors. Resources imply what a firm owns, while capabilities denote what the firm can accomplish (Makadok, 2001).

One of the significant aspects of the RBV is that it puts resources and capabilites rather than market forces into the front. Firms will have motivation to diversify when it possesses excess resources that make diversification economically viable (Teece, 1992; Wernerfelt, 1984). RBV argues that related diversification can lead to better company performance compared to a strategy that concentrates on a single area. With this strategy firms can make the most of their resources across various businesses to gain extra benefits. When businesses are related, they can share important resources among their units, which creates a stronger portfolio of businesses (Wan et al., 2011).

RBV of the firm argues that relatedness has significant importance in diversification efforts. Relatedness refers to the similarity or compatibility of resources and capabilities across different business units or industries within a diversified firm. The RBV suggests that relatedness can lead to synergies and economies of scope, where resources can be shared or leveraged across different units, resulting in cost savings or enhanced capabilities (Wan et al., 2011).

Wernerfelt (1984) argues that existing resources are foundation for diversification and the resources that should be built up through the process of diversification. Optimal growth strategy is about achieving balance between exploitation of available resources and development the new ones. Barney (1991) proposes essential logic to explain why firms choose diversification. He emphasize that resource immobility and diversity are key factors. Moreover, he argues that resources of firms that generate competitive advantage have four main dimension; value, rareness, imitability, and substitutability.

Knowledge within the firm is not static and is shaped by internal and various external factors. Teece et al. (1997) introduce the concept of dynamic capabilities, suggesting that the sustainable advantage of a firm depends on more than the possession of valuable assets. Dynamic capabilities refer to a firm's ability to adapt, integrate, and reconfigure its resources and capabilities in response to rapidly changing environments (Winter, 2003).

Experimentation with new production areas may be risky and costly for firms. Thus, due to the cumulative nature of learning, firms have an incentive to diversify in closely related products (March, 1991). Main principle of the relatedness is that the probability of diversifying into any particular product is the function of presence of multiple related products in the firm. Products are structurally related, either through shared inputs, technologies, or skills. This interconnectedness allows for smoother transition and expansion into related products. In the literature many studies provide empirical evidence on how firm’s diversify into related fields by exploiting internal resources and capabilities.

Patel and Pavitt (1997) explores the world’s largest 400 firms. They show that large firms have multi-field and complex competencies beyond their principal fields. They demonstrate that each firm’s search for a new technological domain is strongly influenced by its prior competencies.

Matsusaka (2001) develops a model with an aim to formalize ideas of Penrose (1959) in terms of dynamic optimization neo-classical model in which firms use diversification as a value-maximizing strategy. In his framework, firms are in a dynamic search process to achieve an optimum match with their organizational capabilities. However, this process is associated with uncertainty to some degree. During the search process, firms experiment through entering new industries and measuring their outcomes by diversification. Diversification occurs when companies shift across industries and eventually exit their original business when they find an optimum match.

Breschi et al. (2003) investigate the role of knowledge relatedness in firms' technological diversification process using the European patent application dataset from 1978 to 1993. Their findings indicate that the firm's innovative search occurs within the technological areas that are proximate to the current technological know-how and capabilities. Moreover, they observe that larger diversifiers are more "coherent" in terms of knowledge-relatedness of their technological activities than smaller diversifiers.

Bryce and Winter (2009) develop an interindustry relatedness index to investigate new product choices of US manufacturing firms between 1987 and 1992. They show that the relatedness index they developed is a strong predictor of the diversification paths of the US firms.

Neffke and Henning (2013) pay special attention to the skills of human resources to measure similarity of the industries depending on their skill requirements. Using data on cross-industry labour flows in Sweden for the period of 2004-2007, they construct a skill relatedness index. Their econometric estimations reveal that firms are highly likely to diversify into new product categories that are connected to the skills of their workforce in order to leverage available human resources.

Using firm level patent data for US firms, Frigon and Rigby (2022) demonstrate that existing innovation assets have significant impact on future technological diversification. Their findings indicate that technological diversification choice of the multi-locational firms is mostly shaped by capabilities present within individual plants.

While these studies emphasize the close connection between diversification choice and existing capabilities, they do not dismiss the possibility of exploring new domains. Firms that possess abundant resources and capabilities will face fewer constraints related to specific resources, providing them with more opportunities for unrelated diversification. (Wernerfelt, 1984; Boschma and Capone, 2016). On the contrary, if the level of the resources and capabilities are weak and limited then the diversification window may be constrained strongly within the limits of relatedness. In management science, an organization's capability for performing both exploring and exploiting is termed organizational ambidexterity (Tushman and O'Reilly, 1996). The ambidextrous strategic capacity of firms is often associated with their size and organizational structure. For example, owing to their large pool of resources, larger firms may assign their subunits with differentiated objectives, encompassing either exploitative or explorative practices. Consequently, large firms may have a greater potential to diversify into more unrelated areas and broaden their portfolio (Tushman and O'Reilly, 1996; Raisch et al., 2009).

Earlier work on firm diversification based on relatedness centrally rests on endogenous factors available at the firm level. The knowledge within a firm is dynamic and is shaped by a combination of factors, including firm-specific elements and external influences. Exogenous factors such as trade and investment relationships, network linkages could also play a role in fostering the emergence of products and economic activities within the firm (Boschma and Iammarino, 2009; Goldberg et al., 2010; Alonso and Martin, 2019).

Especially for firms engaged in foreign trade activities, it is possible to access new sources of information through imports and use them in the development of new products to be produced by the firm. Numerous studies have shown that firms might have the opportunity to expand their knowledge pool with the foreign trade connections they have established (Goldberg et al., 2010; Jun et al., 2020). Particularly, importing activity of exporters not only provides inputs to the exporter firms. Also, it enables the transfer of knowledge through formal and informal channels. When a firm imports new technologies or inputs, it may also gain knowledge about how to use these inputs in innovative ways (Acharya and Keller, 2009). Information obtained through importing activity may be used to develop new products or improve existing ones. For example, a firm that imports advanced manufacturing equipment may learn new production techniques, imitate and adapt these products to develop new products. In this regard, the foreign trade relations of the firm may influence its product innovation capabilities through technology spillovers (Alonso and Martin, 2019).

Goldberg et al. (2010) present empirical evidence demonstrating a robust relationship between the availability of new foreign intermediate inputs and the expansion of product scope by Indian firms. Agosin et al. (2012) show that the trade liberalization process fosters export diversification by expanding the trade destinations and demand for firm's export products. Relatively lower input costs and specialized human capital induces firms to allocate larger amounts of investment to adapt imported goods and technologies to new markets. Kehoe and Ruhl (2013) report that trade liberalization in the countries is generally associated with a significant increase in the traded volume of goods that were not traded before. Using 1.913 bilateral country trade data, they find that growth in the extensive margins accounts for 80 percent of global trade.

Some recent studies in the literature have examined the impact of import activity on diversification within the relatedness approach. Boschma and Capone (2016) examine industrial diversification of EU countries and they find that imported products are significant driver of new product choice such that countries diversify into products related to their import products. Recently, Alonso and Martin (2019) investigate how trade transactions could encourage regional diversification in the cases of Brazil and Mexico. They find that regions have a tendency to diversify into products similar to their imports suggesting that international trade could play a role for external knowledge and technology acquisition.

Even though there are several studies (Boschma and Capone, 2016; Alonso and Martin, 2019) investigating the relationship between importing activity and diversification at country and region level, it is worth noting that, to our knowledge there is not any empirical study examining the effect of import relatedness at the firm level. In the framework of relatedness, one can argue that in the case of absorption of external knowledge and combining existing ideas, might encourage firms to start exporting products that are proximate to their import basket.

2.1.2. Place-Based Capabilities and Agglomerations

Studies exploring firm diversification in RBV approach (Barney, 1991; Matsusaka, 2001 Breschi et al., 2003) mostly focused on internal resources and capabilities. However, these studies generally do not consider the significance of firm-local interactions and agglomeration economies. Economic geography literature often highlights that knowledge externalities at local and regional level have significant role on innovative activities of the firms (Duranton and Puga, 2003; Beaudry and Schiffauerova, 2009; Beugelsdijk, 2009). Besides the internal knowledge resources, place-based knowledge may be significant for the innovative activity of the firm and it can provide firms with access to new and diverse knowledge that may be unavailable or difficult to generate internally.

Embedded socio-economic relations and institutions have a huge role in stimulating knowledge creation at the local and regional level. Economic space is not only a "container" where economic activity takes place further its a place where collective learning occur among agents from different layer such as; firms, customers, universities, institutions, local authorities (Maskell and Malmberg, 1999). It is often highlighted that untraded interdependencies and localized capabilities related with some specific area is generally accumulated and bounded at regional level (Boschma, 2005).

In this process, firms may benefit from the local knowledge base by accessing and absorbing the relevant knowledge and information present in a local environment. Geographical proximity plays a crucial role in facilitating knowledge spillovers and the exchange of tacit knowledge (Howells, 2002). When firms are spatially close to each other they have more chances for face-to-face interaction and collaboration with other stakeholders. Thus, proximity can foster trust and relationship building among firms, which are significant for the transmission of tacit knowledge. Moreover, through social interactions and labour mobility, capabilities dependent on tacit knowledge can diffuse easily. In economic geography literature it is well documented that the likelihood and magnitude of knowledge spillover effects increase as geographical distance decreases (Jaffe et al., 1983; Keller, 2002a; Frenken et al., 2007).

There may be several ways in which a firm can be engaged in the local learning process. The first way may be a firm’s interaction with other firms, customers, and suppliers to identify consumer preferences and market opportunities (Fuchs & Kirchain, 2011). With the help of these insights, firms may develop new products that are tailored to the local market. The second way is the firm’s participation in local knowledge-sharing platforms, including clusters, trade associations, non-formal networks, etc. In these platforms, firms may have the opportunity to interact and learn from each other’s experiences. The third channel is labor mobility, where workers move between firms allowing firm’s to access the new skills and information that are acquired from former work experience (Boschma and Frenken, 2011; Neffke and Henning, 2013).

However, being located in the productive local environment is not a sufficient condition for firm’s to take advantage of present knowledge. When firms’ existing capabilities are related to the local environment, they are better able to understand and interpret the knowledge and information that is available to them. Cognitive proximity to local productive structure may facilitate the exchange of tacit knowledge between firm and other actors in the region. (Bathelt et al., 2004; Boschma, 2005). More specifically we can say that a firm's existing production base should be related to competitive industries of the local economy to effectively benefit from knowledge spillovers. The local-product specific capabilities may influence a firm's choice over new products.

While the role of relatednes on regional diversification have been extensively addressed in the literature (Neffke et al., 2011; Boschma et al., 2013; Boschma et al., 2017a), the dynamics of firm diversification and its interaction with the regional economy remain relatively understudied. A few empirical studies investigated how a firm's diversification process is influenced by local product space and environment.

Lo Turco and Maggioni (2016) analyze how firm and local product-specific capabilities affect the product innovation of Turkish manufacturing firms. They find a strong effect of path dependence on new product choice. They also find that firms in less developed areas are more dependent on internal resources while firms in developed areas benefit from local productive structure much more.

Esposito and Rigby (2019) develop a simulation model of how firms exploit accumulated knowledge stock and recombine technologies available at local and non-local partners. They show that more interaction among firms within the clusters tends to raise both the average productivity of firms as well as the product scope of the firms. In addition to within-cluster interaction, a firm's connection with extra-region clusters has a positive impact on firm performance.

Hazir et al. (2019) investigate the factors that influence changes in the scope of exports at the firm level with particular attention to the role played by the firm's local product space. They utilize microdata from French firms spanning the period from 2002 to 2007. Their findings indicate that the local productive structe has a significant impact on the decisions of firms to enter or exit product markets. Firms tend to introduce export products that align competencies present in their local environment.

Frigon and Rigby (2022) investigate establishment-level patent datasets to identify the main sources of capabilities for technological diversification of multi-locational firms. Their results demonstrate that internal capabilities have the greatest importance in the process of technological diversification, as compared to place-based capabilities.

Studies in the existing literature generally examine the factors affecting firms' product choice by focusing on firm-based and region-based resources (Lo Turco and Maggioni, 2016; Hazir er al., 2019). In reality, many firms are engaged with other regions and countries through trading and partnership relationships. There is an extensive body of literature highlighting the interaction between firms, especially those situated in different geographical locations, as crucial for acquiring new ideas (Bathelt et al., 2004; Defever et al., 2015; Boschma et al., 2017b; Bathelt and Storper, 2023). The main idea is that the required tacit knowledge might acquired through market mechanism thus collaboration with partners elsewhere may provide a channel for accessing alternative knowledge pools (Bathelt et al., 2004). These connections allow them to share information across distances, potentially reducing their reliance on knowledge from their home region. Nonetheless, spread of capabilities are expected to be constrained by pyhsical distance (Jaffe et al., 1993). One can argue that firms are more likely benefit from spillovers when the key source is in the neighbor regions.

To our knowledge, there is not any empirical study that investigates the role of spillovers stemming from neighbor regions on diversification trajectories of firms. However at country and region level, several papers have investigated the role of the knowledge and capability spillovers between neigbor countries/regions on diversification.

Bahar et al. (2014) find a positive relationship between a country's likelihood of acquiring a comparative advantage in a particular industry and the presence of a comparative advantage in the same industry within its neighboring countries. In a similar sense, Boschma et al. (2017) show that US states have a tendency to gain specialization in industries that neighbour state had already comparative advantage.

Agglomerations present within a region can also have an impact on the diversification trajectory of firms. Agglomeration economies are essentially costs and benefits that stem from the co-location of economic units in the same area (Duranton and Puga, 2003). Specifically, agglomeration economies emerge as a result of firms that are engaged in the production of similar or complementary goods, clustered together in a geographic area. This spatial clustering generates positive externalities for these firms due to the spatial proximity of firms, labour, consumer, and capital (Porter, 1998).

Regarding the microfoundations of the agglomeration economies, the literature points out that firms co-located in the same area benefit from agglomeration economies through three mechanisms; sharing, matching, and learning (Duranton and Puga, 2003; Eriksson et al., 2008; Puga, 2010). The agglomeration of economic activity may be industry specific or composed of a variety of industries. Therefore, externalities arising from existing situations may differ depending on the structure of agglomerated firms. In literature, agglomeration economies are often distinguished into three types; localization externalities, urbanization externalities, and Jacobs' externalities (Glaeser et al., 1992; Beaudry and Schiffauerova 2009).

Localization externalities capture benefits that are derived when the firms belonging to the same industries co-locate together. Earlier works of Marshall (1920) envisaged that the concentration of firms in the same industry allows firms to access specialized labour pool, suppliers, and clients much more efficiently. The specialization promotes the transmission of industry-specific tacit and codified knowledge and ideas via close business relationships and the circulation of skilled employees among firms. Localization externalities imply that the specialization of industry in a locality accelerates knowledge spillovers and innovation in a particular industry or sector.

Urbanization externalities are rather associated with the size of the city firm located. Throughout history, cities have always been the engine of growth and innovation. Urbanization externalities claim that the size of the city positively affects the productivity level of firms. Firms located in big cities benefit from common resources such as roads, universities, and large labor pool irrespective of their industries. Nonetheless, the size of the cities may be accompanied by some externalities like congestion, crime, pollution, and high factor costs (Glaeser et al., 2012).

The third type of agglomeration externalities is called Jacobs' externalities. The main idea is that, in contrast to localization externalities, spill-overs may occur between industries that are complementary to each other. Jacobs (1969) suggests that firms embedded in diverse environments take advantage of complementary knowledge from other firms. Jacobs (1969) argues that information may flow from other industries rather than similar industries. The existence of diverse firms and economic agents stimulates cross-fertilization of ideas creating opportunities for search and innovation in the local economy.

There is a large empirical literature exploring the effect of localization and Jacobs externalities on regional growth and firm productivity (Rosenthal and Strange, 2004; Beaudry and Schiffauerova 2009). However, few studies have investigated how agglomeration forces affect firm diversification. When we consider localization economies, externalities are dependent on what firms produce or what they want to produce. When some industries are agglomerated in the region it influences the growth of products they already produce as well as the probability of diversifying into new products (Cainelli and Iacobucci, 2016). Localization economies can impact the firm's product scope through both supply and demand sides. On the supply side, benefits obtained from shared inputs, resources, and infrastructure decrease the marginal cost of producing particular product. On the demand side, product-specific consumer preferences and tastes may create demand for product categories that agglomerated. Agglomerations might attract consumers with specific preferences for certain products or services. For instance, agglomerated areas with a high concentration of tech firms may attract consumers with a preference for technology-related products. Local specialization in specific products is expected to support the firms' diversification efforts into these products.

In urbanization externalities, benefits will be common to all firms in the local economy irrespective of what they produce. These externalities could arise from shared transportation infrastructure, social interactions, and institutions that facilitate exports, or more broadly, knowledge externalities. In practice, the size of the city may affect the growth and extensive margin of the firms regardless of the characteristics of the product (Hazir et al., 2019)

In terms of Jacobs externalities, its effect on firm diversification might change depending on the structure of the industrial composition. Frenken et al. (2007) argue that industrial variety structure of the local economy should be evaluated according to industries within' relatedness level. Recent studies in the evolutionary economic geography literature highlight that depending on the relatedness level of the industrial variety, effect of Jacobs externalities on firm's diversification may vary. Cainelli and Iaobucci (2016) argue that when unrelated variety prevalent in the local economy, it is more likely that firms will move into unrelated – more distant products. On the other hand, when the local economy consists of mostly related industries, firms will have a tendency for moving into nearby, related products that require similar capabilities. Castaldi et al. (2012) show that related variety promotes incremental innovation whereas unrelated variety promotes. technological breakthroughs in a type of radical innovation.

2.2. MEASURING RELATEDNESS

Despite the importance of the relatedness concept, the definition of relatedness, and the methods for measuring relatedness still remain fuzzy and mixed. Measurement of relatedness comes up with significant challenges since relatedness refers to the similarities among the resources used in different industries, therefore relatedness must have as many features as there are distinct types of resources. How can we measure skills, capabilities, know-how? Or how can we quantify them with an aggregate in an index? These are essential questions that are being attempted to be answered by plenty of studies in the economics (Teece et al., 1994; Hidalgo et al., 2007; Bryce and Winter, 2009) innovations studies (Jaffe, 1986; Breschi et al., 2003) and economic geography literature (Frenken et al., 2007; Boschma et al., 2013; Essletzbichler, 2015).

Principle of relatedness characterizes the empirical connection between the likelihood of a firm (or location) entering new economic activity and the existence of related activities within that same firm (or location). Measures of relatedness are essentially designed to evaluate similarity among pairs of products or activities. A review of the empirical literature on relatedness shows that metrics measuring relatedness between products/industries are generally used for two different purposes (Content and Frenken, 2016). Firsty, they are being used for measuring overall coherence of activities within firms or regions. Initially, Frenken et al. (2007) proposed the concept of related variety to measure relatedness within economic activities in the region. They argue that related variety in the region would stimulate employment growth and innovation through re-combination of existing ideas and capabilities leading to creation of novel economic activities. In empirical studies, related variety measures are generally used to explore the effect of related variety on employment growth, value added-growth and other economic performance indicators at regional or national level (Frenken et al., 2007, Saviotti and Frenken, 2008; Davies and Mare, 2021). Another application of the relatedness metrics is to investigate how relatedness affects the diversification pattern of firm, region or countries. Following pioneering study of Hidalgo et al. (2007), many studies questioned whether firms/regions diversify into new products/industries that require similar skills, institutions, infrastructure and technology with the existing productive base (Boschma et al., 2013; Essletzbichler, 2015; Xiao et al., 2018; Balland et al., 2019).

Until now, scholarly work has recognized three main methods for measuring relatedness: those relying on industry classification hierarchies, co-occurrence of products/industries, and resource similarity, as outlined by Neffke and Henning (2013). This section reviews the characteristics of the three main approaches to the empirical measurement of relatedness identified in the literature.

2.2.1. Hierarchical Methods

Earlier works on relatedness metrics take advantage of pre-existing industrial classification systems such as SIC, NACE, SITC etc. In this methodology, relatedness is usually computed based on distance between within the tree structure of hierarchical classification systems (Bryce and Winter, 2009). In these classification systems, each digit represents economic activity category. The first digit denotes the broad product category to which a product belongs, the second digit denotes the sub-product, the third digit denotes the sub-product, and so forth.

In hierarchical methods, relatedness is generally defined as the number of initial digits that industries have in common across tree structure. Implicitly, this approach assumes that the design of the classification correctly reflects relatedness among industries. This measurement approach is therefore ex-ante.

Frenken et al. (2007) developed indices that measure relatedness and unrelatedness variety of sectoral structure of Dutch regions. Particularly, they considered entropy of two digit distribution of sectoral shares in employment for unrelated variety level of regions. Similarly, the weighted sum of entropy at the five-digit level within each two-digit sector is considered the level of related variety for regions.

