THE IMPACT OF THE CHINESE BELT AND ROAD INITIATIVE ON THE EUROPEAN INNOVATION ECOSYSTEM

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ABSTRACT

THE IMPACT OF THE CHINESE BELT AND ROAD INITIATIVE ON THE EUROPEAN INNOVATION ECOSYSTEM

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This thesis examines the impact of the Chinese Belt and Road Initiative (BRI) on the European innovation ecosystem, utilising firm-level data from the Community Innovation Survey of 12 EU countries. The analyses investigate the repercussions of the BRI on the R&D-innovation-productivity nexus by following the well-known CDM framework and a novel dataset constructed to proxy the effects of the BRI at country-sector levels. The results indicate that the BRI has a significant impact on the innovative decisions and activities of firms, with particular differentiation noted in their market orientation. The analyses are developed using spatial econometrics techniques, indicating that firms are heavily affected by the impact of the BRI on proximate firms, whether the proximity is defined geographically or economically. These findings indicate that the EU should devise competition policies that focus on the market orientation of firms and not assume that the impact of external shocks are static.

Keywords: Belt and Road Initiative (BRI), Innovation Ecosystem, Knowledge Spillovers, Spatial Econometrics, Smart Specialisation Strategy (S3)

ÖZ

ÇİN'İN KUŞAK VE YOL PROJESİ'NİN AVRUPA İNOVASYON EKOSİSTEMİ ÜZERİNDEKİ ETKİLERİ

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Bu tez, Çin'in Kuşak ve Yol Girişimi'nin (KYG) Avrupa inovasyon ekosistemi üzerindeki etkilerini, 12 AB üyesi ülkenin Community Innovation Survey'den elde edilen firma düzeyi verilerini kullanarak araştırmaktadır. Analizler KYG'nin etkilerini AR-GE-inovasyon-verimlilik arasındaki ilişkileri, CDM modeli çerçevesinde ve bu tez için oluşturulmuş KYG'nin etkilerini ülke-sektör düzeyinde ölçen yeni bir veri setini kullanarak araştırmaktadır. Sonuçlar, KYG'nin firmaların inovasyona ilişkin kararlarını ve aktivitelerini etkilediğini ve firmaların en yüksek ciro elde ettiği pazarların bu etkileşimde farklılıklar yarattığı görülmektedir. Mekansal ekonometri teknikleri ile geliştirilen analizler, firmaların coğrafi ya da ekonomik olarak kendilerine yakın firmalardan oldukça güçlü bir şekilde etkilendiklerini göstermektedir. Elde edilen bulgular, AB'nin rekabet politikalarını oluştururken firmaların pazar yönelimlerini dikkate almaları gerektiğini, dışsal şokların etkilerinin statik olmadığını göstermektedir.

Anahtar Kelimeler: Kuşak ve Yol Projesi, İnovasyon Ekosistemi, Bilgi Sıçramaları, Mekansal Ekonometri, Smart Specialisation Strategy (S3)

To my beloved cousin Rıdvaniye GÜDEK KOÇ in heaven

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LIST OF ABBREVIATIONS

Abbreviation	: Full Form
AIC	: Akaike Information Criterion
ASEAN	: Association of Southeast Asian Nations
BIC	: Bayesian Information Criterion
BRI	: Belt and Road Initiative
CDM	: Crépon-Duguet-Mairesse Model
CIS	: Community Innovation Survey
EBRD	: European Bank for Reconstruction and Development
EEA	: European Economic Area
EIB	: European Investment Bank
EIS	: European Innovation Scoreboard
EU	: European Union
FDI	: Foreign Direct Investment
GDP	: Gross Domestic Product
ICT	: Information and Communication Technology
IMF	: International Monetary Fund
IO	: Input–Output
IPR	: Intellectual Property Rights
MNE	: Multinational Enterprise
MMK	: Mairesse–Mohnen–Kremp Model
NACE	: Nomenclature statistique des Activités économiques dans la Communauté Européenne
NBER	: National Bureau of Economic Research
NUTS	: Nomenclature of Territorial Units for Statistics
OECD	: Organisation for Economic Co-operation and Development
OLS	: Ordinary Least Squares
R&D	: Research and Development
RIP	: R&D–Innovation–Productivity (Nexus)