Some studies go beyond the classification schemes of sectors and conceptualize relatedness according to correlation of input and distribution structure of products. Rumelt (1974) classifies business and product into related and unrelated categories by considering similarity of input needs, production technology and distribution channels. Particularly this approach allows researchers to clearly identify interpretation of the measure. However, this approach suffers from subjectivity on which dimensions represent relatedness and their relative weights.

Lemelin (1982) treat the relatedness concept in two dimension; (1) industrial complementarity, (2) markets served and distribution system. For the former dimension, he used input-output tables to compute correlation coefficients across industry input structures between the input coefficients of the two goods. For the latter; they utilize Porter's (1976) trichotomy which classifies industries into three types of buyer-seller relationship: producer good industries, consumer convenience good industries, and consumer nonconvenience good industries. If any pairs have the same characteristics then they regarded as related in terms of market and distribution system.

Hierarchical approaches are heavily criticized due to lack of satisfactory formal justification for assuming that the hierarchical structure of industry classifications reflects the degree of scope economies among industries (Fan and Lang, 2000; Neffke and Henning, 2013).

2.2.2. Co-occurrence Based Approach

Co-occurrence approaches on measuring relatedness adopt ex-post and data-driven perspective. While-ante approach[1] is more theoretical and anticipatory, the ex-post approach is more empirical and based on real-world observations. This approach uses historical data and real-world observations to analyze the actual relationships between products that have already occurred. It is more data-driven and relies on factual information rather than predictions or assumptions. Empirical studies using this approach adopt a resource-based view of firms, accounting for many unobservable resources that firms share across different activities. (Whittle and Kogler, 2019).

Teece et al. (1994) suggested the *survivor principle* in economic competition and co-existence of different economic activities. They argue that activities that are more related will be frequently observed within the same firm (Teece, et al. 1994). They develop a relatedness measure by calculating the count of joint co-occurence of different industries and normalizing this frequency. In their methodology, a firm doesn't perform a coherent pattern of technological diversification when its competences are randomly distributed across technological fields. They suggest that the coherence of activities within firms can be understood through five driving forces; (1) organizational learning, (2) path dependencies, (3) technological opportunities associated with core competences of the firm, (4) level of complementarity in firm's assets, (5) selection environment.

Breschi et al. (2003) has enhanced the methodology developed by Teece et al. (1994) but applying on different area that is knowledge relatedness. They take patent

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[1] As seen in the hierarchical approach.

applications as a indicator of firm’s technological competencies assuming that if firm applies for patent in particular sector implies that firm is close to technological frontier in that area. Using European Patent Office (EPO) – CESPRI dataset, they calculated joint occurrences of all possible pairs of classification codes within patent files to obtain symmetric matrix of co-occurrence among 30 technological fieds. Moreover, they utilized the correlation coefficient (cosine index), measuring the similarity between two technological fields based on their mutual relationships with all other fields. This approach offers the advantage of being symmetric.

The Product Space approach proposed by Hidalgo et al. (2007) is a network that formalizes the notion of relatedness between products traded in the global economy. In order to create this network relationship between products, Hidalgo et al. (2007) constructed an indicator of proximity which is based on co-exporting probabilites of each product pair. This approach assumes that co-exporting patterns represent similar requirements regarding institutions, infrastructure, resources, technology, or a combination of these factors.

In Product Space approach, it is assumed that every product necessitates a significant amount of non-tradeable inputs, referred to as capabilities (Haussman and Hidalgo, 2010). A country can only produce a given product if it has all of the required capabilities. The number and type of capabilities needed vary by product, and countries vary in the amount and kind of capabilities they possess. Products that require a greater number of capabilities will be less widely available to countries, while countries that have a higher number of capabilities will be able to produce a greater range of products, resulting in greater diversification.

Product Space integrates these ideas, representing all globally-exported products in a network where products are connected based on the similarity of the capabilities they necessitate. For example, there is a stronger link between chair and tables than there is between chair and computer monitors. An implication derived from the product space model suggests that poor countries may face difficulties in converging with rich countries' income levels due to the lack of connectedness between high- and low-productivity products. In fact, this lack of connectedness exists between products located in the core and periphery of the network, respectively (Haussman and Hidalgo, 2010).

In co-occurence based relatedness methods, researcher doesn’t have to make assumption about the factors influencing product scope such as technology, human resources, raw inputs etc. Instead of making assumptions about the factors, it attempts to estimate the combined presence of many quantifiable and unquantifiable factors as a latent variable (Hidalgo, 2021:1). This is quite consistent with the resource-based view of the firm (Barney, 1991) because in empirical work identifying the resources that are critical for growth of the firm is challenging due to tacit and implicit features of the useful resources.

2.2.3. Resource-Based Methods

The third approach to measure relatedness is called resource-based methods and they essentially assess the similarity of the resources that products or industries utilize. This approach slightly differs from previous methods by taking up bottom up perspective (Whittle and Kogler, 2019).

Jaffe (1989) attempts to measure the technological position of US firms by utilizing the distribution of firm's patents over 49 technology fields they belong to. Employing the k-means clustering algorithm, he categorizes firms into distinct technological groups based on their technology position vectors.

Fan and Lang (2000), use input-output tables to measure similarity of industries according to their input requirements. Two industries are considered to have a vertical relatedness when one industry uses the products or services of the other in its own production process or provides its output as input to the other.

Neffke and Henning (2013) adopts resource-based view and recognizes the crucial role of skills of workforce in a firm's strategic assets. They argue that relatedness among industries may be proxied through their skill similarities in their workforce. They develop an index called skill relatedness which utilizes cross-industry labor movement to predict the direction of a firm's product diversification. Their findings indicate that firms tend to diversify primarily into products that exhibit a strong skill-related connection with the firms' core products, even though these target products are frequently classified in different categories.

Jara-Figueroa et al. (2018) suggest to measure relatedness among industries by analyzing labour flows between industries at the national level. Using econometric approach, they conceptualize relatedness between two industries according to characteristic of labour flow among them. They employed regression equation estimates labour flow within the pair of industries as a function of the size of the industries and their growth rates. They treat residuals as a measure implicity representing relatedness between pair of industries since if labour flow between industries is higher than expected then unexplained part will be captured from residuals.

Some scholars have raised concerns regarding the resource-based relatedness measures due to its industry specific character. Resource requirement differences across industries led to challenges in effectively applying this measure. For instance, relatedness measures based on patent data may be more applicable in knowledge intensive industries while input-output data could provide more value for analyzing traditional manufacturing industries (Essletzibchler, 2015: 4).

CHAPTER 3: DATA AND METHODOLOGY

3.1. DATA

This section explains the primary data sources and construction of the final dataset used in empirical analyses. The product space methodology leverages detailed data on thousands of economic activities to gain insight into both the abstract factors of production and how they come together to yield numerous outputs. Thus, in the scope of this thesis, product level export data of Turkish firms level is used to analyze the diversification of firms. Export data is often used for product space analysis because it provides valuable information about a firm’s capability in various industries and products.

The utilitization of export data has several advantages over using employment or production data. Since exported products represent the final outcome of the production process, it shows a firm’s competitiveness in the global market. Various factors, such as technological capabilities, human-physical capital, and management quality influence firms’ ability to export. By analyzing a firm's export data, one can identify the products that the firm is competitive in producing and exporting to other countries and assess the extent of the firm's product diversification. Furthermore, export data is generally more available and consistent as compared to alternative indicators.

The initial data source in our analysis is the UNCOMTRADE database, which contains import and export data for countries at the product level (UNCTAD, 2023). Product level trade data is available with 1992, 1996, 2002, 2007, 2012, and 2017 versions of the Harmonized System (HS, four-digit level) classification and is updated annually. We work with version 2012 of the HS product classification to make it compatible with firm-level export data. Fourth-digit product level trade data is used to compute the global product proximity matrix and product complexity values.

Second and main data source of this thesis is the Entrepreneurship Information System (EIS) which will be used to perform firm-level analysis. EIS is a firm-level database managed by the Ministry of Industry and Technology of Türkiye. EIS is a vast database of firms with enterprise and establishment-level data. It contains multiple administrative datasets from different public institutions in Turkey. It includes hundreds of firm-level indicators such as social security records, tax records, business registry, financial sheets, custom records, received government support, etc. It covers most of the sectors in the economy only excluding agriculture, finance and public service sectors. EIS provides the most extensive database for firms in Turkey and contains annual data from 2006 to the present and is regularly updated yearly.

In the EIS, our primary focus is the Foreign Trade Database which contains firm-product specific export and import values of Turkish firms. Foreign Trade Database includes columns such as unique firm id, product classification, year, destination, export-import status, monetary value etc.

Foreign Trade Database in the EIS is the unique data source that records detailed annual information on firms export and import product mix in the Türkiye. EIS collects and compiles these detailed data in time, allowing us to track changes in the export-import product basket of Turkish firms. In the database, product specific export-import volume of each firm is disaggregated at Custom Tariff Statistics Number (GTIP) twelfth-digit. GTIP is a national classification system and it is compatible with Harmonized System (HS) classification system[2]. The dataset starts from 2006 and is updated on an annual basis.

Prior to analyzing firm-level foreign trade data, we applied several preliminary aggregation and filtering processes to obtain final cleaned data. Firstly, product-level export and import data at GTIP-12 resolution have been aggregated to fourth-digit HS classification (HS-4). Afterward, observations that any firm's value is less than 1000 USD for any HS-4 product have been filtered out from the dataset. This filtering process allows us to exclude observations that are within the firm's portfolio but are insignificant and result from measurement errors.

Another dataset we use from the EIS is the Registry Records Database of the firms. The Registry Database includes many meta-features of firms such as age, scale, sector, wage level, and employment level. We merged the registry records of each firm with the Foreign Trade Dataset during the construction of the final data frame. Combining these

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[2] The fourth digit of the GTIP system is the same as the HS system.

datasets allows us to explore the diversification performance of firms concerning heterogeneities among the firms.

This study focuses on exporter firms within the manufacturing sector[3]. There are several reasons why manufacturing firms may be significant to focus on when analyzing a firm's export performance. Firstly, manufacturing firms are often more export-oriented than other types of firms. This is because manufacturing firms tend to produce goods that can be easily shipped and sold in other countries, whereas service-based firms may have more difficulty exporting their products or services. Manufacturing firms are directly involved in the production of goods, making them central to understanding product diversification (Dosi et al., 2020). Their activities involve product design, development, and production processes, providing valuable insights into how firms expand their product offerings (Fuchs and Kirchain, 2011). By focusing on manufacturing firms, researchers can gain a more comprehensive understanding of how these firms navigate product diversification challenges and leverage the local productive environment for learning.

Manufacturing firms are often embedded in the local productive environment, relying on local suppliers, skilled labor, and infrastructure. These firms interact closely with the local ecosystem, including suppliers, customers, and other industry players (Fuchs and Kirchain, 2011; Hazir et al., 2019; Furthermore, when we investigate the data, we observe that 52 percent of total export belongs to manufacturing firms in the EIS database.

In this study, the time frame of interest is the 2012-2017 period. This period has been focused on for various reasons. Firstly, we observe that most of the the similar studies use a five year window to account for the time frame needed for a firm to develop a product, test and trials and other adjustments (Neffke et al.; 2011; Boschma et al., 2017; Hazir et al, 2019). Secondly, for the case of Türkiye this period is more appropriate to analyze product diversification patterns of exporters. Becase, Türkiye experienced currency crisis in the 2018 and this year is followed by reccession period caused by Covid-19 pandemic.

This specific period has been chosen for several reasons. Firstly, it aligns with the time frame commonly utilized in similar studies, typically employing a five-year window to

[3] Firms that are registered under NACE “C-Manufacturing” category.

account for the duration required by a firm to develop a product, undergo testing and trials, and make necessary adjustments (Neffke et al., 2011; Boschma et al., 2017; Hazir et al., 2019). Secondly, for the case of Turkey, ending the analysis year as 2017 may be more appropriate for analyzing the product diversification patterns of exporters. This choice is justified by Turkey's experience of a currency crisis in 2018, followed by a subsequent recession period triggered by the Covid-19 pandemic.

We explore how introduction of new export products is influenced by its relatedness to firm and local level capabilities for Turkish manufacturing exporting firms. Therefore, in our sample only the manufacturing exporters that survived from 2012 to 2017 are considered in the analysis. In the EIS foreign trade dataset, there were 55.055 active exporting firms in 2012, which was the initial period, and 41.254 in 2017. The number of firms that continued to exist in both periods was 26.167. When considering only manufacturing exporters within this group of 26.167 firms, the sample size was reduced to 12.666 exporting firms. In the descriptive and stylized facts section of the thesis, we focus on these 12.666 firms. However, in the econometric estimation analysis

Table-1 summarizes the key descriptive statistics of a sample consisting of 12.666 manufacturing firms with respect to their scale. The table demonstrates that most of the firms that participate in exporting activity are small scale firms enterprises which are followed by medium scale firms. However, when the total value of exporting is considered, the result is striking. Aggregate exports are driven by large companies. They account for almost 75 percent of total export within the manufacturing sector.

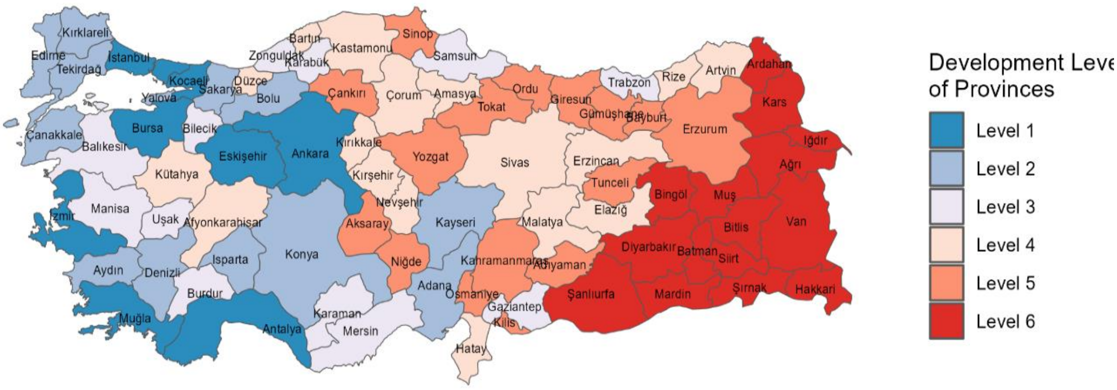
Table 1 - Descriptive Statistics of Firms - 2012

Scale of Enterprise	Total Export Value	Number of Firms	Share of Total Export Value
Large Scale Enterprise	53.656.452.225	1.168	74,18%
Medium Scale Enterprise	12.037.467.471	3.226	16,64%
Small Scale Enterprise	5.732.016.504	6.019	7,92%
Micro Scale Enterprise	908.894.581	2.253	1,26%

Source: Entrepreneurship Information System

The third dataset that we use is province-level socio-economic development status data comes from the study Socio-Economic Development Ranking Research of Provinces and Regions (SEDI) conducted by the Ministry of Development (Ministry of Development, 2013). In this study, the overall socioeconomic development score of each province is estimated using Principal Component Analysis with 61 variables. These variables represent eight distinct dimensions of development, including; demographics, employment, education, competitiveness, finance, accessibility, and life quality. According to their scores, provinces are classified into six ordered development categories in which first-level regions correspond to most developed provinces, whereas sixth-level regions correspond to least developed provinces. Although SEDI studies have been conducted at regular intervals, the most recent studies are for 2011 and 2017. The development categories in the 2011 SEDI study were taken into consideration since they are closer to 2012, which is the starting period of the study. Development levels of each province are used for explorative analysis on product diversification patterns of the manufacturing firms. Figure-1 below demonstrates socio-economic development level of the Turkish provinces according to the SEDI 2011 study.

Figure 1 – Socio-Economic Development Level of the Provinces (2011)



Source: Ministry of Development (2013)

3.2. STYLIZED FACTS ON EXPORT DIVERSIFICATION PATTERNS OF TURKISH MANUFACTURING FIRMS

Before conducting an econometric analysis, it is beneficial to highlight a few noteworthy stylized facts concerning export diversification patterns. Examining the firm level dataset uncovers certain facts about the extensive margin of exports, which are not observable at the macro level. In this section, we only focus on 12.666 exporting firms in our sample.

Table-2 and Table-3 show product switching patterns within firms with different scales. We examine the change in the export product portfolio between 2012 and 2017. In order to investigate what are the characteristic of change in the export baskets of the firms, we define four possible mutually exclusive scenarios: (i) *Both Add and Drop* – the firm both add and drops product; (ii) *Only Add* – the firm adds new product(s) to the basket; (iii) *Only Drop* – the firm drop existing product(s) from basket; (iv) *Steady* – the firm does not change the basket of products.

Table-2 shows firm count values whereas Table-3 shows the proportions of firms according to the classification stated above. As it can be seen from Table-2 and Table-3, there are significant heterogeneity among firms in terms of product switching patterns. Magnitude of product switches can vary greatly among firms.

Table 2 - Product Switching Among Exporting Firms - 2012 to 2017 (Count)

Enterprise Scale	Both Add and Drop	Only Add	Only Drop	Steady	Total
Large Scale Enterprise	913	103	115	37	1.168
Medium Scale Enterprise	1.888	489	506	343	3.226
Small Scale Enterprise	2.845	1.106	1.065	1.003	6.019
Micro Scale Enterprise	1067	412	342	432	2.253
Total	6.713	2.110	2.028	1.815	12.666

Source: Entrepreneurship Information System

Table 3 - Product Switching Among Exporting Firms, 2012 to 2017 (Percentage)

Enterprise Scale	Both Add and Drop	Only Add	Only Drop	Steady
Large Scale Enterprise	78%	9%	10%	3%
Medium Scale Enterprise	59%	15%	16%	11%
Small Scale Enterprise	47%	18%	18%	17%
Micro Scale Enterprise	47%	18%	15%	19%
Total	53%	17%	16%	14%

Source: Entrepreneurship Information System

As indicated in Table 3 between 2012 and 2017, almost 86 percent of the manufacturing firms altered the mix of the product in their export basket. Large majority of firms (53 percent) both added new products and dropped existing products from their product mix. 17 percent by dropping at least one product, 16 percent by adding at least one product. 14 percent of firms stay steady by neither adding nor dropping any product from their export basket. Comparing the results for all firms with different scales, we can observe that as the scale of firms increases, firms are more likely to change the mix of export products. The specific drivers of product switching patterns may also vary among firms, with some responding more to changes in consumer preferences or market conditions, while others may be more influenced by internal R&D to drive product innovation, sourcing ideas and technologies from external partners or acquiring other firms to access new product lines.

Table-4 provides an overview of product switching activity across different sectors during the 2012 to 2017 period. The data highlights that the majority of firms are engaged in the "Manufacturing" and "Wholesale and Retail Trade" sectors. Notably, more than half of the companies operating within these sectors experienced both product additions and reductions throughout this time frame. 70 percent of exporters working in the Manufacturing NACE-1 industry added at least 1 product to their portfolio. The same rate is 74 percent for exporters in the Wholesale and Retail Trade sector. The change in the product portfolio of the Turkish economy between 2012 and 2017 was mainly driven by firms in the manufacturing industry and wholesale and retail trade sectors. In terms of total number; manufacturing, wholesale and retail sectors have the highest number of product additions and subtractions. When the share of these sectors in total foreign trade is taken into account, the results are not unusual.

A total of 47 percent of exporters operating in Agriculture, Forestry and Fishing NACE-1 added at least 1 product to their portfolio. With this rate, exporters in the Agriculture, Forestry and Fishing industry have been the most stable in terms of product diversification. 81 percent of firms operating in the Construction NACE-1 industry added at least 1 product to their portfolio. With this rate, the Construction sector performed above average. Firms operating in Professional, Scientific and Technical Activities were also above average with a diversification rate of 80 percent. The mining sector ranks at the top with 39 percent of firms with steady state. The product portfolio of 39 percent of firms in this sector has not changed. As seen, the number of exporting firms operating under some NACE-1 industries is quite small. Therefore, the ratios for firms under these categories have small sample sizes.