SAR	: Spatial Autoregressive Model
SARAR	: Spatial Autoregressive Model with Autoregressive Disturbances
SDG	: Sustainable Development Goals
SMEs	: Small and Medium-sized Enterprises
SNA	: System of National Accounts
STI	: Science, Technology and Innovation
S3	: Smart Specialisation Strategy
TFP	: Total Factor Productivity
UNCTAD	: United Nations Conference on Trade and Development
UNIDO	: United Nations Industrial Development Organization
VAR	: Vector Autoregression
VIF	: Variance Inflation Factor
WIPO	: World Intellectual Property Organization
WTO	: World Trade Organization

CHAPTER 1

INTRODUCTION

In recent decades, the European Union (EU) has established itself as one of the world's most advanced and coordinated innovation hubs. This reflects a strong commitment to leveraging new ideas and technologies to boost its economy and maintain competitiveness. The EU's success stems from its interconnected markets, robust public research facilities, and a policy system that aligns EU goals with regional strengths. The EU's innovation strategy is not merely focused on promoting cutting-edge science or breakthrough technologies. Instead, it also aims to bridge regional divides, support inclusive growth, and contribute to overall economic and social well-being. This dual focus has been emphasised in recent policy efforts and academic research, which explore how innovation and cohesion go hand in hand in European development (McCann & Ortega-Argilés, 2015).

Through significant policy instruments such as Horizon Europe, the EU has allocated substantial funding to facilitate cross-border research and development (R&D) collaboration, enhance knowledge transfer, and scale innovation across diverse firms and sectors. Concurrently, Cohesion Policy and Smart Specialisation Strategies (S3) have been instrumental in customizing innovation support to leverage each region's specific comparative advantages. S3, in particular, has emerged as the EU's signature framework for promoting place-based innovation, encouraging regions to specialise in areas where they possess inherent strengths while simultaneously developing robust governance capacities for long-term innovation planning (Foray, 2015, 2018).

Thanks to these coordinated efforts, businesses in the EU benefit from a large and unified internal market. Shared standards, consistent rules, and good cooperation between institutions support this market. These features help lower costs and reduce uncertainty for businesses, making it easier for them to develop new ideas, collaborate with partners across borders, and integrate into regional and global supply chains. Often, these businesses are part of strong innovation communities, frequently built around universities, research centers, industry groups, and government agencies. These communities offer not just access to facilities and skilled personnel, but also opportunities for businesses to learn from one another and benefit from shared knowledge—essential for both incremental improvements and major breakthroughs (Asheim, Grillitsch, & Trippl, 2016; Balland, Boschma, Crespo, & Rigby, 2019). The EU's innovation success is further strengthened by its commitment to stable institutions, well-managed economies, and long-term investment in research and infrastructure. Importantly, the European innovation model has also emphasised adaptability and openness, maintaining competitiveness through teamwork and flexibility rather than through protectionism or favouring only national industries.

However, despite these strengths, the world in which European businesses operate has become increasingly unstable. Over the past decade, external forces have begun to transform the global landscape of innovation, trade, and investment. These changes are introducing new uncertainties and risks for businesses that have traditionally relied on stable and predictable environments.

One of the most significant of these developments is China's Belt and Road Initiative (BRI), a large-scale, state-led global strategy launched in 2013. The BRI aims to build and expand economic connections across Asia, Africa, the Middle East, and Europe through huge investments in transportation, logistics, digital, and energy infrastructure. While often presented as a development project, the BRI also serves as a strategic way for China to become more deeply integrated into global markets, shift trade routes in its favor, and increase its influence through economic means. The initiative is supported by a mix of government funding, political agreements, state-backed companies, and diplomatic partnerships that are reshaping the global flow of goods, money, and information (Hurley, Morris, & Portelance, 2018).

Although the BRI directly targets countries along its routes, its broader impact extends far beyond those immediate participants. For Europe, the BRI creates significant indirect pressures by introducing unfair competition, altering the global trade landscape, and establishing alternative infrastructure and institutional networks that bypass traditional EU-centered routes. Chinese companies—often backed by government funding and diplomatic support—are increasingly entering markets that were once key destinations for European exports or partnerships. At the same time, new logistics hubs, purchasing agreements, and investment flows are emerging outside of traditional European supply chains, making some EU companies less central in global production and distribution networks.

This broader shift has made the EU—and its businesses—more vulnerable to outside pressure than ever before. The BRI has helped alter global competitive dynamics, enabling non-European companies to grow rapidly while weakening the strategic position of many European firms that operate within established supply and innovation networks. Trade routes are being redirected, supplier relationships are being reorganized, and logistics problems are moving to new corridors. For EU businesses that rely on steady demand, reliable infrastructure, and predictable environments, these changes present significant challenges, particularly in maintaining innovation, competitiveness, and growth.

One of the most significant implications of the BRI for the EU is expected to have a significant impact on the European innovation ecosystem. As the EU is also on the verge of radically changing the system, analysing the impact of the BRI in this period is crucial. Projections surrounding the BRI involve altering global value chains and redirecting technology flows toward platforms governed by Chinese rules and regulations. Additionally, the enhanced global trade facilitated by the BRI could create competitive pressures for EU firms in their traditional markets. Additionally, the lack of transparency in BRI projects, contracts, or agreements could pose a threat to the financial well-being of EU countries involved, potentially leading to situations that require EU rescue plans.

This thesis postulates that the impact of the BRI on firms is realised through enhanced trade opportunities. In this vein three research questions are presented: First, does the Chinese Belt and Road Initiative (BRI) have any significant impact on the innovative decisions and activities of European firms? Second, does the effect of the BRI have any spatial dimension? Third, does the impact of the BRI change over time and in relation to the market orientation of the firms?

In light of these questions, this thesis examines the impact of the Chinese Belt and Road Initiative (BRI) on the European innovation ecosystem, utilising firm-level data from 12 countries in the Community Innovation Survey for the period from 2012 to 2018. The firm-level data from 2014, 2016, and 2018 CIS are analysed in the well-known MMK framework by integrating the implications of the Chinese BRI into the models within the framework. The MMK framework, developed by Mairesse et al. (2005), is based on the CDM framework introduced by Crepon et al. (1998), with an increase in the number of equations from four to five. The CDM and MMK frameworks are used interchangeably in this thesis, as a common rationale drives them both. This rationale relies on building a set of relations in three blocks, which correspond to a firm's innovation inputs (i.e., R&D activity), innovation outputs, and productivity. This framework is also labelled as the framework modelling the nexus among R&D, innovation, and productivity, (RIP). The CIS data, provided by the Eurostat, is not longitudal, preventing the use of panel data techniques. This feature of CIS indeed is the main reason behind using three different survey periods. By using the three surveys corresponding to the first five years of the BRI, the time-varying impact is examined through three different cross-sectional analyses.

In addition to the CIS firm-level data, a novel dataset is constructed using the World Bank's BRI Global Dataset, which involves trade cost declines between countries at the sectoral level, along with auxiliary datasets from the CEPII. Following the approach of Aghion et al. (2018), an exogenous demand shock variable is constructed for the export markets of the sample countries. By incorporating this instrumental variable into the MMK framework in conjunction with the firm's market orientation, the impact of the BRI is examined across local/national, EU-EFTA, and nonEU-nonEFTA markets.

This thesis makes three significant contributions to the literature. The first contribution is based on theoretical grounds, as there is no previous study that focuses on the impact of a global project, such as the Belt and Road Initiative, on the firm-level innovation dynamics. Some studies investigate the firm-level effects of BRI. Still, they mostly focus on Chinese firms and do not utilise a full-fledged model dedicated to understanding the firms' innovative decisions and their repercussions, as is done in this thesis. The second contribution is methodological. This thesis is the first study to extend the conventional CDM framework by considering the spatial dependence among firms. No prior research has transformed models in each block of the framework into models with spatial dependence. In this respect, the spillover effects from other firms are integrated into each block of the CDM structure for the first time. Studies incorporate the existence of spillovers into their frameworks, as seen in works by Goya et al. (2012) and Doyar (2023). Yet, they do not integrate the spatial effects by using spatial weight matrices for all blocks of the MMK framework.

The third contribution is based on empirical grounds. It includes efforts in two aspects. The first step is the construction of a novel dataset to proxy the expected effects of the BRI-led decline in trade costs. The construction method of the dataset, as outlined by Aghion et al. (2018), serves as an exemplary approach for further studies that aim to capture the implications of exogenous shocks. Second, this thesis is the first study in the CDM literature that uses solely the CIS data. As will be presented in the following sections, studies combine the CIS survey data with auxiliary datasets, such as the Business Register Data or firm-level patent data. However, there was no opportunity during the preparation of this thesis to access other European firm-level data. Data limitations have resulted in pioneering work in the CDM literature. In line with the research questions, the analyses rely on two approaches. In the first one, the traditional MMK framework is estimated using the Heckman selection procedure. In the second case, this conventional framework is extended by incorporating spatial dependence, represented by geographical and economic proximity. Economic proximity is calculated by using Eurostat’s Figaro input-output tables.