Table 4 - Product Switching Among NACE-1 Sector Exporters - 2012 to 2017 (Count)

NACE-1	Both Add and Drop	Only Add	Only Drop	Steady
ACCOMMODATION AND FOOD SERVICEs	37	4	7	6
ACTIVITIES OF HOUSEHOLDS	0	0	0	1
ADMINISTRATIVE AND SUPPORT SERVICE	87	12	17	25
AGRICULTURE, FORESTRY AND FISHING	34	32	31	44
ARTS, ENTERTAINMENT AND RECREATION	12	0	3	4
CONSTRUCTION	560	80	77	70
EDUCATION	7	0	2	2
ELECTRICITY, GAS, STEAM AND AIR CONDITIONING SUPPLY	26	6	4	8
FINANCIAL AND INSURANCE ACTIVITIES	19	5	2	3
HUMAN HEALTH AND SOCIAL WORK ACTIVITIES	16	10	6	6
INFORMATION AND COMMUNICATION	86	21	23	12
MANUFACTURING	6713	2110	2028	1815
MINING AND QUARRYING	74	31	33	88
OTHER SERVICE ACTIVITIES	29	11	9	22
PROFESSIONAL, SCIENTIFIC AND TECHNICAL ACTIVITIES	277	54	45	35
PUBLIC ADMINISTRATION AND DEFENCE	0	0	0	1
REAL ESTATE ACTIVITIES	10	0	3	1
TRANSPORTATION AND STORAGE	381	29	44	38
WATER SUPPLY; SEWERAGE, WASTE MANAGEMENT AND REMEDIATION ACTIVITIES	13	6	0	2
WHOLESALE AND RETAIL TRADE	6533	1569	1563	1193

Source: Entrepreneurship Information System

Table 5 - Product Switching Among NACE-1 Sector Exporters - 2012 to 2017 (Percentages)

NACE-1	Both Add and Drop	Only Add	Only Drop	Steady
ACCOMMODATION AND FOOD SERVICEs	69%	7%	13%	11%
ACTIVITIES OF HOUSEHOLDS	0%	0%	0%	100%
ADMINISTRATIVE AND SUPPORT SERVICE	62%	9%	12%	18%
AGRICULTURE, FORESTRY AND FISHING	24%	23%	22%	31%
ARTS, ENTERTAINMENT AND RECREATION	63%	0%	16%	21%
CONSTRUCTION	71%	10%	10%	9%
EDUCATION	64%	0%	18%	18%
ELECTRICITY, GAS, STEAM AND AIR CONDITIONING SUPPLY	59%	14%	9%	18%
FINANCIAL AND INSURANCE ACTIVITIES	66%	17%	7%	10%
HUMAN HEALTH AND SOCIAL WORK ACTIVITIES	42%	26%	16%	16%
INFORMATION AND COMMUNICATION	61%	15%	16%	8%
MANUFACTURING	53%	17%	16%	14%
MINING AND QUARRYING	33%	14%	15%	39%
OTHER SERVICE ACTIVITIES	41%	15%	13%	31%
PROFESSIONAL, SCIENTIFIC AND TECHNICAL ACTIVITIES	67%	13%	11%	9%
PUBLIC ADMINISTRATION AND DEFENCE	0%	0%	0%	100%
REAL ESTATE ACTIVITIES	71%	0%	21%	7%
TRANSPORTATION AND STORAGE	77%	6%	9%	8%
WATER SUPPLY; SEWERAGE, WASTE MANAGEMENT AND REMEDIATION ACTIVITIES	62%	29%	0%	10%
WHOLESALE AND RETAIL TRADE	60%	14%	14%	11%

Source: Entrepreneurship Information System

We can also investigate the firms' diversification characteristics depending on the diversification pattern of the firms. Adapting the classification methodology of Breschi et al. (2003), we categorize firms into two types according to their diversification profiles:

(i) Firms that add new four-digit HS products which belong to different two-digit HS product category that wasn't present in their export basket in the initial year over the period 2012-2017.

(ii) Firms that add new four-digit HS products which belong two-digit HS product category that are already present in their export basket at the initial year over the period 2012-2017.

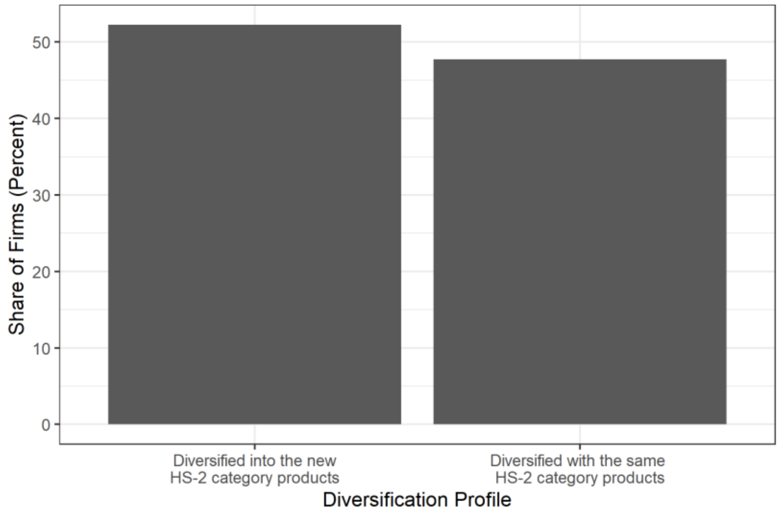
Classifying firms in this way can provide important information on what percentage of firms are able to diversify into relatively unrelated[4] fields. Based upon these classification, following stylized facts on export product diversification facts in Turkish manufacturing firms emerge from the analysis of micro data:

From the year 2012 to 2017, not all firms introduced new products to their basket. Within the general sample consisting of 12.666 manufacturing firms, only 8.821 of them introduced new products. In line with the typology written above, Figure-2 reports the relative share of firms which have added at least one product from other HS-2 category over the period of 2012-2017. It can be seen that the share of firms among these categories are close to each other. 54 percent of the exporters introduced new products from unpresent two-digit HS product categories (Figure-2).

Figure-3 reports the same diversification profile of the firms with respect to their size. Graph shows that there is significant heterogeneity in terms of characteristic of product diversification. It shows that almost half of micro/small firms have only diversified into new HS-2 areas.

[4] The notion of relatedness here can be considered in the ex-ante context (Rumelt, 1974; Frenken et al., 2007).

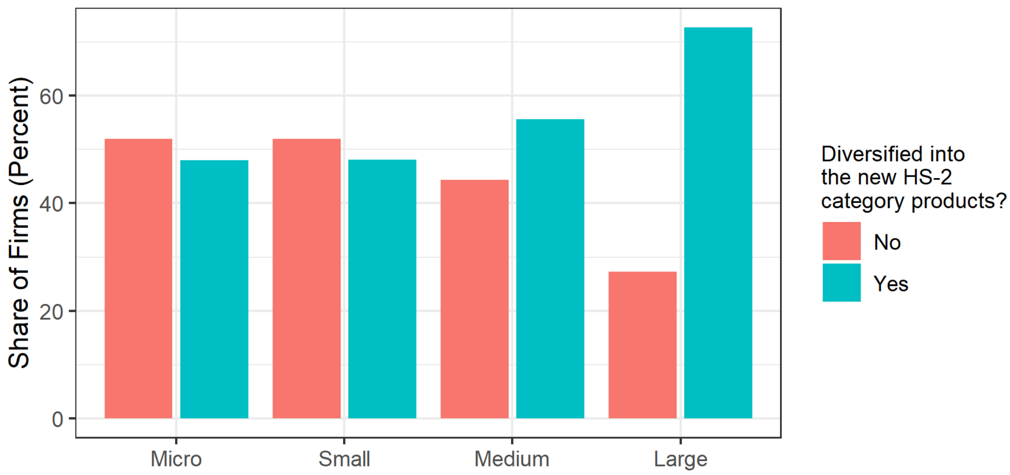
Figure 2 - Diversification Profile of Manufacturing Firms (2012 to 2017)



Source: Entrepreneurship Information System

We observe that the share of firms that diversified into new HS-2 categories is slightly higher for medium sized firms. Gap between related and unrelated diversifiers is much more evident in large scale firms. More than 70 percent of the large firms added at least one product from other HS-2 category. This situation indicates that firms' size have serious implications regarding their capacity to diversify into relatively unrelated fields. Unrelated diversification performance of firms monotonically increases with the size of other firms.

Figure 3 - Diversification Profile of Manufacturing Firms According to Scale (2012 to 2017

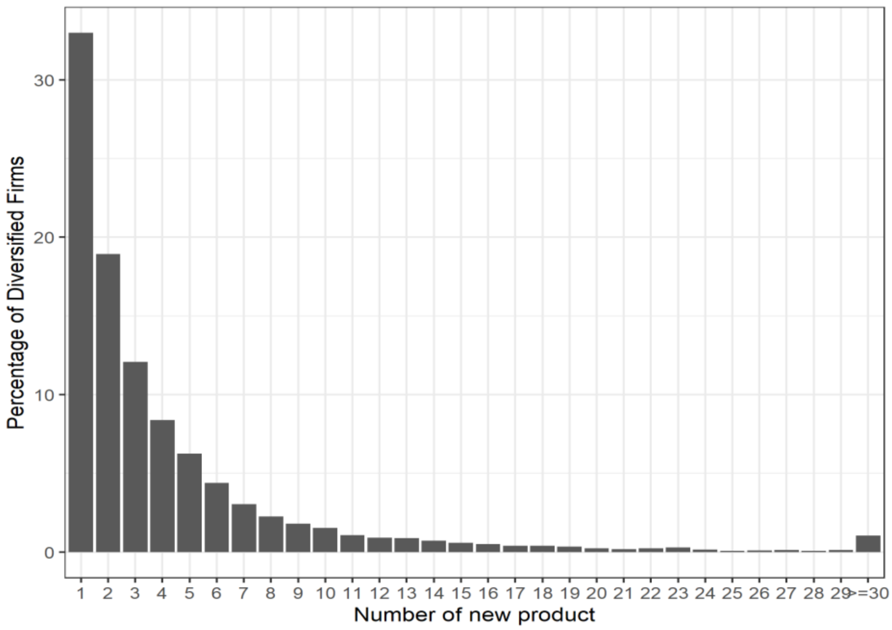


Source: Entrepreneurship Information System

Figure-4 reports the distribution of the diversified exporters according to the number of new HS-4 products they introduced in 2017. Looking at the distribution in the number of new products by the manufacturing firms, it is evident that the majority of the firms add one or two products to their portfolios. The distribution shows a decaying pattern, as the number of products increases, the share of the firms decreases in the sample. Firms diversified in one or two product categories hold, respectively, only around 33 percent and 19 percent of all firms in our sample. Few proportions of the firms diversified in relatively high numbers of products. In our sample, firms that started to export more than 30 new HS-4 products constituted 1 percent of the firms. In fact, these firms are very large innovators. Micro data shows that firms which diversified into more than 30 new HS-4 products account for almost 16 percent of all added new products over the period 2012–2017 in the sample. When the data is analyzed in more detail, we see that only 93 firms introduced more than 30 products. These 93 firms also account for 25 percent of overall export value within the manufacturing industry.

In a nutshell, aggregate exports are driven by a few top exporters that are relatively large and supply several foreign markets with differentiated products in Türkiye. When we investigate the sectoral mix of these 93 firms, we observe that the majority of the firms are concentrated on NACE-2 sectors such as *Manufacturing of wearing apparel, manufacturing of machinery and equipment, and manufacturing of motor vehicles, trailers and semi-trailers*. These sectors also have a significant share in Turkey's total manufacturing sector total export volume. According to the microdata, by NACE-2 sectors *Manufacturing of wearing apparel, manufacturing of machinery and equipment, and manufacturing of motor vehicles, trailers and semi-trailers* account for 14 percent, 17 percent and 5 percent of the manufacturing exports respectively.

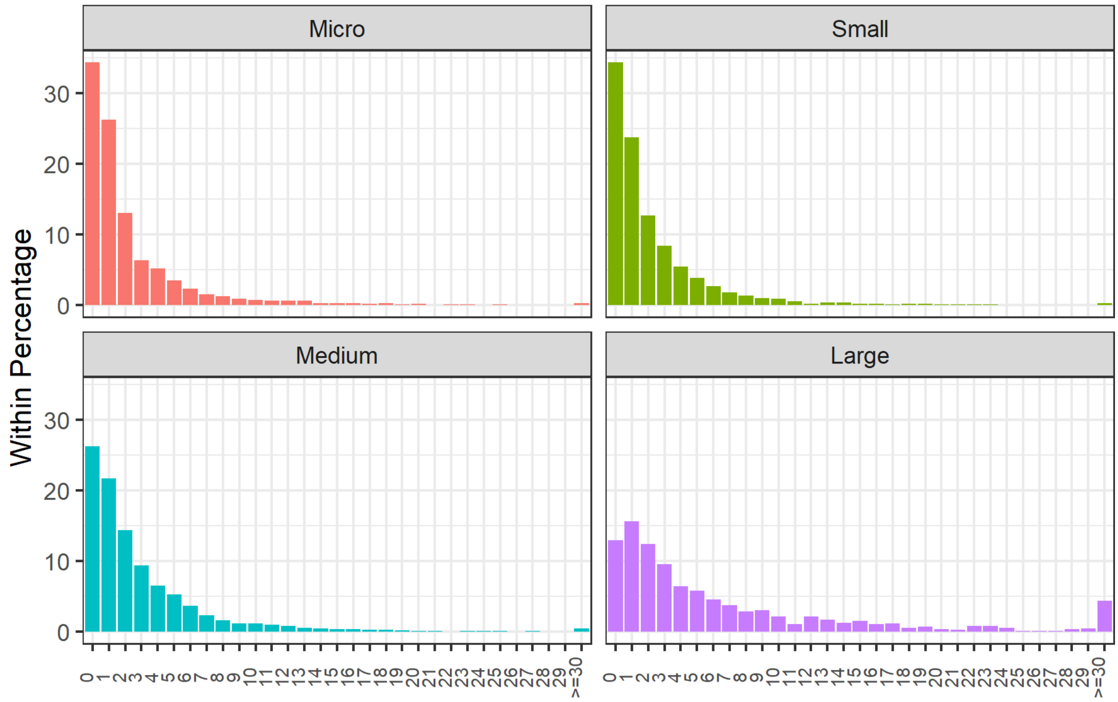
Figure 4 - Distribution of Firms According to the Number of New Product They Added (Percentage values, 2012-2017)



Source: Entrepreneurship Information System

Figure-5 illustrates distribution of firms according to the number of new products over the scale of the firms. Figure clearly shows that distribution of firms are left skewed for micro, small and medium sized firms which implies that most of the firms at these scales introduce relatively few export products. Distribution characteristics are very similar for micro and small sized firms. Whereas distribution of firms with respect to number of products they introduced within the large scale firms have relatively uniform distribution patterns. Then together, results could suggest that relatively smaller firms may struggle to develop and launch new products due to limited resources, such as financial capital and research and development capabilities. In contrast, large companies may have the resources and infrastructure to support a more steady stream of new product development and introduction.

Figure 5 - Distribution of Firms According to Number of New Product They Added by Scale

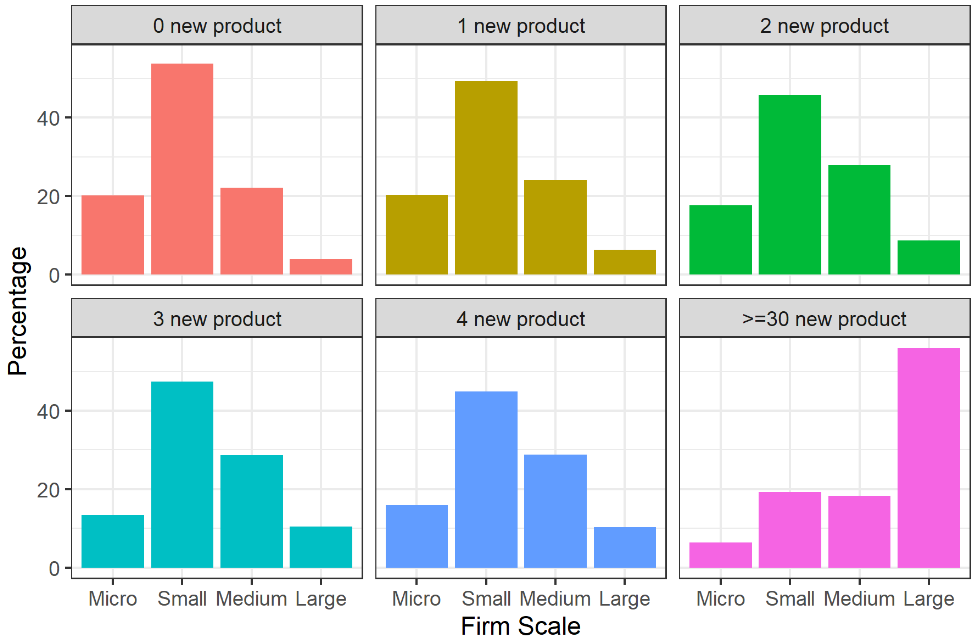


Source: Entrepreneurship Information System

As it can be seen from the Figure-6, majority of the firms in our sample introduced one, two or three HS4 products. When we look further at the distribution of the firm according to their scale within these product counts, we observe that generally small and medium sized firms account for more than half of the firms within 1,2 and 3 new product categories. However this distribution is highly correlated with the distribution of the firms in our sample as indicated in the Table-1. As expected, when we look at the distribution of the firms according to their scale within 30 or more new product introduced firms, large firms take the lion’s share.

As an extra to firm-specific analysis, we also provide product-specific stylized facts on the diversification of Turkish exporting firms. Table-6 below shows which HS-2 product categories were most frequently added to firms' export portfolios between 2012 and 2017. The 'Count' column shows the number of new HS-4 products added under the HS-2 category. The 'Share in Total Export (Value)' column indicates the share of the HS-2 product category within the total exports in Türkiye for the year 2012.

Figure 6 - Distribution of Firms by Scales by Number of Added Products



Source: Entrepreneurship Information System

As seen from the Table-6, between 2012 and 2017, most firms added products in the HS-2 category 84 (machinery and machinery parts) group to their portfolios. This is followed by electronic products, plastics and products, and iron and steel industries. The results are not surprising when considering the number of new products added and their share in total exports together. The shares of the most added product categories in total exports are already high. These four HS-2 product categories account for 55 percent of overall new product additions. In terms of export value, the share of these four product categories in total exports is around 25 percent. This also indicates that diversification is concentrated on certain product categories

Table 6 – Most Added Product Count By HS-2 Product Categories

HS2 Category Name	Count	Share in Total Export (Value)
CHAPTER 84 - NUCLEAR REACTORS, BOILERS, MACHINERY AND MECHANICAL APPLIANCES; PARTS THEREOF	8559	10,15%
CHAPTER 85 - ELECTRICAL MACHINERY AND EQUIPMENT AND PARTS THEREOF; SOUND RECORDERS AND REPRODUCERS, TELEVISION IMAGE AND SOUND RECORDERS AND REPRODUCERS, AND PARTS AND ACCESSORIES OF SUCH ARTICLES	3995	6,19%
CHAPTER 39 - PLASTICS AND ARTICLES THEREOF	3664	4,36%
CHAPTER 73 - ARTICLES OF IRON OR STEEL	3380	4,28%
CHAPTER 61 - ARTICLES OF APPAREL AND CLOTHING ACCESSORIES, KNITTED OR CROCHETED	1717	2,88%
CHAPTER 90 - OPTICAL, PHOTOGRAPHIC, CINEMATOGRAPHIC, MEASURING, CHECKING, PRECISION, MEDICAL OR SURGICAL INSTRUMENTS AND APPARATUS; PARTS AND ACCESSORIES THEREOF	1544	0,51%
CHAPTER 62 - ARTICLES OF APPAREL AND CLOTHING ACCESSORIES, NOT KNITTED OR CROCHETED	1423	1,85%
CHAPTER 94 - FURNITURE; BEDDING, MATTRESSES, MATTRESS SUPPORTS, CUSHIONS AND SIMILAR STUFFED FURNISHINGS; LAMPS AND LIGHTING FITTINGS, NOT ELSEWHERE SPECIFIED OR INCLUDED; ILLUMINATED SIGNS, ILLUMINATED NAMEPLATES AND THE LIKE; PREFABRICATED BUILDINGS	1324	0,94%
CHAPTER 48 - PAPER AND PAPERBOARD; ARTICLES OF PAPER PULP, OF PAPER OR OF PAPERBOARD	1294	0,68%
CHAPTER 76 - ALUMINIUM AND ARTICLES THEREOF	1056	1,44%
CHAPTER 83 - MISCELLANEOUS ARTICLES OF BASE METAL	911	0,45%
CHAPTER 40 - RUBBER AND ARTICLES THEREOF	879	3,12%
CHAPTER 82 - TOOLS, IMPLEMENTS, CUTLERY, SPOONS AND FORKS, OF BASE METAL; PARTS THEREOF OF BASE METAL	860	0,09%
CHAPTER 72 - IRON AND STEEL	790	8,98%
CHAPTER 63 - OTHER MADE-UP TEXTILE ARTICLES; SETS; WORN CLOTHING AND WORN TEXTILE ARTICLES; RAGS	769	0,75%
CHAPTER 44 - WOOD AND ARTICLES OF WOOD; WOOD CHARCOAL	721	0,36%
CHAPTER 32 - TANNING OR DYEING EXTRACTS; TANNINS AND THEIR DERIVATIVES; DYES, PIGMENTS AND OTHER COLOURING MATTER; PAINTS AND VARNISHES; PUTTY AND OTHER MASTICS; INKS	710	0,31%
CHAPTER 70 - GLASS AND GLASSWARE	599	0,28%
CHAPTER 87 - VEHICLES OTHER THAN RAILWAY OR TRAMWAY ROLLING STOCK, AND PARTS AND ACCESSORIES THEREOF	557	21,57%
CHAPTER 38 - MISCELLANEOUS CHEMICAL PRODUCTS	507	0,28%

Source: Entrepreneurship Information System

Economic complexity literature (Hidalgo et al., 2007; Balland et al., 2022), argues that economic development does not solely involve enhancing the production of existing goods. Instead, it involves acquiring more intricate sets of abilities to transition towards new activities that are linked with higher levels of productivity (Felipe et al., 2012).