The results of the analyses are striking. According to the first approach, it is observed that the BRI increases the R&D expenditures of firms oriented in national markets, while decreasing their tendency to engage in R&D. For firms oriented in either EU-EFTA or nonEU-nonEFTA markets, however, the BRI has negative implications for both measures. The results for the innovation output are similar, albeit at smaller magnitudes. These findings suggest that the BRI may have an eliminative effect on firms operating within national borders, causing those with lower productivity and absorptive capacity to withdraw from R&D activities. For EU-EFTA firms, it may be suggested that competitive pressures are primarily at play, and these firms may not be resilient enough to withstand the changing economic landscape introduced by the BRI.

The findings obtained with the second approach align with those of the first approach. The spatially lagged terms indicate that as the focal firm approaches the firms located in EU-EFTA and nonEU-nonEFTA regions, the R&D expenditure of the focal firm decreases. In other words, the negative impact of the BRI detected in the first approach without spatial dependence is extended to the surrounding firms, regardless of whether they are geographically or economically “neighbours”. Still, it is worthwhile to emphasise that models relying on geographical proximity provide more robust results.

As the impact of the BRI on innovation output is considered, a more complex picture arises. While the BRI’s inclusion reduces the R&D expenditure of firms as they are surrounded by firms oriented towards markets outside national borders, the reverse could also be observed in analysing innovation output. That is, the positive effect of (surrounding firms) could be negative and vice versa. Regardless of the initial effect, it is essential to note that the BRI can disrupt existing relationships among firms.

The results of the analyses provide answers to the research questions proposed. Regarding the first question: Yes, the BRI has significant impact on the innovative decisions and activities of European firms. This effect also has a spatial dimension, positively responding the second research question. Lastly, the BRI impact varies with respect to market orientation of both focal and proximate firms. This differentiaiton with respect to market market orientation evolves on a more stable pattern compared to the changes observed for different survey periods. That is, it is not possible to state that the BRI effect has increased or decreased in time across all periods.

These findings have important policy implications for the EU. First, they indicate that neither economic integration alone nor geographic proximity guarantees resilience in innovation systems. While firms often benefit from clustering (increased geographical proximity) and inter-firm linkages (increased economic proximity) under stable conditions, such advantages may deteriorate—or even reverse—when broader geopolitical or economic shifts disrupt the underlying strategic alignment of firms. The capabilities of proximate firms matter as to whether they are capable of transmitting adaptive knowledge or remain locked in rigid, localised routines. Incapacitation of proximate firms can result in fragmented spillovers, suboptimal knowledge diffusion, and reduced capacity for collective upgrading —benefits that would indeed be expected from enhanced global trade opportunities.

Second, they suggest that innovation policy should be designed to consider both regional and relational information. EU policy instruments such as Smart Specialisation Strategies (S3) provide a valuable framework for tailoring support to regional strengths. However, S3 implementation must be updated to account for new global interdependencies and geopolitical disruptions. Regional innovation strategies should no longer be based solely on internal capabilities or technological priorities of the regions; instead, they must also assess the orientation of the included firms' networks, especially firms' abilities to not only engage in global knowledge and value chains, but also respond quickly and efficiently to changing global dynamics with possible repercussions on the EU single market. Funding under the S3 program should be re-designed so that firms perceive they are insured against the inevitable effects of global shocks.

Third, policy frameworks that prioritise cross-border collaboration, such as Horizon Europe, the European Innovation Council (EIC), and ERA Hubs, should be supported and realigned with a perspective that considers exogenous shocks on innovation capacities. The funding mechanisms should make it lucrative for firms not only to innovate, but also expand their networks both locally and globally.

Identifying the systemic vulnerabilities of firms, whether in their supply chains, ability to increase absorptive capacity, or integration in knowledge flows, is also crucial in solidifying the EU's innovation ecosystem.

Unless the EU recognises that changing global dynamics can disrupt firm-level innovation decisions and outcomes, deployment of resources to improve regional innovation will remain misaligned with the real drivers of competitiveness. Global supply chain restructuring and changes in the priorities of the global partners (in the BRI case, those of China) can significantly reform the incentives and constraints facing European firms. In this context, merely addressing internal cohesion by disregarding external disruptions risks reinforcing innovation asymmetries in both regional and global metrics, rather than resolving them. A more adaptive and outward-looking innovation policy is therefore essential. EU policymakers should combine resilience planning and mitigation of dependencies at the EU level with the design of regional development efforts.