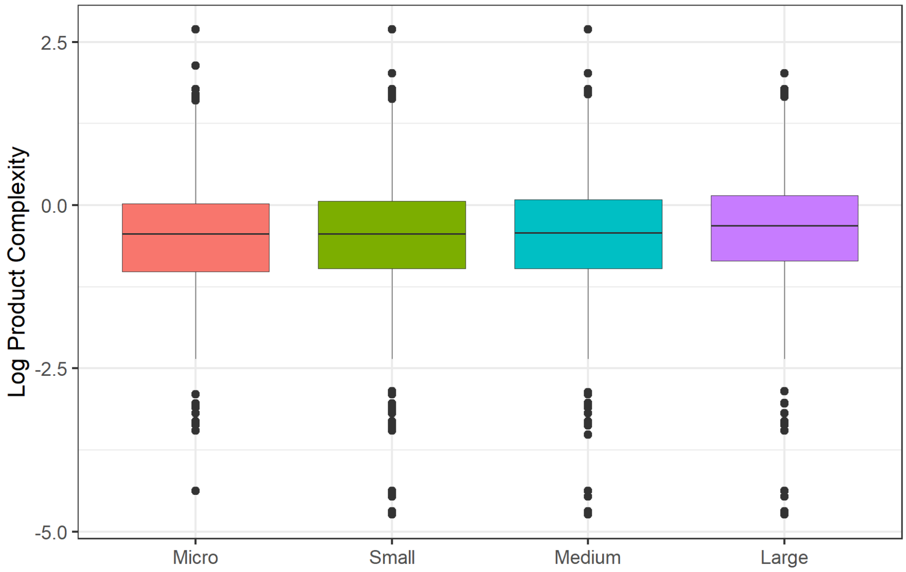
In the following figures, we question whether firms diversify into more complex activities or not. For this purpose, we initially calculate the product complexity value of each product using the method of reflections methodology proposed in Hausmann and Hidalgo (2010). Details of the computation steps for product complexity are provided in Appendix-A.

The method of reflections (Hidalgo and Hausmann, 2009) utilizes an iterative approach to identify products that necessitate increased diversity and greater complexity in capabilities, as well as countries that possess a greater array and complexity of capabilities. These capabilities are not predetermined, and the method doesn’t seek to identify them explicitly. Nevertheless, it is important to note that in the computation process, countries demonstrating revealed comparative advantage in the same products are assumed to share such capabilities.

Product complexity is a measure of the diversity and complexity of the underlying capabilities required to produce the product. It is based on the idea that products embody the collective knowledge of the societies that produce them (Hidalgo and Hausmann, 2009; Felipe et al, 2012). Products that require a high degree of knowledge and know-how are more complex than those that require less. For example, the production of a microprocessor chip requires a high degree of specialized knowledge and complex technology, while the production of a basic commodity such as rice requires much less.

In this regard, after calculating product complexity values of HS-4 products using *method of reflection* approach, we merged complexity values of each HS-4 product into the main data frame table containing firm-product entry data over the period over the 2012-2017. Figure-7 shows the distribution of product complexity values of the new products with respect to the size of the companies. Natural logarithm of the product complexity values was taken to normalize the distribution and prevent skewed distribution in the box plots.

Figure 7 – Product Complexity Value Distribution of New Introduced Products (By Scale of Firms)



Source: Entrepreneurship Information System

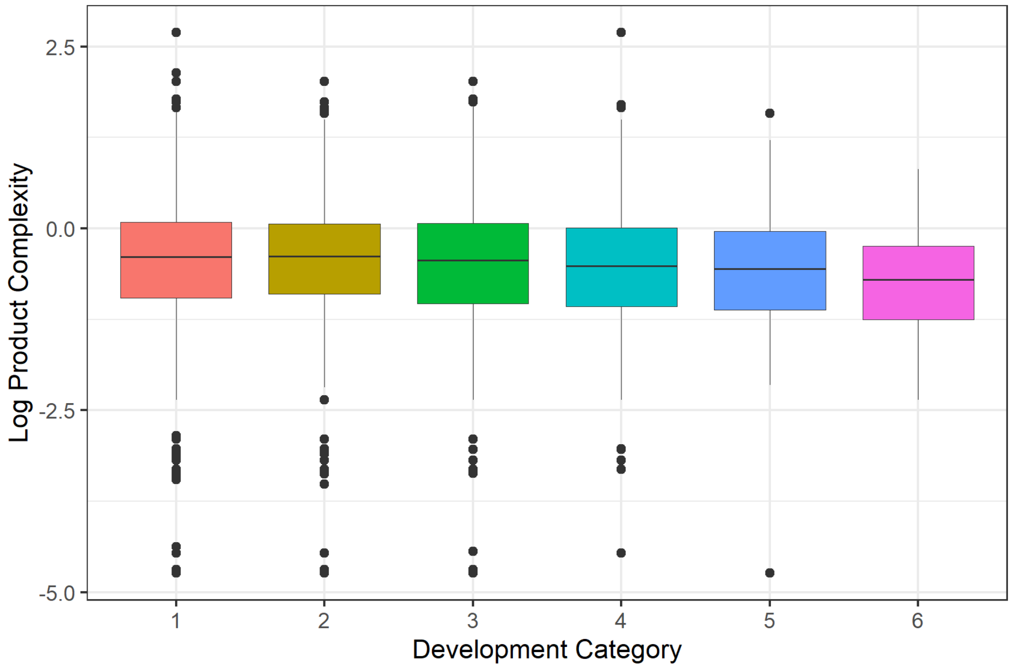
As can be seen from the box plots (Figure-7), the average values of the complexity values of the products added by micro, small and medium-sized firms within 5 years are close to each other. However, the product complexity values added by large companies are higher on average. Average complexity values without logs for micro, small, medium and large firms are 0.78, 0.78, 0.80 and 0.88 respectively.

Since large firms have more strategic vision, resources, experience, and market power to pursue diversification into more complex products, making them better suited for such strategies compared to small and medium-sized firms. Firms with higher learning capabilities can leverage their network connections to acquire the requisite knowledge and diversify into new products (Cohen and Levinthal, 1990).

Eventually, in Figure-8, we investigate distribution of complexity values of newly introduced export products according to the development category province that they are located in. In this context, we question whether any inter-regional difference exists regarding the characteristic of diversification patterns of the firms.

Development categories defined for each province in the SEDI study is used to denote development level of the province firm located at. Boxplot indicates heterogeneity in both the distribution structure and the mean values of the complexity level of the products added by firms depending on the level of development of the regions.

Figure 8 - Product Complexity Value Distribution of New Introduced Products (By Development Categories)



Source: Entrepreneurship Information System

As can be seen from the graph, as the development level of the provinces in which the firms are located increases, there is a tendency to shift towards relatively more complex products. In particular, average complexity without logs for development categories is reported in Table-7. The tendency of firms in developed regions to introduce more complex products during their diversification process can be explained with various points. Agglomerations create knowledge spillovers, enabling firms to access a pool of specialized knowledge. In developed regions, such agglomerations are more pronounced, facilitating the acquisition and application of advanced technologies and know-how, leading to the development of more complex products (Duranton & Puga, 2003). Moreover, developed regions typically have sophisticated and diverse consumer markets. Firms in these regions may diversify into more complex products to meet the demand for innovation and differentiation.

Table 7 - Average Product Complexity Values of New Export Products for Development Levels

Level-1	Level-2	Level-3	Level-4	Level-5	Level-6
0.82	0.80	0.80	0.77	0.70	0.60

3.3. DENSITY MEASURES

In order to estimate the effect of relatedness on firm export diversification patterns, we use proximity indicators developed by Hidalgo et al. (2007). The methodology of Hidalgo et al. (2007) is found to be superior to the other relatedness measures outlined in Section 2.2 because of its most comprehensive and relatively less computationally demanding feature. Product Space methodology of Hidalgo et al. (2007) is based on co-occurrence analysis and aim to address the shortcomings of hierarchical relatedness measures. Co-occurrence based relatedness measures the relatedness between two products by assessing whether two products are frequently found together in one and the same economic entity (Teece et al. 1994; Hidalgo et al. 2007; Bryce and Winter 2009). Due to its aforementioned advantages, product space methodology has been adopted in many recent empirical works (Felipe et al., 2012; Bahar et al, 2014; Poncet and Waldemar, 2015).

The product space is a network representation of economic activities, estimated by considering co-occurrence patterns among export products. In product space, product categories which are similar to each other in terms of common inputs and capabilities are spatially more close in the graph. Bidirectional interaction between nodes demonstrates co-occurrence and degree of connectedness between products. Product space structure also implies that countries or regions are more likely to gain competitive advantage in products which are closer to existing productive bases (Haussman & Hidalgo, 2010; Hidalgo, 2021).

Many factors may influence the co-occurrence patterns of product pairs in countries' export baskets. These include; input-output relations, common skills and similar production factors needed for production as well as institutions and networks facilitating production-exportation of certain products. The underlying logic of the proximity index is that when two products are related because their production necessitates similar capabilities such as institutions, skills, technology. Therefore, they are likely to be exported in tandem.

The first step in the current analysis is developing a measure that shows degree of relatedness between distinct product pairs. To accomplish this, we calculate the proximity matrix for HS-4 products based on the frequency of co-occurrence of pairs in the export basket of the countries.

In order to calculate the product proximity matrix which shows proximity values between each pair of products *i* and *j*, expression written in Equation-1 is used. $RCAx_{i,t}$ indicates whether a certain country has comparative advantage in product i. $P(RCAx_{i,t}|RCAx_{j,t})$ is the conditional probability of having comparative advantage in product *i* given that country has a comparative advantage in product *j*. Proximity is equal to the lowest value of these two conditional probabilities (Hidalgo et al., 2007: 484). Proximity value ($\theta_{i,j,t}$) between pair product *i* and *j* at time *t* is calculated as:

$$\theta_{i,j,t} = min\{P(RCAx_{i,t}|RCAx_{j,t}), P(RCAx_{j,t}|RCAx_{i,t})\} \quad (1)$$

Prior to computing proximity among products, it’s necessary to determine whether any country has a comparative advantage in a particular product. We calculated the revealed comparative levels of each country in each product according to the Revealed Comparative Advantage (RCA) definition proposed by Balassa (1965).

The proximity measure developed by Hidalgo et al. (2007) utilizes product level international trade data and analyzes how often countries (or regions) have a comparative advantage in a pair of goods simultaneously. Specifically, having a revealed comparative advantage (RCA) in a product means that the country is a significant exporter of that good. Applying Balassa’s (1965) Revealed Comparative Advantage methodology on UN COMTRADE data for countries’ exported product, we calculate RCA values of country-product pair as shown in Equation-2.

$$RCA_i^r = \begin{Bmatrix} 1, & if \quad {\left.\dfrac{x_{r,i}}{\sum_i x_{r,i}}\right/ \dfrac{\sum_r x_{r,i}}{\sum_r \sum_i x_{r,i}}} > T^* \\ 0, & otherwise \end{Bmatrix} \tag{2}$$

Where $x_{r,i}$ is the value of product i exported by country r. T^* represents threshold value for determining competitive advantage which is generally taken as 1. RCA_i^r takes value one if country r has comparative advantage in product i at time t and zero otherwise. We use calculated RCA values of the country-product pair to compute $\theta_{i,j,t}$. For country – HS4 product level export data we use UN COMTRADE database export data of 163 countries at HS 4-digit breakdown.[5]

Figure-9 illustrates product space network visualization constructed according to the Equation-1 using UN COMTRADE data for the reference year 2012. In order to visualize the network, we use the Kamada-Kawai network visualization algorithm to clearly show main links connecting all products. In the product space each node is a different HS-4 product. Different product classes are grouped in distinct color classes. This product space network is built upon co-occurence of each HS-4 product among countries in 2012. The size of each node are proportional to the total trade value of each product in overall international trade volume. Less distance between any two nodes indicates that these two products tend to be co-exported more frequently. In other words, these products are related to each other.

Product space below has two main parts: central and periphery sections of product space. Central part of the product space consists of products that have high connections with other products. These HS-4 products have significant relationships with nearby products. In network analysis terms, they have high centrality values. Periphery part of the product space associated with products that have low number of cross connections. Structure of the product space is important because it has implications on how countries/regions increase their overall complexity. A densely interconnected product space means that neighbouring products share many of necessary capabilities. In such a scenario, it would be much straightforward to add a new product by acquiring the

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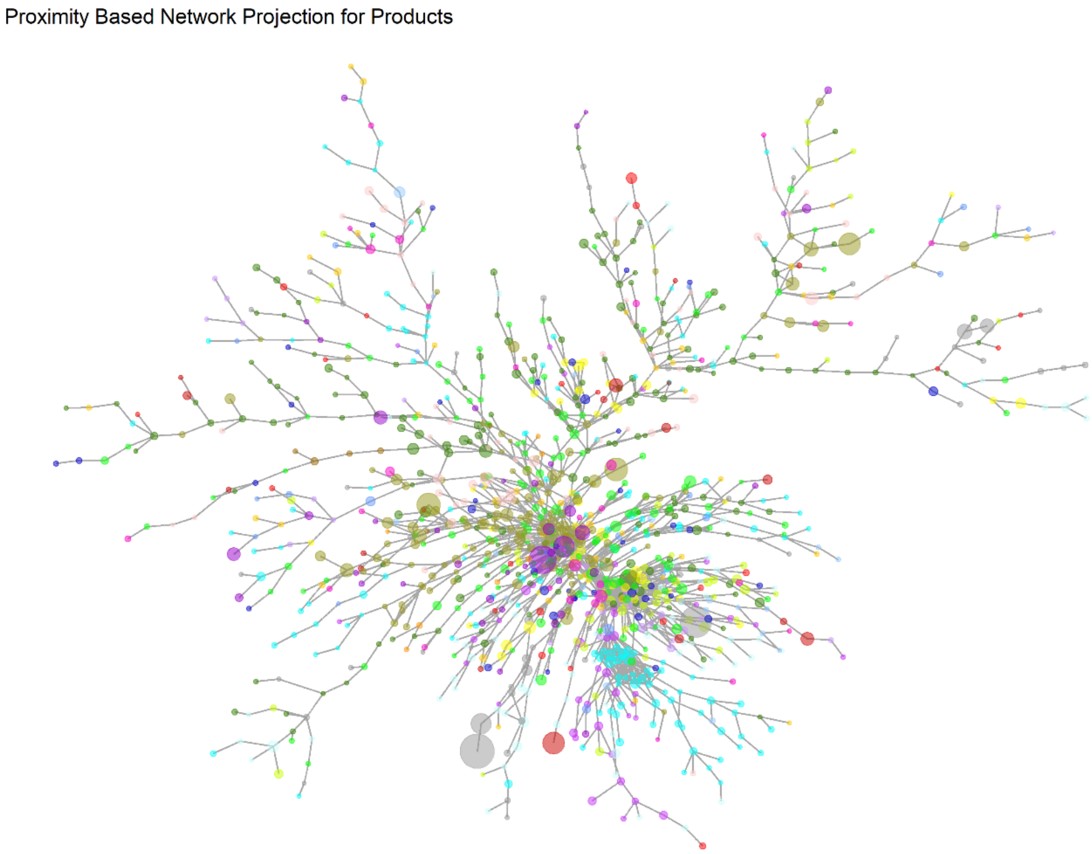
[5] We use trade data at 4 digit since beyond 4 digit firm's exports exhibits sparse distribution characteristics which also impose huge computational burdens.

capabilities countries/regions lack (Hidalgo et al., 2007; Hausmann and Hidalgo, 2010). In opposite, product space with sparse structure indicate that neighbouring products share fewer similarities, meaning that they require different capabilities. Introducing a new product is more challenging in this case because it requires acquiring multiple and distant capabilities.

Figure 9 – Product Space (Global Co-occurence of Products for 2012)

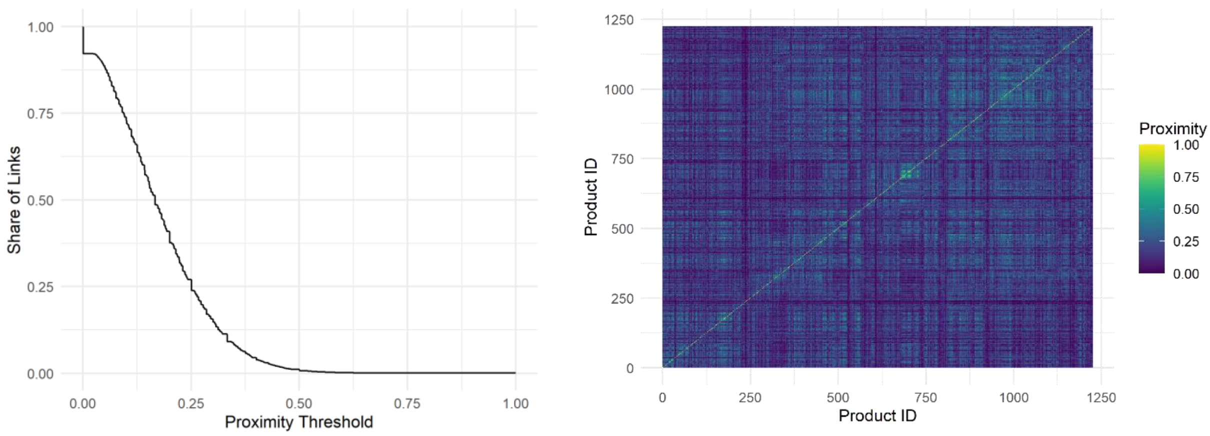


Source: UN COMTRADE | Created by author using R and igraph library

Figure-10 below shows some of the network properties of product space. Panel (a) shows the share of total links in the overall network as a function of the proximity threshold. Figure reveals negative relationship between proximity threshold and number of links. Particularly, after exceeding 0.5 threshold value, share of links in network converges to zero. Plot in Panel (b) also visualizes product space in heatmap format. It shows that while some of the products are highly connected while others are disconnected. Heatmap shows that many of the pixels have the dark color. In the proximity matrix, sparse matrix characteristics are evident. For instance, out of 1.500.625 (1225×1225) possible connections among products, 37 percent of them have proximity value less than 0.1. Also 60 percent of the total connections have proximity values less than 0.2. Due to sparse characteristics of the data, it's much more functional to demonstrate relatedness with network vizualisation by applying threshold cutoff values.

Figure 10 - Proximity Network Characteristic

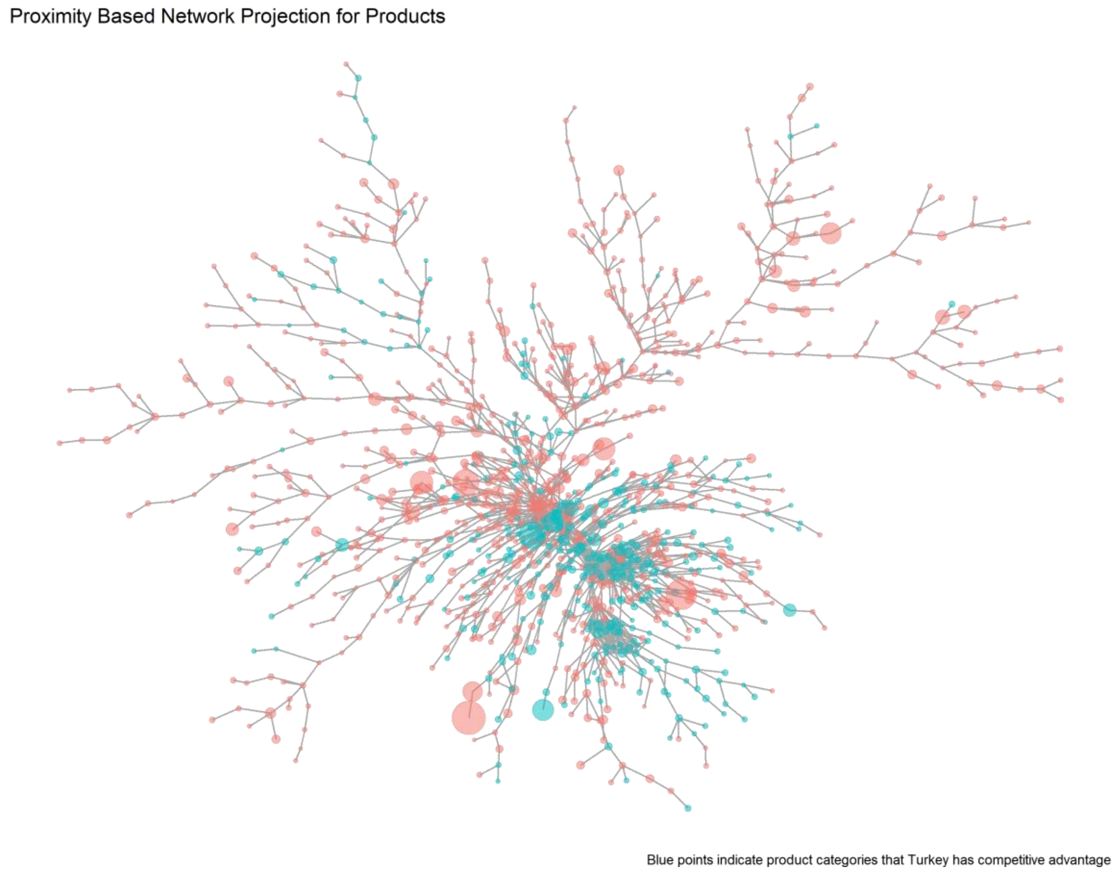
(a) (b)



Source: UN COMTRADE | Created by author

Figure-11 shows Turkey's position in the visualization of product space. Blue coloured points indicate product categories that Turkey holds competitive advantage (RCA > 1). Literature has provided empirical evidence on the fact that countries gradually diversify into closer products and their ability on moving into complex products is essentially dependent on their initial position in the product space (Haussman and Klinger, 2006; Dosi et al., 2020). In this sense, the position of country in the product space holds crucial information about the productive capabilities in the economy and how likely it is to move into other products as well as growth potential. Graph shows that Türkiye has specialized in products that are positioned in the central part of product space. This indicates that the country can diversify more easily into products in the core of the space. We can also observe that blue dots are spreaded across the product space suggesting that the country has a diverse economic base. If a country is heavily concentrated in a specific region of the product space and lacks proximity to more advanced products, it may face challenges in upgrading its economic capabilities. Understanding these challenges is crucial for policymakers to design targeted interventions, such as investing in education, research and development, and infrastructure to support economic diversification and technological upgrading.

Figure 11 - Position of Türkiye in Product Space



Source: UN COMTRADE | Created by author using R and igraph library

After computing product proximity matrix, we make use of product proximity matrix to measure extent to which a product is related to the existing firm, local and neighborhood region's product structure. We modify the density measure developed by Hidalgo et al. (2007) measure proximity of any product to to given portfolio. In our setting, this density measure will measure any potential new export product's relatedness to firm's existing product portfolio. These density measures particularly allows us to measure capability distance between new products and the existing capabilities of firm, region and neighborhood regions.

Firstly, for each firm p and product i, we calculate *Firm Density* variable as follows:

$$Firm\ Density_{p,i} = \frac{\sum_j \theta_{i,j} * d_{p,j}}{\sum_j \theta_{i,j}} \tag{3}$$

Proximity value between a pair of products i and j is represented by $\theta_{i,j}$. Value of $d_{p,j}$ is equal to 1 when product *j* is already exported by the firm and is equal to 0 otherwise. $Firm\ Density_{p,i}$ measures the average proximity of new export product *i* to firm's current productive structure. In other words, it indicates the extent to which the potential new product i is related to the set of productive capabilities that exist in firm p, taking into account the export portfolio of firm p.

Second, we calculate the following *Firm Density Import* variable which allows us to measure the proximity between potential new particular product and the firm’s import basket.

$$Firm\ Density\ Import_{p,i} = \frac{\sum_m \theta_{i,j} * m_{p,j}}{\sum_j \theta_{i,j}} \tag{4}$$

Again, where $\theta_{i,j}$ represents proximity value between product *i* and *j*. Values of $m_{p,j}$ equal to 1 when product *j* is already imported by the firm *i* and is equal to 0 otherwise. This measure is very similar to the previous firm density indicator. Only difference is that instead of the export basket of the firm, we calculate the average proximity of new product to firm's imported products basket. We assume that when a certain product is related to the import basket, firm can easily utilize the external knowledge stock obtained from its trade linkages.

In addition to firm-specific capabilities, this study also aims to investigate the role of a firm's interaction with the local environment and to what extent new products are connected with local productive structure. In order to analyze how regional export competencies affect firms’ product switching strategies we utilize two different density indicators.

In order to measure how potential new products densely related to the province's competitive export basket, following Lo Turco and Maggioni (2016) we calculate *Regional Density* variable below:

$$Regional\ Density_{p,i} = \frac{\sum_j \theta_{i,j} * x_{l,j}}{\sum_j \theta_{i,j}} \tag{5}$$

In Equation-5, ι denotes the province where firm p is located and $\theta_{i,j}$ represents proximity value between product *i* and *m.* Dummy variable $x_{l,j}$ equals to one for products in which province l has a revealed comparative advantage in product *j* and equal to zero otherwise. Regional density could be considered as a proxy for source of potential spillovers and knowledge externalities from locality due to connectedness with local productive structure. Regional density measure focuses on the products exported by the province with comparative advantage. If a candidate product is proximate to these core products in locality, it is considered densely connected to the local product structure.

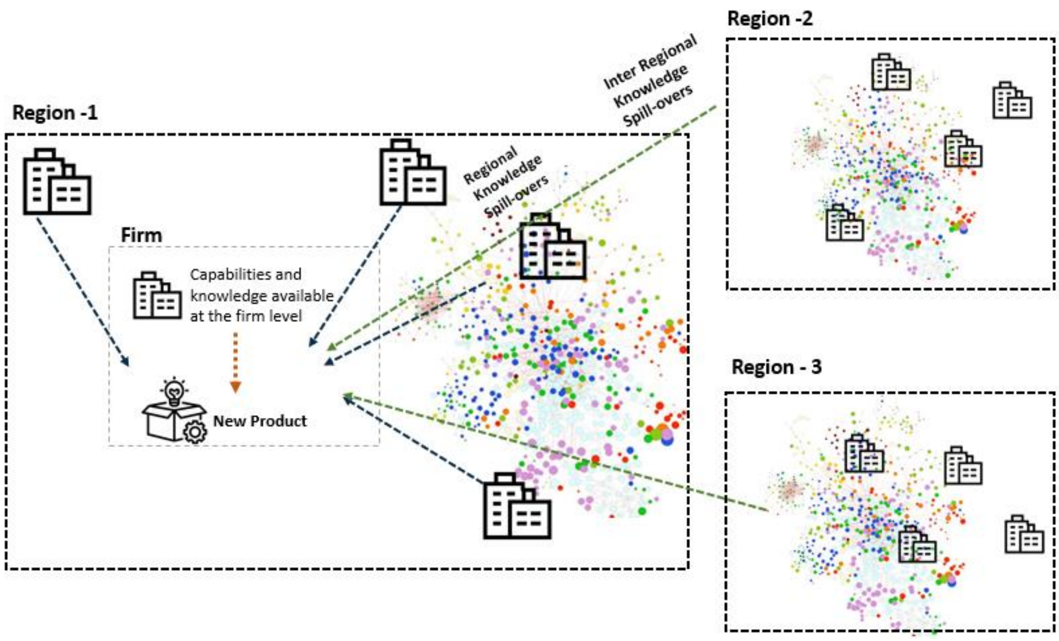
Along with the host province, this study also aims to assess the presence of spatial dependence on the evolution of the product scope of the firms by taking into account neighbour provinces. Neigbourhood provinces might foster the development of new export products through spillover effect. Thus, for each firm p, we calculate neighbourhood density around product i. In this measurement, similar to provincal density, firstly we calculate provincal density around product *i,* but this time we only consider provinces which are spatially contiguous to province l where firm p is located (denoted as n). Then, we sum up all of these provincial density values by weighting with their relative total gross domestic product share.

$$Neighborhood\ Density_{p,i} = \frac{gdp_n}{\sum_n gdp_n} \frac{\sum_j \theta_{i,j} * x_{n,j}}{\sum_j \theta_{i,j}} \tag{6}$$

So, the coefficient estimate on *Neighborhood Density* captures the impact of neighboring regions' specialization on the probability of adding a product firm's export basket within 5 years. However, it should be noted that as highlighted by Boschma et al. (2017), this is a net effect since neighbor provinces can promote the emergence of new products through knowledge spillovers, but it can also hinder the diversification of products due to competition effect.

Eventually, Figure-12 depicts the role of firm and place specific capabilities on new product choice in a visual way. In our framework, we expect that firm and place dependent relatedness will influence a firm's decision regarding the addition of new products. Firm specific capabilites indicate capabilities embodied in the export and import basket of the firm. Because these activities take place at the firm level. Place specific capabilities are seperated into two categories; (1) capabilities available at the region where firm is located, (2) capabilities available at neighbour regions.

Figure 12 – Visual Representation of Multi-Scaled Relatedness Framework



Source: Created by the author

3.4. ECONOMETRIC SPECIFICATION

Through econometric analysis, our aim is to evaluate whether a firm's choice of a new export product is influenced by its relatedness with existing firm-specific capabilities and local-based capacities. It is crucial to emphasize that we are not investigating any causal link between overall product relatedness *within a firm* (or in other words coherence of portfolio) and export diversification performance of firm. Since it’s possible that overall coherence of the portfolio may be shaped by firm’s diversification activities. Purpose of our exercise is to investigate the role of firm and local specific space on new product choice of the firms. Equation-7 tests to what extent diversification into new product is influenced by its relatedness to existing firm and local based capabilities.

$$\begin{aligned} Y_{i,p,t+5} = \ & \beta_0 + \beta_1 Firm\ Density_{i,p,t} + \ \beta_2 Firm\ Density\ Import_{i,p,t} \\ & + \beta_3 Regional\ Density^{\iota}_{p,t} + \ \beta_4 Neighborhood\ Density^{\iota}_{p,t} \\ & + \ \beta_5 RCA^{\iota}_{p,t} + \ \beta_7 rpcount_{p,t} + \ \beta_8 Export\ Variety_{p,t} \\ & + \beta_9 Multi\ Regional_{p,t} + \ \vartheta_{\iota} + \ \xi_i + \ \epsilon_{i,p,t} \end{aligned} \qquad (7)$$

In the specification; i denotes HS4 product, p denotes firm and t denotes time. In order to model firm's evolution into new export product, possible new product choices have been defined for each firm p. Following this procedure, each firm has option to choose among HS-4 products which was not in firm's export basket in year t. For example, if firm p has 8 products in its export basket in year t, then among set of 952[6] products firm will have the option to pick 946 product.

In our sample, there are 12.666 exporters that survived the 2012-2017 period. Since we are using Import Density variable, we are focusing on 8.404 two-way trader firms in the econometric analysis. Constructing a modelling data frame with this appropriate firm – HS4 product pair leads to 8.127.117 number of observations with 8.404 unique firms. We restrict our sample to a firm-product pair series of zeros followed by a decision to start exporting. In other words, we are interested in the new HS-4 products introduced by firms which hasn't been in its export portfolio at the initial period (Year 2012).

The dependent variable measures the extensive margin of a firm, whether a firm adds a certain HS-4 product to its portfolio. Entry dummy variable takes on the value on 1 if a HS-4 export product i does not belong to the export portfolio of firm p at 2012 but entered this portfolio by year 2017 (Equation-8).

$$Y_{i,p,t+5} = I(i\ \notin PF(p, 2012) \wedge i \in PF(p, 2017)) \qquad (8)$$

A five year time window is assumed to account for the time frame needed for a firm to develop a product, test and trials and other adjustments. Similar earlier studies also used 5 year lag to account for prior exploratory phases (Neffke et al.; 2011; Boschma et al.,

[6] Total number of unique HS-4 products in our dataset is 945.

2017; Hazir et al, 2019). For the values of the independent variables, the initial period of the 5-year time interval is taken into account

In Equation-7, β_0 is the constant term, β_1 captures the effect of *Firm Density* variable. This effect includes existing, skills, knowledge base and resources within the firm. β_2 coefficient shows the effect *Firm Density Import* variable that captures the spillovers from importing activity of firm. β_3 coefficient captures the effect of knowledge base and resource available at the province where the firm is located (*Region Density*). Finally, β_4 coefficient captures the effect of capabilities present at neighbour provinces (Neighborh. We expect these four coefficient to be positive. The main hyphothesis of the study is that capabilities available at different spatial levels can contribute to a firm's diversification into new products through spillover effects.

Furthermore, we use additional control variables that we expect might influence a firm's diversification choice into certain products. Firstly, we use dummy variable $RCA_{p,t}^{\iota}$ which indicates whether product i is already exported with comparative advantage in province ι in the initial year 2012. Sign of β_5 is expected to be positive because when the region has the comparative advantage in any particular product, it might be more likely that consumer taste associated with the product will be higher. $RCA_{p,t}^{\iota}$ also capture the effect of localization economies, economic benefits that can be gained by locating certain activities or industries in a specific place. Due to better access to specialized resources, lower costs due to proximity to suppliers or customers, firms will have more the ability to take advantage of local expertise or knowledge.

Secondly, we include dummy variable denoted $multi-regional$ to specify firms that have multiple plants in different provinces. Multi-regional firms are located in various provinces and work within more extensive networks. As a result, they are expected to rely less on the connections with the local surroundings. This variable is expected to capture potential knowledge externalities that might be gained from a firm’s presence at different locations. In the EIS, export and import transactions of firms are recorded at the enterprise level where the firm’s headquarter are located. However, a firm may have more than one plant that might spread across different provinces of the country. Following Hazir et al. (2019), we classify each firms into two categories; *mono-regional firms and multi-regional firms*. Mono-regional firms are firms where more than 80 percent of their workforce are situated in the same province. The firms less than 80 percent of their workforce are situated in the same province are encoded as multi-regional-firms. In the dummy variable, multi-regional firms are encoded as 1 whereas mono-regional firms are encoded as 0. According to this classification, a large part of manufacturing firms in our sample consists of mono-regional firms such that 92 percent of firms are mono-regional.

Thirdly, $exportvariety_{p,t}$ control variable is defined to measure the extent to which firms' portfolios are diversified in the initial period. Following Jacquemin and Berry (1979), we calculate following entropy index given in Equation-9 to measure to what extent firm's initial portfolio is diversified. The diversity of economic activities within the firm can have an impact on its product innovation behaviour. When a firm is engaged with different kind of activities, diverse knowledge background and skills may interact which can lead cross-fertilization of ideas. Therefore, this variable is expected to have positive effect on product innovation of the firms.

$$exportvariety_{p,t} = \sum_{i=1}^{n} q_i \log_2 \left(\frac{1}{q_i}\right) \tag{9}$$

Lastly, we include $rpcount_{p,t}$ control variable which measures number of already exported product that fall in the same second digit product category for the product p. In this variable, we adopt the ex-ante view that if any product falls into same second digit HS product category, we assume them as a related. The fact that the firm already exports a large number of products that may be related to the relevant product is expected to have a positive effect on the addition of a similar new product. Existence of related products may create economies of scope allowing the firm to leverage its resources and capabilities across multiple products (Teece, 1980).

It might be argued that path-dependence constraints may not be the same for all firms. Capabilities can encompass a wide range of domains, with some being specific to certain products or groups of products (such as specialized technological knowledge) and others being relevant for all products and unique to particular firms or regions (such as management quality, vision, innovation capacity, social capital).

Capabilities that apply to multiple or all products provide significant advantages for firms, as they reduce the uncertainties involved in diversifying into new products and decrease the impact of product relatedness on this process. In contrast, firms endowed primarily with capabilities specific to certain products face greater constraints in their diversification efforts, as they are reliant exclusively on product linkages.

Taking all these factors into account, in our modeling framework, there might be other factors that are omitted in the main econometric specification. As stated, the main observation units are firm-product pairs. In this specification, there might be unobservable factors that are specific to firms but common to products. Also, there might be unobservable factors that are specific to products but common to all firms. There may be product specific factors such as demand shock on particular product or supply shock on products (e.g. technological changes, industrial policy) which in turn affect emergence of products. Furthermore, firm specific individual factors such as productivity, management quality, innovation capacity of firms etc. These firm specific factors may affect new product innovation capacity of a firm irrespective of characteristics of the product.

These types of omitted variables may cause endogeneity if they are correlated with both the independent variables and the dependent variable in the model. In this case, the omitted variables may be acting as an intermediary between the independent and dependent variables, causing a correlation between the independent variables and the error term. In order to correct this problem, it is important to account for potentially ommited variables in the model to ensure that the estimates are unbiased and consistent. Thus, we include both product and province level fixed effects in the econometric specifications.

Since some of control variables in the model are firm specific (such as multi-regional status of firm, variety of firm's export basket), we are not able to include firm level fixed effect because it would be perfect collinear with these control variables. Instead of that, we use province level fixed effect (ϑ_l) to account for unobservable factors that are common to all firms in the same province irrespective of what they produce. These unobservable factors may be urbanization externatilies and Jacobs externalities at the provinde level. HS4 product fixed effect is denoted as ξ_i and its expected to capture unobservable product specific factors.

Four main relatedness measures used in this study aim to capture any HS-4 product's proximity to firm level and local level capabilities. As explained in the previous sections, the computation of the relatedness measures depend on the global product proximity matrix and are not observed or measured at the firm level. In this regard, these relatedness measures can be regarded as satisfactorily exogenous for the endogeneity concerns. Observation values of these variables are not affected by the firm of region specific unobservables. They are entirely product specific measures.

3.5. ESTIMATION METHODOLOGY

Since the dependent variable is in a binary form, the identification of the effect of product relatedness on the decision of a firm to start exporting a particular product relies on logistic regression estimation. Logistic regression is a widely employed econometric method that is particularly useful when modeling binary outcomes or events. The logistic regression model transforms the linear combination of explanatory variables into a probability scale through a logistic function, allowing for the modeling of probabilities between 0 and 1.

Let $\pi(x) = E(Y|x)$ to denote conditional mean of Y variable given x when we use logistic distribution. The form of the logistic regression model is used is:

$$\pi(x) = \frac{e^{\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_k X_k}}{1+ e^{\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_k X_k}} \tag{10}$$

When logit transformation is applied into $\pi(x)$ we obtain:

$$g(x) = ln\left[\frac{\pi(x)}{1-\pi(x)}\right] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k \tag{11}$$

The logit transformation is useful because it transforms the probability scale (which has a restricted range between 0 and 1) into a scale that spans the entire real number line. $g(x)$ possesses desirable properties of linear model. This transformed value is then used as the linear predictor in logistic regression models.

Parameter estimation of the logistic regression model depends on maximum likelihood estimation. In a broad context, the method of maximum likelihood finds the values for unknown parameters that maximize the probability of observing the original dataset. To employ this method, firstly likelihood function should be written. In this function, probability of observing that specified as a function of unknown parameters (Hosmer and Lemeshow, 2000: 9). Optimum values found are the parameter that maximize this function. $\pi(x)$ shows the conditional probability that dependent variable Y equals to 1. Since the observations are assumed to be independent, the likelihood function is derived as the product of the terms provided in Equation-12 as follows:

$$l(\beta) = \prod_{i=1}^{n} \pi(x_i)^{y_i}[1 - \pi(x_i)]^{1-y_i} \tag{12}$$

Equation-12 implies that optimum estimate of coefficients (β) should satisfy maximum likelihood principle. However, for mathematical convenience, it is often preferable to work with the logarithm of Equation-12. This expression, referred to as the log-likelihood, is defined as:

$$L(\beta) = \sum_{i=1}^{n} \{y_i \ln[\pi(x_i)] + (1 - y_i) \ln [1 - \pi\,(x_i)]\} \tag{13}$$

Another alternative approach may be the employment of Linear Probability Model as some scholars have used (Lo Turco and Maggioni, 2016; Boschma et al., 2017; Boschma et al., 2013). However, there are several advantages of logistic regression models over linear probability models in the context of this study.

Firstly, logistic regression estimations produce more reliable estimates: Linear probability models assume that the relationship between the predictor variables and the outcome is linear, which can lead to estimates that are outside the range of 0 to 1. On the contrary, logistic regression models use a logistic function to model the relationship between the predictor variables and the outcome, which ensures that the predicted probabilities always fall within the range of 0 to 1.

Another advantage of the logistic regression models is that it can handle unbalanced data. Linear probability models can produce biased estimates when the outcome is rare, which can lead to incorrect conclusions about the relationship between the predictor variables and the outcome. In contrast, logistic regression models can produce reliable estimates even when the outcome is rare, which makes them a good choice for data sets where the outcome is unbalanced. (Gelman and Hill, 2006)

Also, in general logistic regression models are robust to the heteroscedasticity problem because the errors in the model are assumed to follow a logistic distribution, which has constant variance. This means that the spread or dispersion of the errors is the same across all values of the predictor variables (Hosmer and Lemeshow, 2000).

CHAPTER 4: ESTIMATION RESULTS

This section reports the estimation results for specification stated in Equation-7. Since some of the model specifications includes large number of fixed effects (such as firm fixed effects or HS4 product fixed effects) estimating a logistic regression model with a large number of fixed effects can be computationally intensive, which can make the model estimation process slow and time-consuming.

In order to address these issues we use the “fixest” package in R programming language based on procedures developed by Berge (2018). The package utilizes a highly optimized framework to perform very fast fixed effect estimations in the presence of a large number of fixed effects.

Since observation unit is firm-product pair and observations are clustered across product categories, firms and provinces, observations may be not independent from each other. This situation, in turn may lead to estimation of biased and inefficient standard errors if traditional standard errors are used. Moulton (1990) shows that estimating the effect of aggregate variables on micro units may lead to biased estimates of standard error. In order to address these issues, standard errors are clustered at the same level of fixed effects which are HS-4 product and province levels.