This thesis consists of eight chapters. In the second chapter, the theoretical background of the study is presented by sketching the evolution of models that integrate innovative activity into economic growth. The second chapter provides an overview of contemporary developments in the EU's innovation performance and the Chinese BRI, along with the possible repercussions of the BRI on the EU. In this thesis, two main approaches to analysis are presented, as stated above. In this respect, every following chapter is divided into two. In the third chapter, literature is presented under three sub-chapters. The first one is related to the traditional MMK framework, while the second one covers studies on the impact of infrastructure investment on trade and innovation. The third sub-chapter covers the studies on the effects of knowledge spillovers on innovation performance. The fifth chapter is devoted to the data and presented in two sub-chapters. In the first sub-chapter, data used in the traditional MMK framework is presented, whereas in the second one, data used in the analysis with spatial dependence are also presented. The sixth chapter presents the methodology, which is divided into two sub-chapters corresponding to the two analysis approaches. The seventh chapter presents the empirical results, and the eighth chapter concludes.

CHAPTER 2

THEORETICAL BACKGROUND

This thesis examines the impact of the decline in BRI-led trade costs on the R&D, innovation, and productivity frameworks of selected European countries. This section presents a chronological overview of theories on innovation, with particular reference to the channel in which innovation is incorporated into growth theories. Also, the definitions introduced in the innovation literature and the standardisation of these terms are explained. Finally, the frameworks that connect R&D, innovation and productivity are presented. Among them, the MMK framework constitutes the basic bone of the approach adopted in this study.

2.1. Innovation Theories and the Implications on Growth Theory

2.1.1. Brief Overview of Innovation Theories

The first reference point of any study focusing on the impact of growth on innovation is the Schumpeterian growth theory, first introduced in 1911 and further elaborated in 1942.[1] Starting with the statement that innovation is the primary driver of long-term growth; Schumpeter describes five types of innovation: the introduction of new production processes, new products, new materials or resources, new markets, and new forms of organisation.

Second, the entrepreneur is located at the heart of innovative activities and regarded as "the pivot on which everything turns". The diffusion of innovations through other

[1] His first theory about the evolution of economies was introduced in 1911 during his professorship of economics and government at the University of Czernowitz. This book was translated into English as "The Theory of Economic Development" in 1934.

firms by replicating the original ideas can cause economic growth, even though such diffusion may eliminate the initial profits accrued by the innovation's owner. The theory states that "competition in product innovation" is more effective in promoting economic growth than traditional price competition. The former type of innovation reduces price competition in the market. Since the desire to reap profits due to innovation is the primary motivation for entrepreneurs, temporary monopolies may be created as a result of the innovation. However, as the diffusion mentioned above ensues, the profits accruing to the original innovator decrease while new investment is attracted to the relevant market. In the long run, profits decrease to such an extent that firms exit the market to pursue new, disruptive innovations. Despite the decreasing profits, Schumpeter underlines that larger firms (mainly large corporations) still have the resources to initiate the innovation process, providing them a huge advantage. In addition to the firms' size, intellectual property rights (IPR), decent patenting, and low inflation increase the odds of firms to innovate.

The third idea is related to the *creative destruction* process, which is an inevitable result of the diffusion process mentioned above. Schumpeter states that innovations disrupt the existing economic structure from within, destroying the old one uninterruptedly and unpredictably, while creating space for new ones. In this process, it is evident that firms are the first agents to experience such destruction, paving the way for a struggle between incumbent and newcomer firms. Increased price competition in a market is expected to decrease innovative activity; the initial positions of firms determine their response to newcomers entering the market. Schumpeter's theory depends on the activation of inactive firms, and increased price competition curbs their enthusiasm for innovation. Therefore, increased concentration in a sector is expected to increase innovative activity up to a level beyond which inertia prevails due to the absence of any rivals in the market. Such a relationship renders an inverse U-shaped relationship between concentration and innovation (Lewin, Cohen and Mowery, 1985). However, Aghion (2018) demonstrates that a relationship exists between competition and innovative activity when firms are divided into two groups based on their initial proximity to the sector's technological frontier. In such a case, innovations brought about by newcomers trigger the (already) frontier firms to invest in further innovation.