4.1. FULL SAMPLE RESULTS

Table-8 shows logistic regression estimation results for a full sample that consists of 8,3 million observations. In columns 1-4, each of the main density variable is used as a single explanatory variable. In column 5, all of the main density variables and all control variables are included in the estimation (as specified in Equation-7). The coefficients in the Table-8 shows how the log odds of whether a new product is added to the firm’s portfolio are affected by each variable.

Inclusion of all density variables significantly alters the coefficients on *Firm Density* and *Firm Density Import* variables. Size of Firm Density coefficient is halved and Firm Density Import Variable decreased relatively less. Coefficient on Region Density is not affected by the inclusion of all variables. It is important to note that relative size of *Firm Density Import* coefficient exceeds the coefficient on *Firm Density* variable.

The literature on the structure of product space and its implications on the evolution of firm's capabilities implies that firms tend to move towards closer products (Hidalgo et al., 2007; Hazir et al., 2019). Our findings are consistent with these expected pattern. All of the density variables except *Neighbourhood Density* variable have positive sign and statistically significant effect. The coefficients on *Firm Density, Firm Import Density* and *Regional Density* are statistically significant at the 1 percent level. Model results suggest that for a given product–firm pair, a denser connection with the firm and region level productive structure has a significant positive impact on the product entry decisions of the Turkish manufacturing exporters. New candidate products that require similar capabilities with present capabilities at firm and region are more likely to be introduced by the firm in a 5 year window.

As seen in Column (5), the size of the coefficients gets smaller as we move from firm-based density variables to place-based density variables. This indicates that for a given firm, new potential export products' connectedness with firm level capabilities is more important than connectedness to region or neighborhood level capabilities. This observation is valid in both single variable estimations (Columns 1-4) as well as in specification that includes all variables (Column 5).

Looking at the Column (5), we see that *Firm Density Import* variable has the largest and *Firm Density* variable has the second largest value in terms of coefficient magnitude. Firm-based capabilites appear to be more important than region-based based capabilities in driving product innovation of firms. But interestingly, at the firm level, import-based knowledge is more important than current export-based knowledge.

Positive and statistically significant effect of the *Firm Density* variable indicates that products with higher density with the firm's existing productive structure are more likely to be introduced. The decision of a firm to introduce a new export product is being influenced by its existing import and export activities because there might be shared resources, skills, knowledge bases, or institutions that could be utilized or complemented. Percentage increase in the *Firm Density* would lead to all else being equal to 9 percent increase [exp(8.50 * 0.01) = 1.088] in the odds of introducing the relevant product for firm p.

Table 8 – Estimation Results (Full Sample)

	(1)	(2)	(3)	(4)	(5)
Firm Density	18.21*** (2.584)				8.500*** (1.716)
Firm Import Density		13.54*** (0.9347)			11.56*** (0.8871)
Regional Density			4.556** (1.420)		4.423** (1.400)
Neigbourhood Density				1.291 (1.939)	1.619 (1.970)
RCA	0.4445*** (0.0714)	0.4475*** (0.0726)	0.3790*** (0.0628)	0.4415*** (0.0716)	0.3914*** (0.0651)
Export Variety	0.1623*** (0.0445)	0.2902*** (0.0310)	0.3106*** (0.0341)	0.3104*** (0.0343)	0.2285*** (0.0374)
Number of Related Product	0.1459*** (0.0113)	0.1666*** (0.0098)	0.2208*** (0.0132)	0.2213*** (0.0133)	0.1378*** (0.0114)
Multi-Regional	0.3414*** (0.0394)	0.1395* (0.0586)	0.4251*** (0.0382)	0.4257*** (0.0381)	0.1261* (0.0559)
Fixed-Effects:	------------------	------------------	------------------	------------------	------------------
HS4 Product	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Region	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
S.E.: Clustered	by: HS4 Prod & Region	by: HS4 Prod & Region	by: HS4 Prod & Region	by: HS4 Prod & Region	by: HS4 Prod & Region
Observations	8,342,644	8,342,644	8,342,644	8,342,644	8,342,644
Squared Cor.	0.01810	0.02194	0.01679	0.01672	0.02206
Pseudo R2	0.18248	0.18957	0.17731	0.17686	0.19095
BIC	331,519.9	328,794.6	333,510.1	333,683.5	328,311.9

*p < 0:10;**p < 0:05;***p < 0:01. Standard errors are clustered at HS-4 product and region level.

The new export products that firms introduce are also highly related to their initial import basket. This situation supports the hypothesis that imports may play a role in knowledge diffusion in which obtained knowledge through importing activity may foster firms to develop the products that require similar resources with the import products (Goldberg et al., 2010; Alonso and Martin, 2019). Importing activity may provide access to new ideas and knowledge through interaction with different markets. These ideas could inspire firms for related new product ideas and facilitate diversification. Percentage increase in the *Firm Density Import* would lead to all else being equal to 12 percent increase [exp(11.56 * 0.01) = 1.12] in the odds of introducing the product for firm p.

We find that influence of *Firm Density Import* is stronger as compared to *Firm Density* variable. In this respect, it is observed that learning through imports has a stronger effect than learning through exports in the product diversification process. These results are consistent with the similar studies exploring the role of exporting and importing activities on firm performance of Turkish firms. Dalgıç and Fazlıoğlu (2015) and Dalgıç et al. (2015) show that extensive margin of import has stronger positive influence on the productivity of firms was compared to exporting activity for Turkish firms. Firms' engagement with foreign countries may facilitate the assimilation of external technological knowledge. This mechanism becomes a catalyst for the wider exported product scope and productivity growth for developing economies by importing new intermediate goods in their production processes.

As seen, *Regional Density* has the third largely statistically significant impact on the dependent variable. This suggests that similar resources and capabilities in the region may provide firms to benefit from the existing knowledge and expertise in the local network. Firms tend to diversify into products that exhibit a higher degree of commonality and complementary capabilities with products that their regions have competitiveness. Percentage increase in the *Regional Density* would lead to all else being equal to 4 percent increase [exp(4.42 * 0.01) = 1.04] in the odds of introducing the product for firm

Neighborhood Density variable is found to be having no statistically significant effect on the dependent variable. This suggests that the capabilities present in neighboring provinces do not influence firms' decisions on new product selection. This result contradicts with the findings of the previous studies focusing on country level (Bahar et al., 2014; Jun et al., 2020) and region level (Boschma et al., 2017) assessing the effect of neighbouring countries/regions on diversification choices. However, when we work.

with fine-grained firm level data, the neighbouring effect is found the be insignificant. The variation in the impact of knowledge spill-overs by geographical distance may differ depending on the context of the country under study. In the case of Turkey, it is observed that the capabilities in neighboring provinces do not have a significant effect on firms' choice of new products. Insignificant effect of the *Neighborhood Density* variable might be explained by the decay of knowledge spill-overs with the geographical distance (Jaffe et al., 1986; 1993; Boschma et al., 2014). Relationship between knowledge spillovers and geographical distance is often explored in economic geography literature (Audretsch and Feldman, 1996; Boschma, 2005). Tacit knowledge, which is often crucial for innovation, is difficult to transfer over long distances. Face-to-face interactions facilitate the sharing of tacit knowledge (Polanyi, 1966). Even though diffusion of information is consistent regardless of distance, the cost of transmitting knowledge increases as distance grows (Audretsch and Feldman, 1996). As firms located close to each other are more likely to experience knowledge spillovers, fostering innovation. In our empirical setting, the economic structure of the region where firms are located significantly influences their new product choices, however as the geographical distance increases impact of inter-regional spillovers decreases.

In general, there is a significant jump in the size of the coefficients when one moves from region level density variables to the firm level density variables. Coefficient values of *Firm Density* and *Firm Density Import* variables are quite higher than *Regional Density*. This observation is quite consistent with the previous literature that explores the relative importance of the firm resources or regional environment on firms' innovation activity (Pfirrman, 1994; Breschi et al., 2003; Beugelsdijk, 2007; Frigon and Rigby, 2022). The literature provides empirical evidence that firm-based resources have a higher impact on a firm's innovative activities than the regional environment. The results obtained from the model estimation show that capabilities existing at the firm level are more influential for development of new products than capabilities existing in the regional environment. Internal capacity and external knowledge acquired through imports are relatively more critical for new product innovation.

We use further control variables that are expected to influence a firm's new export product diversification: regional RCA on the product, firm's export basket variety, number of related products in the export basket of the firm and multi regional status of the firm. Among the control variables, *Regional RCA* variable is expected to capture the effect of localization economies on emergence of particular product. As shown in Column (5), the coefficient on RCA variable is statistically significant and has the expected positive sign implying that local specialization in the same product category positively affect firms' probability of starting to export that particular product. Odds of introducing a new export product that province specialized is 47 percent higher that non-specialized products [exp(0,394) = 1,478]. An agglomeration in the relevant industry within the region is considered to facilitate the transition of firms that will start exporting in this field. This observation is quite consistent with the economic geography literature highlighting the role of localization economies (Feldman et al., 1999; Duranton and Puga, 2001; Glaeser and Resseger, 2010). Commercialization of new products requires knowledge that is cumulative and place-dependent. Therefore, existence of product specific clusters may provide opportunity for firms to acquire of new knowledge or technology from other firms in the same or related industries.

One of the firm-specific control variables is *Export Variety*, which captures the diversity structure of firms' export product portfolio. Fundamentally, this variable measures the distribution and composition characteristics of firm's export portfolio. A statistically significant and positive value on the coefficient indicates that an increase in the export basket diversity of a firm increases the likelihood of the emergence of any product. High degree of diversity may allow for the integration of distinct knowledge domain and ideas, which can lead to better product innovation performance.

The coefficient associated with the *Number of Related Product* variable has positive sign. Firms with more related products in their portfolios are more likely to add new products. Result may be interpreted as product diversity leads to economies of scope, allowing the firm to leverage its resources and capabilities across multiple products and markets. Coefficient estimate for dummy variable *Multi-Regional* firm dummy is positive and statistically positive. It shows that the multi-regional nature of a firm has an overall positive impact on product innovation of firms.

Interesting result obtained from the full-sample estimation is the insignificant effect of the *Neighborhood Density* variable (Column-5). As illustrated in Equation-6, the calculation of the *Neighborhood Density* variable considers the competitive product portfolio structure of the neighboring provinces of the province where the firm is located. Given that approximately 50 percent of the manufacturing exporters in the dataset are located in Istanbul, there might be bias arising from the portfolio structure of Istanbul firms and its neighboring provinces; Kocaeli, Kırklareli, and Tekirdağ. To assess the robustness of these findings, the econometric analyses were replicated with the exclusion of firms located in Istanbul.

Table-9 reports the logistic regression estimates for the subsample that excludes the firms located in İstanbul. We observe that the statistical significance of the variables remains consistent with the estimations made on the standard sample. Among the density variables; *Firm Density, Firm Density Import and Regional Density* variables are still statistically significant, while the *Neighborhood Density* variable is still insignificant. In addition, the coefficient magnitudes and significance of the other control variables are similar to the full-sample estimates. This indicates that there is no bias in the *Neighborhood Density* variable attributable to the presence of firms in Istanbul. In this regard, the model results seem to be robust.

In this subsample, size of coefficients for main density variables are higher than full sample results. This suggests that firms located outside Istanbul typically exhibit more pronounced characteristics of related diversification. Moreover, unlike the previous results, the coefficient size of the *Regional Density* variable is higher for firms not located in Istanbul. This indicates that the tendency to diversify into products that are more related to the regional production structure is higher in cities outside Istanbul. When comparing coefficient magnitudes, it is evident that the *Regional Density* variable has an approximately 1.6 times stronger effect on new product choice compared to other firm-based density variables. Studies in the industrial organization literature shed light on the sources of knowledge among small and large firms. In the standard models of Schumpeterian technological change (Griliches, 1979), the knowledge production function within firms outlines the relationship between the inputs in the innovation process and innovative outputs. Since much of the industrial R&D takes place in large firms, it can be expected that a great proportion of the innovative output will be attributed to large firms. However, empirical studies that explore the connection between patent activity and firm size typically do not provide substantial support for the Schumpeterian Hypothesis (Pavit et al., 1987; Rothwell, 1989). In fact, in many economies small firms emerged as significant actors of the technological change. Empirical studies show that small firms can achieve innovation by leveraging knowledge generated externally, beyond the confines of the firm (Audretsch and Vivarelli, 1996). In this regard, since in the cities outside the Istanbul consists of relatively smaller firms we would expect that these firms would be much more dependent on local sources of knowledge rather than their of capabilities. In this regard, sub-sample results are in line with the related research (Pavit et al., 1987; Rothwell, 1989; Audretsch and Vivarelli, 1996).

We also examine the robustness of the findings concerning the *Neighborhood Density* variable by considering an alternative approach for weighting neighboring provinces. As stated in the Equation-6, baseline *Neighborhood Density* variable is constructed by considering only adjacent provinces with their GDP weights. In addition to a weighting mechanism based solely on GDP, it may be useful to examine the results of a weighting mechanism that also takes into account social relations. As an alternative specification for neighboring relationships, we utilize the proximity matrix for Türkiye developed by Kaygalak (2023).

Table 9 - Estimation Results (Non İstanbul Firms)

	(1)	(2)	(3)	(4)	(5)
Firm Density	23.71*** (5.215)				13.39*** (3.067)
Firm Import Density		15.09*** (0.7824)			12.69*** (0.9398)
Regional Density			20.90*** (4.084)		20.72*** (4.018)
Neigbourhood Density				3.850** (1.474)	-0.1073 (1.624)
RCA	0.5368*** (0.1050)	0.5369*** (0.1067)	0.3457*** (0.0721)	0.5175*** (0.1022)	0.3652*** (0.0737)
Export Variety	0.0803. (0.0457)	0.2417*** (0.0402)	0.2516*** (0.0397)	0.2491*** (0.0396)	0.1609*** (0.0428)
Number of Related Product	0.1381*** (0.0132)	0.1661*** (0.0164)	0.2224*** (0.0241)	0.2264*** (0.0239)	0.1186*** (0.0138)
Multi-Regional	0.3633*** (0.0868)	0.2588** (0.0957)	0.3998*** (0.0843)	0.3995*** (0.0844)	0.2615** (0.0937)
Fixed-Effects:	------------------	------------------	------------------	------------------	------------------
HS4 Product	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Region	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
S.E.: Clustered	by: HS4 Prod & Region	by: HS4 Prod & Region	by: HS4 Prod & Region	by: HS4 Prod & Region	by: HS4 Prod & Region
Observations	3,761,383	3,761,383	3,761,383	3,761,383	3,761,383
Squared Cor.	0.02007	0.02589	0.01841	0.01780	0.02743
Pseudo R2	0.18086	0.18996	0.17593	0.17296	0.19492
BIC	170,575.0	168,843.3	171,512.3	172,077.6	167,944.4

*p < 0:10;**p < 0:05;***p < 0:01. Standard errors are clustered at HS-4 product and region level.

Kaygalak (2023) use social network and gravity analysis to calculate inter-provincial (81×81) proximity matrix based on social interactions among all provinces. In particular, the author uses inter-provincial population flow data and gravity modeling to capture social connectivity among provinces. In the study, he calculates proximity matrix for years 1990, 2000, 2010 and 2020. In this analysis, we use the proximity matrix for 2010 since it is the closest to the beginning period of our sample. In the proximity matrix, the proximity of the province shown in each row with other provinces is shown in the other columns.

Before using the proximity matrix, 0-1 normalization process was applied to each row and the inverse values were taken. Equation-14 shows the calculation of alternative neigbourhood density measure around product i and firm p located in province ι. In this specification, $\omega_{\iota\iota'}$ value represent social proximity between ι and ι'. $\theta_{i,j}$ value show product relatedness product i and j. $x_{\iota',j}$ is dummy variable takes value 1 if other province (among 80 provinces) has a RCA for product j. Alternative measure differs from the previous *Neighborhood Density* specification (Equation-6). In this specification, we are not only considering spatially adjacent provinces. Instead, for a specific province-product pair, we take all other provinces into account by weighting their relative social distance.

$$Neighborhood\ Density - Alt_{i,p}^{\iota} = \frac{\omega_{\iota\iota'}}{\sum_{\iota'}^{\iota \neq \iota'} \omega_{\iota\iota'}} \frac{\sum_j \theta_{i,j} * x_{\iota',j}}{\sum_j \theta_{i,j}} \tag{14}$$

Estimation results reported in Table-17 in Appendix-D. As seen, results are robust to alternative definitions of neigbouring relationships. Results show that Neighbourhood Density-Alt variable has still insignificant effect. Furthermore, we find that this alternative *Neighbourhood Density* is highly positively correlated with original specification (0.75 correlation). We can infer that the role of neigbourhood regions' capabilities on new product introduction at the firm level is robust to diferent inter-regional relationship specifications.

4.2. SUBSAMPLE RESULTS

4.2.1. Subsample Estimates by Firm Scale

In this section, we perform subsample estimations to explore the heterogeneous effect of relatedness on product diversification across different firm size groups as well as different product complexity categories. By doing so, we aim to shed light on how the determinants of new product choices may vary across different contexts and settings. Subsample estimations can also serve as robustness checks to assess the robustness of the estimated relationships. Recent literature on firm heterogeneity emphasizes that firm's performance in terms of both intensive and extensive margin can show variation depending on the firm characteristics (Bernard et al., 2007; Poncet and de Waldemar, 2015; Morales et al., 2019).

Firstly, we repeat the estimations shown in the Equation-7 for four different firm size (micro, small, medium, large) categories. Official definition of the Small and Medium Enterprises Development Organization of Türkiye is used to classify firm according to their size (See Appendix-C for the definition of the firms sizes). Depending on the heterogeneity of the firms, role of firm and place specific capabilites may show variations. Table-10 shows the subsample estimations. Signs and statistically significance of the coefficients are almost same as the full-sample estimation. Regression outputs are robust to different subsamples.

When we compare the results for different subsamples, we see significant differences in terms of the size of the density variables' coefficients. Firstly, there is significant variation in the coefficient on the *Firm Density* variable by firm size. As the firm size decreases, the coefficient value of the *Firm Density* variable increases. Particularly, the coefficient size on *Firm Density* variable is highest for the small firms. In terms of the log odds values, coefficient for subsample of small firms is four times higher than the subsample of large firms.). Specifically, for small firms a percentage increase in *Firm Density* would, all else being equal, result in a 42 percent increase [calculated as exp(35.62*0.01) = 1.42] in the odds of firm p introducing the product. For the large firms, effect on odds ratio equals to 11 percent [calculated as exp(10.54*0.01)]. This indicates that smaller firms tend to rely on their internal capabilities to drive product innovation. Small firms may lack the absorptive capacity needed to effectively assimilate and apply external knowledge (Cohen and Levinthal, 1990).

Table 10 – Subsample Estimations (Firm Size)

	(1)	(2)	(3)	(4)	(5)
	Full Sample	Large	Medium	Small	Micro
Firm Density	8.500*** (1.716)	10.57*** (1.914)	22.39*** (2.247)	35.62*** (5.113)	31.51*** (3.015)
Firm Import Density	11.56*** (0.8871)	8.891*** (1.114)	19.61*** (1.450)	31.42*** (1.470)	41.69*** (2.042)
Regional Density	4.423** (1.400)	3.302* (1.541)	4.970*** (1.467)	5.538*** (1.318)	7.789*** (1.769)
Neigbourhood Density	1.619 (1.970)	3.683** (1.387)	-0.1700 (1.620)	-0.8945 (3.450)	-4.798 (7.896)
RCA	0.3914*** (0.0651)	0.3518*** (0.0750)	0.3977*** (0.0779)	0.4018*** (0.0630)	0.3539** (0.1305)
Export Variety	0.2285*** (0.0374)	0.0544 (0.0900)	0.1035* (0.0466)	-0.0171 (0.0290)	-0.0131 (0.0326)
Number of Related Product	0.1378*** (0.0114)	0.0827*** (0.0070)	0.2158*** (0.0314)	0.2607*** (0.0389)	0.1431* (0.0592)
Multi-Regional	0.1261* (0.0559)	0.0844 (0.1214)	-0.0193 (0.0433)	0.1601 (0.1245)	-0.5808*** (0.0551)
Fixed-Effects:	------------------	------------------	------------------	------------------	-------------------
HS4 Product	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Region	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
S.E.: Clustered	by: HS4 Prod & Region	by: HS4 Prod & Region	by: HS4 Prod & Region	by: HS4 Prod & Region	by: HS4 Prod & Region
Observations	8,342,644	942,082	2,327,338	2,970,339	392,817
Squared Cor.	0.02206	0.04924	0.02156	0.01519	0.01309
Pseudo R2	0.19095	0.19742	0.17884	0.16871	0.11961
BIC	328,311.9	89,748.8	112,138.4	118,035.3	27,721.0

*p < 0:10;**p < 0:05;***p < 0:01. Standard errors are clustered at HS-4 product and region level.

The variation in the coefficients on the *Firm Density* and *Firm Density Import* variables have similar pattern across subsamples. The size of the coefficient on *Firm Density Import* variable is highest for the micro-scale firms. Coefficient size decreases monotonically as the scale of the firm grows. Results show that capabilities coming from abroad through importing have a crucial role in the process of new product development of small firms. Learning through the importing effect is the strongest within micro-scaled firms. Particularly, a percentage increase in Firm Density Import would, all else being equal, result in a 51 percent increase [exp(41.69*0.01) = 1.51] in the odds of firm p introducing the product.

The size of the *Firm Density* variable is higher than the *Firm Density Import* variable in all subsamples except for micro-scale firms. Closeness to import basket is found to be a more significant driver of new product choice for only micro-scale firms. The coefficient values for the two density variables are highest among micro-scale firms. These results suggest that the process of productive change within firms is highly path-dependent and what a firm currently exports will significantly condition what it will be able to export in the future. Besides the available internal capacity embodied in the export basket of firms, importing activity also facilitates the emergence of new related products. Results are quite in line with the predictions of the recent international trade literature which considers importing as one channel of technology transfer (Acharya and Keller, 2007; Goldberg et al. 2010; Dalgıç and Fazlıoğlu, 2015; Alonso and Martin, 2019). Firms tend to introduce new products that share similar capabilities with the products they import.

According to results, the *Regional Density* variable has a positive significant effect on the introduction of new products among all groups. A new product is more likely to be introduced when it is related to local product space. For firms of all sizes, proximity to competitive industries in the region facilitates the development of relevant new products. Similar to previous density variables, the effect of *Regional Density* is stronger as the firm size gets smaller. The contribution of a regional set of product based capabilities is the highest micro-scaled firms. Since large companies are more engaged with R&D activity and the production of complex goods, they possess a significant reservoir of technical knowledge (Lo Turco and Maggioni, 2016). As a result, they rely relatively less on spillovers from local productive structure.

The effect of *Neighbour Density* is statistically insignificant across all subsamples except for large firms. In the full-sample estimation results, coefficient on this variable was insignificant. In the subsample estimations, we see that large firms leverage the capabilities and knowledge present in neighboring provinces to their advantage. In the case of smaller firms, the lack of statistical significance might be attributed to their constrained outreach capacity for extra-territorial knowledge resources. Literature emphasizes that large firms often have more adequate resources to overcome geographical barriers and establish connections beyond region (Cooke and Morgan, 1998). Large firms tend to have established networks and collaborative relationships with other entities, including suppliers, and complementary businesses. These networks contribute to a collaborative advantage, facilitating access to capabilities.

Coefficient estimates for *RCA* are positive and statistically significant for all subsamples. The obtained coefficient values are very close to each other for all subsamples. It reveals that existing agglomeration in certain product categories can enhance firms' diversification towards these products by facilitating access to the specialized labour pool, supplier network and exchange of ideas for all firm categories.

Export Variety variable is found to be significant only for medium-sized firms. For all subsamples, having a larger export basket consisting of related products is associated with higher probability of introduction of that product. The coefficient associated with the number of related products has positive sign for all subsamples. Firms with more related products in their portfolios are more likely to add new products. Regarding the role of *Multi-Regional* dummy variable, results are quite surprising and inconsistent. Coefficient estimate of this variable is positive and statistically significant for the full sample. However, at subsample estimation, coefficient is only significant for micro firms and the sign is negative. Although the results are not in line with expectations, the issue can be examined in more depth in future studies.

As can be seen from the regression results, the coefficient size on all of the density variables except neighbourhood density are lowest for large firms. This indicates that large firms are less likely to engage in related diversification as compared to small firms. By nature, large-scale firms are more connected with external partners and have access to extensive networks including suppliers, distributor and strategic partnerships. These connections may provide them valuable resources and market insights that smaller firms may not have access to (Rumelt, 1974; Teece, 1980). These superiorities can support large firms in their efforts to diversify into unrelated products. As a result, involvement in multiple environments may diminish the reliance on location-specific capabilities for product innovation, as they can tap into different pools of knowledge resources.

As put forth by Penrose (1959) and Jacobs (1969), firms must continually expand their product (knowledge) portfolios to maintain competitiveness in the long term. From this aspect, unrelated diversification serves as a crucial means for firms to prevent stagnation and ensure long term growth (Saviotti and Frenken, 2008). Large firms often have a diverse portfolio of business units and divisions. By engaging in unrelated activities, they may spread their risks across different business units and products. For instance, if there is a demand shock for one product category and sales decline, the firm's revenues can be mitigated by the success of other unrelated products. Model results show that capabilities available at firm and region level have important implications for the diversification path of the Turkish manufacturing exporters. One of the most important findings obtained is the impact of micro level and regional related capabilities on new product choice of the firms. Triggered by the emergence of regional innovation systems concept, several studies explored the interplay between internal resources and regional environment regarding innovative activity of firms (Pfirrman, 1994; Sternberg and Arnd, 2009; Lo Turco and Maggioni, 2016; Hazir et al., 2019; Frigon and Rigby, 2020). Results obtained in this study are quite consistent with the prior empirical study indicating that internal resources matter most for product innovation of the firms.

4.2.1. Subsample Estimates by Product Complexity Levels

In addition to subsamples based on firm characteristics, we also examine the effect of relatedness on the emergence of new products depending on the nature of the knowledge. Products with higher complexity require a more diverse set of capabilities, including specific skills, technology, and organizational know-how (Hidalgo and Hausmann, 2009). Many disciplines seek to understand why some types of knowledge diffuse widely, while other types of knowledge cannot. For instance, highly complex knowledge may disperse slowly, because except from its original innovator only a limited number of firms may possess necessary baseline knowledge and skills to absorb it (Cohen and Levinthal, 1990). In this respect, we distinguish products according to their complexity and assess the role firm and region specific capabilities.

Table-11 shows the subsample estimation results for different product complexity categories. Since the complexity value of each product is in continuous form, we categorize them based on the quartile values of the variable. Between Column (1) and Column (4) subsample estimations for quartiles are reported. Products are categorized into low (Column 1), medium (Column 2 and Column 3) and high (Column 4) complexity (See Appendix-A for computation details for product complexity values).

As evident from the subsample estimations by product complexity level, the three main density variables are statistically significant. We find that value of coefficient on the *Firm Density* variable increases with the rise in product complexity. A similar pattern is noted for the *Firm Density Import* variable. The opposite is true regarding the variation of the coefficient size of the *Regional Density* variable across subsamples. It can be seen that coefficient on *Regional Density* decreases as the product complexity level increases. While the *Regional Density* has the highest effect for low-complexity products, it has the lowest effect for high complexity products. It implies that, regional spillovers appear to exert a more significant impact on firms' product innovation for products characterized by low complexity values. Just as observed in the previous estimations, *Neigbourhood Density* variable does not have any significant effect in any subsample.

Looking at the Column (1)*, Firm Density* variable has a coefficient of 7.8, while the *Regional Density* variable has a coefficient of 15.5 for products in the low-complexity category. In terms of their impact on odds ratios, we see that regional factors have an approximately two times higher impact. Under the high-complexity category, the estimation results indicate that the effect of the *Firm Density* variable on the odds ratio is 2.2 times greater than that of the *Regional Density* variable (Column 4).

The results suggest that proximity to firm-based resources and capabilities is more important for the emergence of high-complexity products. The direct capabilities that firms have through products that they can already export and that they acquire through direct import activity are critical for more complex products. This actually provides important clues about the fact that the diffusion of highly complex knowledge is more difficult (McEvily and Chakravarty, 2002). The diffusion of complex knowledge is often regarded as challenging for several reasons. Firstly, complex knowledge often includes tacit elements, which are challenging to codify and transfer explicitly. Tacit knowledge relies on personal experience, intuition, and context-specific understanding. Transferring such knowledge requires more than just documentation; it often involves hands-on experience and mentorship (Polanyi, 1966). Certain types of knowledge may be challenging because the sender of the knowledge could struggle to perfectly specify and communicate the original idea (Sorenson et al., 2015).

Especially for the firms engaged in manufacturing of complex product, they generally have in-house experts and experienced personnel who possess domain-specific knowledge. Internal knowledge diffusion needed for complex products can leverage this existing expertise, making it more accessible for employees within the organization (Sorenson et al., 2015). Complex products often require specialized knowledge, skills, and capabilities that may not be readily available in the regional productive resources. Even if they exist in the local economy, it is often challenging and costly to access and absorb it (Teece, 1977).

Model results are in line with the expectations of the literature. Literature predicts that complex knowledge tends to diffuse more slowly than simple knowledge (Nelson and Winter, 1982; Sorenson et al., 2015). The learning curve for complex knowledge is steeper, and it may take time for individuals and organizations to grasp and adopt these advanced ideas.

Table 11 - Estimation Results (Product Complexity Levels)

	(1)	(2)	(3)	(4)
	Low Complexity	**Medium-1 Comlexity**	**Medium-2 Complexity**	**High Complexity**
Firm Density	7.880*** (1.661)	8.432*** (2.036)	7.376*** (1.798)	10.61*** (1.752)
Firm Import Density	8.408*** (1.555)	11.61*** (1.084)	12.35*** (0.7708)	12.85*** (0.7754)
Regional Density	15.55*** (2.156)	6.609** (2.286)	7.346** (2.253)	4.754** (1.627)
Neigbourhood Density	-0.2822 (3.215)	6.498* (2.599)	4.078 (3.056)	0.3143 (2.063)
RCA	0.5040*** (0.0752)	0.3464*** (0.0760)	0.2968*** (0.0724)	0.2072* (0.0942)
Export Variety	0.1516*** (0.0279)	0.2428*** (0.0367)	0.2428*** (0.0401)	0.2145*** (0.0480)
Number of Related Product	0.4116*** (0.0414)	0.1575*** (0.0238)	0.1268*** (0.0139)	0.0647*** (0.0107)
Multi-Regional	0.2662*** (0.0796)	0.1742** (0.0622)	0.0246 (0.0622)	0.0672 (0.0695)
Fixed-Effects:	------------------	------------------	------------------	------------------
HS4 Product	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes
S.E.: Clustered	by: HS4 Prod & Region	by: HS4 Prod & Region	by: HS4 Prod & Region	by: HS4 Prod & Region
Observations	1,999,143	2,166,820	2,092,344	2,064,615
Squared Cor.	0.02277	0.02592	0.02490	0.02256
Pseudo R2	0.19823	0.20295	0.18727	0.19467
BIC	75,973.1	89,027.2	95,278.6	66,988.3

Product Complexity Quantiles

Low: 0.0087 - 0.38 | **Medium-1:** 0.38 - 0.71 | **Medium-2:** 0.71 - 1.24 | **Large:** 1.24 - 14.80

*p < 0:10; **p < 0:05;***p < 0:01. Standard errors are clustered at HS-4 product and region level.

CONCLUSION

In this thesis, we explore the role of firm and place based capabilities on product diversification choices of the firms, with a focus on Turkish manufacturing exporters. The assessment of product relatedness in this study utilizes the density indicator proposed by Hidalgo et al. (2007). This methodology measures the degree of relatedness among products by analyzing their co-occurrence patterns observed in the export portfolios of countries.

Using logistic regression methodology with a large firm-level database obtained from the Entrepreneurship Information System (EIS), we investigate whether proximity to firm- and local-level product space is a significant driver of new product choices for the firms. We focus on Turkish manufacturing exporters' product diversification choices for cross-section period of 2012-2017. We find that Turkish exporters' product diversification exhibits a strong path dependence, stemming from firm and region-level capabilities relevant to specific products. Firms tend to diversify towards products that require similar capabilities and resources available at the firm and local level. Findings remain robust even when accounting for different subsamples, the effects of agglomeration economies, and other firm-specific controls.

Our findings indicate that product diversification of the firms is mainly influenced by the capabilities present within the firms. Internal capabilities of firms and external knowledge acquired through importing activities of firms are critical for the introduction of new products. In the broader context, the capabilities of the firm as a whole have a stronger impact on the choice of new products compared to the capabilities available at the regions. Nonetheless, we find evidence of a positive and significant impact of region-specific capabilities on diversification at the firm level as well. This outcome highlights the importance of local knowledge spillovers in influencing the product diversification patterns of firms. On these points, empirical findings for the Turkish case are found to be consistent with similar studies conducted in other country contexts. Concerning the effect of inter-regional spillovers, we do not find a significant effect of capabilities available in neighboring regions. Results are found to be robust to alternative subsamples and neighboring specifications. This may indicate a decay in knowledge diffusion with increasing geographical distance (Jaffe et al., 1993).

We also examine how firm- and place-based capabilities influence product diversification choices in various subsamples. Subsample estimations based on firm size reveal that the role of relatedness is more significant for smaller firms. As firm size increases, the impact of density variables gradually diminishes. Subsample estimations based on product complexity show that the role of relatedness varies as the complexity level of the product changes. We find that as the complexity level of the product increases, the impact of firm-level resources on product diversification increases, and the impact of local resources decreases. This finding confirms the expectations of theoretical literature that the diffusion of complex knowledge is relatively difficult due to its tacit dimension (Nelson and Winter, 1982; Sorenson et al., 2015). When the overall results are evaluated, the findings align closely with the theoretical literature (Barney, 1991; Teece et al., 1997; Boschma and Frenken, 2011). Among other factors, economies of scope, slack resources, local knowledge spillovers, and learning through importing can provide essential inputs for diversification.

This thesis contributes to the literature in several aspects. Firstly, in the previous literature, most of the empirical studies analyzing the link between diversification and relatedness focus on country (Hidalgo et al., 2007; Haussman and Hidalgo, 2010; Bahar et al., 2014; Boschma and Capone, 2016) or region scale (Neffke et al., 2011) Boschma et al., 2013; Essletzbichler, 2015; Boschma et al., 2017b). This thesis provides a firm-level evidence. Moreover, its particular emphasize is the role of local knowledge diffusion in the diversification process of firms.

Secondly, by adopting a spatially multi-scaled perspective, this study contributes to the literature by simultaneously considering firm-, region-, and neighbor region-level capabilities. In this regard, the findings of this thesis offer a significant insight to the ongoing discussion on the measurement of the relative impact of the regional environment compared to firm-specific factors on the product innovation performance of firms.

Lastly, as far as we know, no study has analyzed the role of potential spillovers from neighboring regions and import activities on firms' decisions regarding new products. In this respect, our work makes an important contribution to the literature by taking into account the effect of these variables.

The findings of this thesis allow to make several possible policy recommendations. As it is shown, product space holds a significant impact on the process of emergence of new activities. The product space maps the relationships between different products. Policymakers can use relatedness metrics to prescribe feasible new production areas to be targeted. Despite the importance of economic diversification, in the long run what matters most is not the rate of diversification but rather the complexities of products (Haussman et al., 2007). For some regions, most related products in the opportunity space may be low-complexity products. In this case, primarily focusing on related activities may lead to technological lock-in. Therefore, it is important to consider the diversification agenda with complexity dimension as well. An optimum strategy may be targeting more related and complex areas. Products with high relatedness are closely linked to the current productive base of the region. Diversification into those products may be less a costly and low cost strategy. On the other hand, products that are distant from the productive base of the region may be associated with more cost and risk (Balland et al., 2019). Gaining competency in each new product category leads to change in the overall complexity of regional economy. In this respect, targeting high-related and high-complexity areas may offer more value-added potential to local economies.

The concept of relatedness is regarded as a useful tool in the Smart Specialization Strategies being developed within EU member and candidate countries (Balland et al., 2019). Smart Specialization Strategies aims to foster innovation-driven growth by leveraging a region's existing assets and capabilities to develop unique competitive advantages in specific areas of economic activity. Most critical part of it is the identifying and prioritizing a region's strengths, building upon existing capabilities, and creating an environment that fosters innovation and entrepreneurship in those areas (Whittle and Kogler, 2019). In this regard, findings of the thesis could be utilized in smart specialization strategies being developed in the Türkiye (Gültekin et al., 2023).

Another potential application of relatedness measures is for the detection of bottlenecks in the local economy. For instance, for any industry to gain a comparative advantage in the local economy, there should be many complementary factors such as a skilled workforce, well-functioning infrastructure, entrepreneurs, effective institutions, and so forth. If relatedness measures cannot accurately identify new products, these anomalies may indicate potential constraints discouraging the development of new industries within the local economy. Identifying these bottlenecks is crucial for policymakers to formulate targeted strategies and interventions. However, policymakers may conduct in-depth growth diagnostics (Haussman et al., 2008) to correctly identify those bottlenecks and tailor interventions effectively. While relatedness measures provide valuable insights into which products and industries have the potential to grow in the economy, a more detailed examination is necessary to identify specific constraints and formulate precise policy responses. This thesis provides the supporting empirical evidence that product diversification of the firms is path dependent, but not completely pre-determined. Results show that the related diversification pattern is more evident for smaller-sized firms. Whereas, large firms have a relatively higher tendency to shift to unrelated areas. In this respect, it is useful to consider the composition of firms in the regions according to their scale in terms of the design of industrial policy. While it may be more feasible to focus on highly related areas in regions with a relatively high concentration of small-scale firms, in areas with a relatively high concentration of medium-sized and large firms, it is useful to consider the potential for shifting to unrelated areas.

We suggest that our study can be enhanced in several aspects in further studies. Our analysis focuses on manufacturing firms. Further studies may explore both manufacturing firms and service sector firms. This would allow an examination of whether various types of firms in different sectors are influenced differently by their firm and local-level product space. In this study, we only focus on the cross-section of the 2012-2017 period. Further studies may employ a panel binary modeling methodology to analyze the causal relationship between firm and local-specific capabilities and diversification.

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APPENDIX A

Calculation of Product Complexity Values

In order to use calculate product complexity value of each HS-4 product, we utilize *method of reflections* developed by Hausmann and Hidalgo (2010). This method considers bilateral trade data as a network connecting the set of countries and the set of products that they export with revealed comparative advantage (RCA). To make their method operational, Hausmann and Hidalgo (2010) define diversification as the number of products that a country exports with RCA. We utilize country-level export data, available through UNCOMTRADE, at the HS-4 product resolution level to carry out the following steps.

M_{cp} is a product-country matrix in which rows denotes countries, columns denotes products. Any element of matrix equals to 1 if country c has revealed competitive advantage in product p. Diversity of countries can be obtained by summing the row, ubiquity of products can be obtained by summing the columns.

$$Diversity = k_{c,0} = \sum_{p} M_{cp} \tag{15}$$

$$Ubiquity = k_{p,0} = \sum_{c} M_{cp} \tag{16}$$

In order to correctly measure number of existing capabilities in country in a country, or required by product, we need to extract the information that diversity and ubiquity metrics contain by recursively correct each one to correct each other. Firstly, for countries we compute average ubiquity of products that countries export and average diversity of countries that export those products. Analogously for product, firstly we compute average diversity of the countries the countries that export them and average ubiquity of other products that these countries export. All of these calculations can be expressed by recursive iteration (Ourens, 2013).

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_{p} M_{cp} \,.\, k_{p,N-1} \tag{17}$$

$$k_{p,N} = \frac{1}{k_{p,0}} \sum_{c} M_{cp} \,.\, k_{c,N-1} \tag{18}$$

If we insert (last) into (first) we obtain

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_{p} M_{cp} \frac{1}{k_{p,0}} \sum_{c'} M_{c'p} \; k_{c',N-2} \tag{19}$$

$$k_{c,N} = \sum_{c'} k_{c',N-2} \sum \frac{M_{cp} M_{c'p}}{k_{c,0} \, k_{p,0}} \tag{20}$$

$$k_{c,N} = \sum_{c'} \widetilde{M_{cc'}} \; k_{c',N-2} \tag{21}$$

where

$$\widetilde{M_{cc'}} = \sum_{p} \frac{M_{cp} M_{c'p}}{k_{c,0} \, k_{p,0}} \tag{22}$$

Equation-21 is satisfied when $k_{c,N} = k_{c,N-2} = 1$. This expression equals to eigenvector of $\widetilde{M_{cc'}}$. Authors argue that this element is not informative because its vector of ones. Hence, authors consider second eigenvector which have largest variance in the system as measure of economic complexity. Eventually, Economic Complexity Index (ECI) is defined a follows:

$$ECI = \frac{\vec{K} - <\vec{K}>}{stdev(\vec{K})} \tag{23}$$

Where < > denotes an average, and stdev represents standart deviation

$$\vec{K} = Eigenvector\ \ of \widetilde{M_{cc'}}\ \ associated\ with\ second\ largest\ value \tag{24}$$

Symetrically, authors compute Product Complexity Index (PCI) as follows. Computation steps of PCI is same as ECI, only alteration is that we change index of countries (c) with product (p) in the expressions above.

$$PCI\ = \frac{\vec{Q} - < \vec{Q} >}{stdev(\vec{Q})} \tag{25}$$

$$\vec{Q} = Eigenvector\ \ of \widetilde{M_{pp'}}\ \ associated\ with\ second\ largest\ value \tag{26}$$

APPENDIX B

Before interpreting the results of a logistic regression analysis, it is essential to assess whether the model's assumptions are met. These assumptions help ensure the validity and reliability of the estimated coefficients and predictions. In this Appendix section, we discuss the key assumptions associated with logistic regression and outline the methods used to check them.

Logistic regression model assumes that each observation in the dataset is independent from each other. Since the main observation unit in the model is firm-HS4 product, observation in the dataset is clustered in various units such as firm, province and product level. In order to adress this issue, I use cluster-robust standart errors (province and HS4 product level) to adjust for the corrleation within clusters.

Secondly, logistic regression model reqires that there is not problem of multicollinearity problem in the model. If the variables are highly correlated with each other, it can make it challenging to isolate the individual effect of each independent variable. To adress this concern, Pearson correlation matrix for continuous variables are reported in Table – 12. As can be seen from the table, there is no strong correlation between the variables. There is only a moderate correlation between *Firm Density* and *Firm Density Import* variables that does not pose a problem in model estimation.

Table 12 – Pearson Correlation Values Among Numeric Predictors

	Firm Density	**Firm Density Import**	**Regional Density**	**Neighborhood Density**	**Export Variety**	**Number of Related Product**
Firm Density	1	0,489	0,023	0,039	0,524	0,349
Firm Density Import	0,489	1	-0,038	0,099	0,165	0,199
Regional Density	0,023	-0,038	1	-0,129	0,085	0,007
Neighborhood Density	0,039	0,099	-0,129	1	0,006	0,025
Export Variety	0,524	0,165	0,085	0,006	1	0,154
Number of Related Product	0,349	0,199	0,007	0,025	0,154	1

The relationship between the independent variables and the log-odds of the dependent variable should be linear. This means that the log-odds of the outcome variable should change linearly with changes in the predictor variables. To check validity of this assumption, one possible solution may be visually inspecting the scatter plot between each continious predictor and and associated logit values of the dependent variable. However, since we have 8,3 million observation in our sample, visual inspection option in found to be unfeasible. In order to deal with this issue, I take random sample of whole dataset and plot the relationship between these two variable. Figure-13 illustrates the relationship between logit and four main density variables. Through rigorous examination, via visual inspections, there are indications that this linearity assumption may not be perfectly met in our dataset especially for the Region Density and Neighbour Density variables. Problem arises becase as it can be seen from the graphs that some of the observations are clustered at the upper part of the plot. We deeply investigate this issue and find that distribution of the Regional Density variable is towards a higher average value in the observations within the Istanbul province compared to other provinces (Figure-14). As can be seen from Equation-5, by nature Regional Density value for any firm is expected to increase as the number of products in which the province has a comparative advantage increases. In order to address this situation, we include the province level fixed effect. Logistic regression, despite its assumption of linearity, offers flexibility in capturing various relationships. The substantial size of our dataset, comprising nearly 8 million observations, provides statistical advantages, enhancing the stability of our parameter estimates and increasing the sensitivity of our analyses. It is important to recognize that real-world relationships are often intricate and may not conform to linear patterns. Our dataset reflects the complexity inherent in many phenomena.

Figure 13 – Relationship Between Main Predictors and Logit

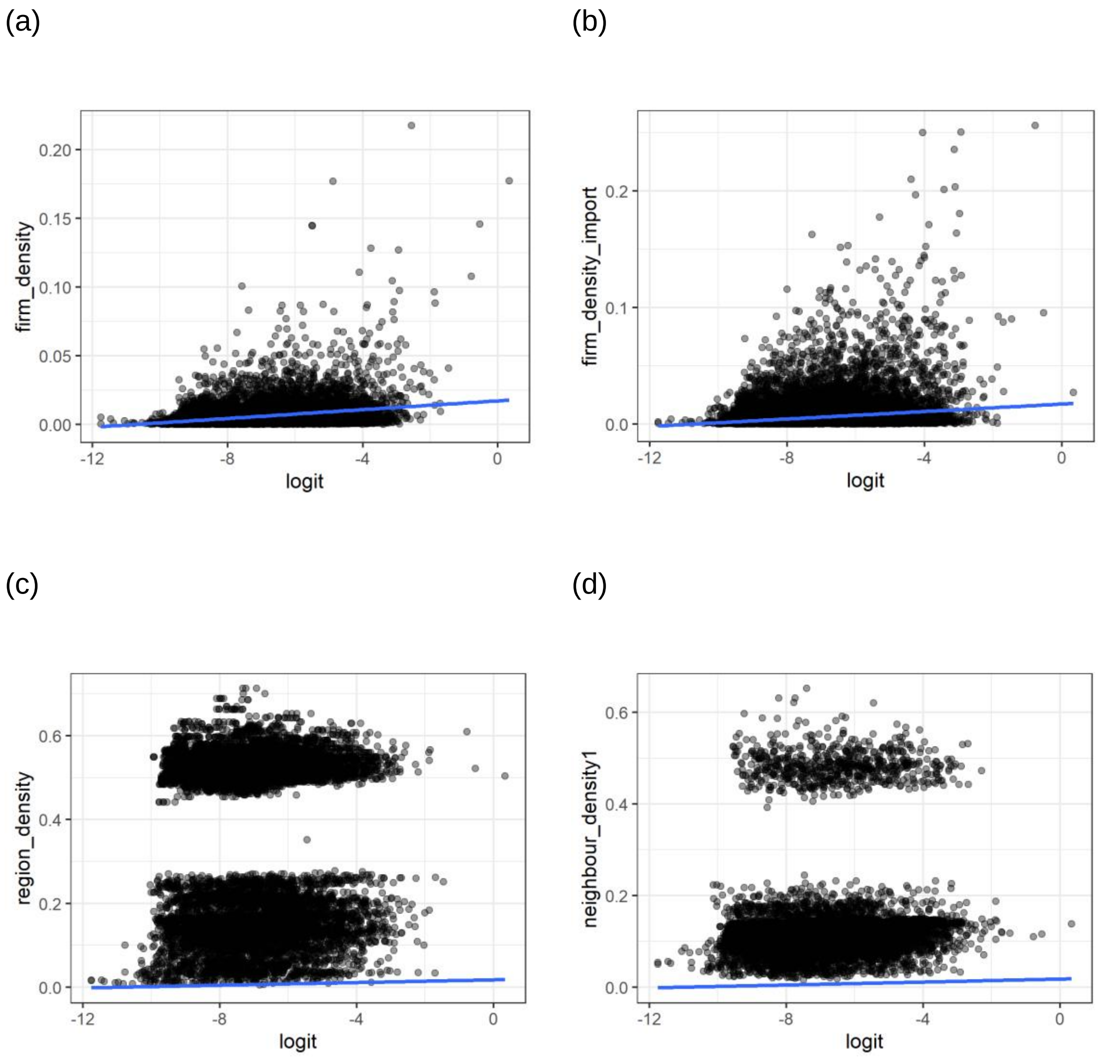
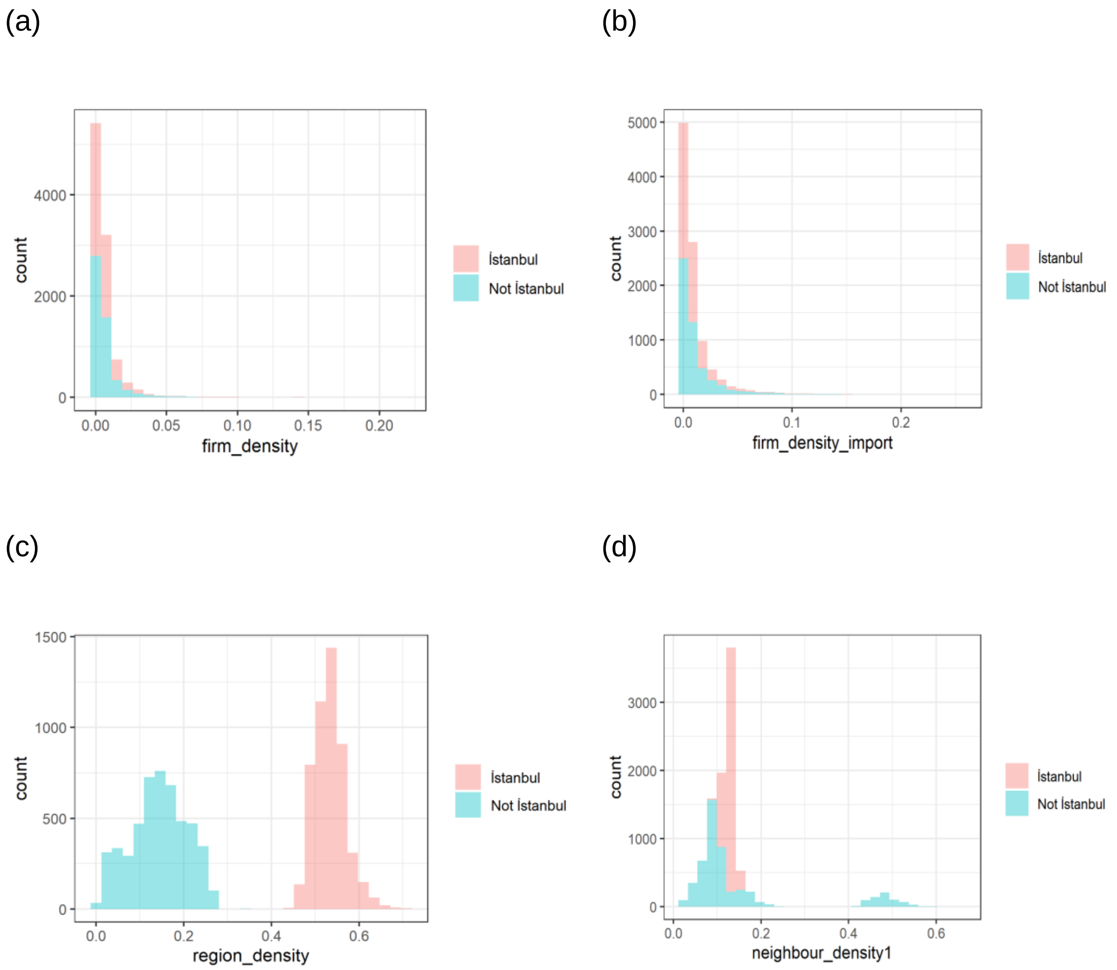


Figure 14 – Distribution of Main Predictors



APPENDIX C

Box 1 – Official Definition of Enterprise Size

a) Micro-enterprise: Enterprises that employ less than ten employees and whose annual net sales revenue or financial balance sheet does not exceed five million Turkish Liras.

b) Small enterprise: Enterprises that employ less than fifty employees and whose annual net sales revenue or financial balance sheet does not exceed fifty million Turkish Liras.

c) Medium-sized enterprise: Enterprises employing less than two hundred and fifty employees and having an annual net sales revenue or financial balance sheet not exceeding two hundred and fifty million Turkish Liras.

d) Large enterprise: Enterprises employing more than two hundred and fifty persons or having an annual net sales revenue or financial balance sheet exceeding two hundred and fifty million Turkish Liras.

Source: Small and Medium Enterprises Development Organization

APPENDIX D

Table 13 – Estimation Results (Micro Firms)

	(1)	(2)	(3)	(4)	(5)
Firm Density	27.57*** (2.785)				31.51*** (3.015)
Firm Import Density		39.78*** (2.734)			41.69*** (2.042)
Regional Density			7.536*** (2.054)		7.789*** (1.769)
Neigbourhood Density				1.028 (7.335)	-4.798 (7.896)
RCA	0.4562*** (0.1314)	0.4531*** (0.1299)	0.3629** (0.1159)	0.4567*** (0.1360)	0.3539** (0.1305)
Export Variety	0.0476 (0.0342)	0.2024*** (0.0269)	0.2409*** (0.0266)	0.2411*** (0.0266)	-0.0131 (0.0326)
Number of Related Product	0.1544* (0.0660)	0.2067** (0.0683)	0.2116** (0.0718)	0.2106** (0.0730)	0.1431* (0.0592)
Multi-Regional	-0.5482*** (0.0226)	-0.5980*** (0.0295)	-0.5585*** (0.0168)	-0.5595*** (0.0216)	-0.5808*** (0.0551)
Fixed-Effects:	-------------------	-------------------	-------------------	-------------------	-------------------
HS-4 Product	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes
S.E.: Clustered	by: HS4 Prod & Region	by: HS4 Prod & Region	by: HS4 Prod & Region	by: HS4 Prod & Region	by: HS4 Prod & Region
Observations	392,817	392,817	392,817	392,817	392,817
Squared Cor.	0.01114	0.01081	0.00979	0.00952	0.01309
Pseudo R2	0.11066	0.11481	0.10893	0.10776	0.11961
BIC	27,894.0	27,795.9	27,934.9	27,962.6	27,721.0

*p < 0:10;**p < 0:05;***p < 0:01. Standard errors are clustered at HS-4 product and region level.

Table 14 – Estimation Results (Small Firms)

	(1)	(2)	(3)	(4)	(5)
Firm Density	35.04*** (5.873)				35.62*** (5.113)
Firm Import Density		31.50*** (1.637)			31.42*** (1.470)
Regional Density			5.986*** (1.599)		5.538*** (1.318)
Neigbourhood Density				-0.0742 (3.615)	-0.8945 (3.450)
RCA	0.4771*** (0.0682)	0.4733*** (0.0684)	0.4012*** (0.0591)	0.4770*** (0.0718)	0.4018*** (0.0630)
Export Variety	0.0133 (0.0348)	0.2056*** (0.0233)	0.2355*** (0.0246)	0.2353*** (0.0247)	-0.0171 (0.0290)
Number of Related Product	0.2676*** (0.0419)	0.3318*** (0.0344)	0.3375*** (0.0360)	0.3378*** (0.0360)	0.2607*** (0.0389)
Multi Regional	0.2309* (0.1037)	0.1800 (0.1311)	0.2556* (0.1160)	0.2554* (0.1160)	0.1601 (0.1245)
Fixed-Effects:	------------------	------------------	------------------	------------------	------------------
HS-4 Product	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes
S.E.: Clustered	by: HS4 Prod & Region	by: HS4 Prod & Region	by: HS4 Prod & Region	by: HS4 Prod & Region	by: HS4 Prod & Region
Observations	2,970,339	2,970,339	2,970,339	2,970,339	2,970,339
Squared Cor.	0.01348	0.01499	0.01353	0.01349	0.01519
Pseudo R2	0.16245	0.16381	0.15885	0.15818	0.16871
BIC	118,780.1	118,609.3	119,234.6	119,319.4	118,035.3

*p < 0:10;**p < 0:05;***p < 0:01. Standard errors are clustered at HS-4 product and region level.

Table 15 – Estimation Results (Medium Firms)

	(1)	(2)	(3)	(4)	(5)
Firm Density	27.89*** (2.375)				22.39*** (2.247)
Firm Import Density		21.98*** (1.479)			19.61*** (1.450)
Regional Density			5.419*** (1.615)		4.970*** (1.467)
Neigbourhood Density				-0.1231 (1.934)	-0.1700 (1.620)
RCA	0.4661*** (0.0862)	0.4601*** (0.0857)	0.3921*** (0.0762)	0.4626*** (0.0879)	0.3977*** (0.0779)
Export Variety	0.0940* (0.0427)	0.2674*** (0.0351)	0.2980*** (0.0322)	0.2981*** (0.0321)	0.1035* (0.0466)
Number of Related Product	0.2228*** (0.0321)	0.2723*** (0.0310)	0.2971*** (0.0305)	0.2976*** (0.0303)	0.2158*** (0.0314)
Multi-Regional	0.0684 (0.0638)	-0.0054 (0.0389)	0.0939 (0.0652)	0.0955 (0.0649)	-0.0193 (0.0433)
Fixed-Effects:	------------------	------------------	------------------	------------------	------------------
HS-4 Product	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes
S.E.: Clustered	by: HS4 Prod & Region	by: HS4 Prod & Region	by: HS4 Prod & Region	by: HS4 Prod & Region	by: HS4 Prod & Region
Observations	2,327,338	2,327,338	2,327,338	2,327,338	2,327,338
Squared Cor.	0.01925	0.02054	0.01816	0.01813	0.02156
Pseudo R2	0.17142	0.17546	0.16750	0.16682	0.17884
BIC	112,987.9	112,501.5	113,459.3	113,540.6	112,138.4

*p < 0:10;**p < 0:05;***p < 0:01. Standard errors are clustered at HS-4 product and region level.

Table 16 – Estimation Results (Large Firms)

	(1)	(2)	(3)	(4)	(5)
Firm Density	16.85*** (2.455)				10.57*** (1.914)
Firm Import Density		11.17*** (0.9796)			8.891*** (1.114)
Regional Density			3.175* (1.535)		3.302* (1.541)
Neigbourhood Density				2.916* (1.439)	3.683** (1.387)
RCA	0.3898*** (0.0796)	0.3912*** (0.0789)	0.3377*** (0.0736)	0.3864*** (0.0743)	0.3518*** (0.0750)
Export Variety	-0.0240 (0.0959)	0.1801* (0.0854)	0.2117* (0.0926)	0.2115* (0.0928)	0.0544 (0.0900)
Number of Related Product	0.0892*** (0.0080)	0.1229*** (0.0092)	0.1646*** (0.0140)	0.1652*** (0.0143)	0.0827*** (0.0070)
Multi-Regional	0.2092** (0.0756)	0.0859 (0.1238)	0.2002** (0.0748)	0.2003** (0.0747)	0.0844 (0.1214)
Fixed-Effects:	------------------	------------------	------------------	------------------	------------------
HS-4 Product	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes
S.E.: Clustered	by: HS4 Prod & Region	by: HS4 Prod & Region	by: HS4 Prod & Region	by: HS4 Prod & Region	by: HS4 Prod & Region
Observations	942,082	942,082	942,082	942,082	942,082
Squared Cor.	0.03928	0.04726	0.03336	0.03321	0.04924
Pseudo R2	0.18455	0.19324	0.17275	0.17257	0.19742
BIC	90,949.4	90,111.0	92,088.7	92,106.2	89,748.8

*p < 0:10;**p < 0:05;***p < 0:01. Standard errors are clustered at HS-4 product and region level.

Table 17 – Estimation Results (Full Sample, Alternative Neigbouring Specificiation)

	(1)	(2)	(3)	(5)	(7)
Firm Density	18.21*** (2.584)				8.501*** (1.715)
Firm Import Density		13.54*** (0.9347)			11.56*** (0.8845)
Regional Density			4.556** (1.420)		4.819** (1.587)
Neigbourhood Density - Alt				2.170 (2.779)	5.035 (3.366)
RCA	0.4445*** (0.0714)	0.4475*** (0.0726)	0.3790*** (0.0628)	0.4436*** (0.0733)	0.3930*** (0.0647)
Export Variety	0.1623*** (0.0445)	0.2902*** (0.0310)	0.3106*** (0.0341)	0.3104*** (0.0343)	0.2286*** (0.0373)
Number of Related Product	0.1459*** (0.0113)	0.1666*** (0.0098)	0.2208*** (0.0132)	0.2213*** (0.0133)	0.1378*** (0.0114)
Multi-Regional	0.3414*** (0.0394)	0.1395* (0.0586)	0.4251*** (0.0382)	0.4257*** (0.0381)	0.1262* (0.0560)
Fixed-Effects:	------------------	------------------	------------------	------------------	------------------
HS-4 Product	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes
S.E.: Clustered	by: prod. & regi.	by: prod. & regi.	by: prod. & regi.	by: prod. & regi.	by: prod. & regi.
Observations	8,342,644	8,342,644	8,342,644	8,342,644	8,342,644
Squared Cor.	0.01810	0.02194	0.01679	0.01672	0.02206
Pseudo R2	0.18248	0.18957	0.17731	0.17686	0.19101
BIC	331,519.9	328,794.6	333,510.1	333,682.2	328,289.4

*p < 0:10;**p < 0:05;***p < 0:01. Standard errors are clustered at HS-4 product and region level.

APPENDIX F – ETHICS BOARD FORM

HACETTEPE UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES
Ethics Board Form for Ph.D. Thesis

HACETTEPE UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES
DEPARTMENT OF ECONOMICS

Date: 15/02/2024

ThesisTitle (In English): Product Diversification And Relatedness: Evidence From Turkish Manufacturing Firms

My thesis work with the title given above:

1. Does not perform experimentation on people or animals.
2. Does not necessitate the use of biological material (blood, urine, biological fluids and samples, etc.).
3. Does not involve any interference of the body's integrity.
4. Is not a research conducted with qualitative or quantitative approaches that require data collection from the participants by using techniques such as survey, scale (test), interview, focus group work, observation, experiment, interview.
5. Requires the use of data (books, documents, etc.) obtained from other people and institutions. However, this use will be carried out in accordance with the Personal Information Protection Law to the extent permitted by other persons and institutions.

I hereby declare that I reviewed the Directives of Ethics Boards of Hacettepe University and in regard to these directives it is not necessary to obtain permission from any Ethics Board in order to carry out my thesis study; I accept all legal responsibilities that may arise in any infrigement of the directives and that the information I have given above is correct.

I respectfully submit this for approval.

Leventcan Gültekin

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Name-Surname	Leventcan Gültekin			
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Programme	Economics (English) - PhD			
Status	**PhD**	☒	**Combined MA/MSc-PhD**	☐

<u>**SUPERVISOR'S APPROVAL**</u>

APPROVED
Assoc. Prof. Dr. Zühal KURUL