In contrast, newcomers discourage the (already) laggard ones as they are left much behind in the further shifting technological frontier. From the perspective of endogenous growth through innovation, increased competition may compel frontier firms to innovate further (and thereby drive subsequent growth). After a certain level, increased competition in innovative activities might cause most firms to fail due to creative destruction. Similarly, in terms of patent rights, Schumpeter advocates further patenting; however, more patents might imply less hope for laggard firms to increase their profits. Therefore, the initial position of the firms significantly matters for the ultimate growth effect of innovations.

Another significant contribution to the theory of innovation is provided by Nelson and Winter (1982), which challenges the existence of ceteris paribus in the profit-maximisation process of firms. More specifically, they define concepts of routine, selection and search. While the routines refer to the decisions of the firms related to hiring, inventory, production, R&D and advertising, they are presented similarly to human genes. Selection refers to the elimination of unprofitable firms from the market. Search, on the other hand, is similar to the concept of mutations in biology and implies that firms do not necessarily have to rely on a set of predetermined choice sets imprinted in routines. Firms can change their routines through new organizational practices. This process creates the evolution of a firm, which is not constrained with itself. As a firm evolves, it changes the firms in its vicinity, either by forcing them to change their routines or eliminating them with the relatively higher profits acquired by the evolutionary firm.

2.2. Transition from Innovation Theories to Growth Theories

The first step in transitioning from innovation theories to growth theories is related to productivity measurement. Productivity is calculated by dividing total output by total inputs. Output is calculated by estimating the production functions, which indicate the maximum output that can be produced with a given input level (Varian, 1992). Among them, the Cobb-Douglas production function is the one primarily used in analyses. Cobb and Douglas (1928, as cited in Doyar, 2023) estimated the production function, which consists of capital and labour as inputs, using data from the U.S.

manufacturing industry for the 1899-1922 period. This function, shown in Eq. 1 below, has an elasticity of substitution equal to one and is homogeneous of degree one. The alpha and beta indicate the labour and capital elasticity of substitution, respectively. They are obtained as the coefficients of labour and capital, and the function is generally estimated in logarithmic form. The A term stands for total factor productivity and is independent of other inputs.

$$Q = AL^{\alpha} K^{\beta}$$
$$\alpha + \beta = 1 \qquad \textbf{(1)}$$
$$\sigma = \frac{dln(K/L)}{dln(MRTS)} = 1$$

It is noted that firms should strive for efficiency in production to maximize their productivity. Productivity is often defined as equivalent to efficiency by many economists, making it a critical concept to analyse (Perloff, 2013). Labour productivity, which is equal to Q/L, and total factor productivity, A, are two types of productivity that are most commonly used in studies.

The neoclassical growth theory relies on the Cobb-Douglas production function and evaluates technological change in an economy as part of total factor productivity. Even though this function does not explicitly recognise technological change in the form of R&D investment, design, or patent as an input, some studies estimate the contribution of technological change using the Cobb-Douglas production function, while the term A, as used in the above equation, remains intact. Griliches (1964) makes the first study that uses the R&D investment as an explicit input. In the following equation, Griliches (1979) recognises R&D investment as a variable in the technical knowledge production function.

$$Q = AZ^{\alpha+\beta} k^{\gamma} e^{\delta t + e} \qquad \textbf{(2)}$$

Here, Q represents production, A is a constant term, Z is the total input index, and k represents the current level of technical knowledge. $Z = K^{(\alpha/(\alpha+\beta))} L^{((1-\alpha)/(\alpha+\beta))}$ represents the total input index. K stands for physical capital, whereas L stands for labour. α, β, γ and δ represent the elasticities of factors of production. The total factor productivity in the neoclassical production function becomes a function of k, the level of technical knowledge, indicating that the relation between R&D and productivity has long been established. Technical knowledge is defined in a closed function as follows:

$$k = f[W(B)R, v] \quad \textbf{(3)}$$

Here, v stands for the error term, whereas W(B) indicates the lags needed to transform the R&D investment, R, into knowledge. Griliches (1980) underlines that it is hard to measure R&D stock in a cumulative sense. Measuring R&D as a flow variable, i.e., as investment, provides the rate of return in R&D investment, whereas the stock measure provides the actual elasticity. Hall (2007) states that in cases where depreciation is slight, there would be little difference between the elasticities calculated in both manners.

Parkes and Griliches (1980) is the first study to distinguish between innovation input and output, albeit the distinction was not made using these labels. Yet, they explicitly define a knowledge production function used for modelling the number of patents issued by a firm, not a vague concept of total factor productivity as in Griliches (1980). They use the knowledge production function to explain the current increase in knowledge stock by utilising past R&D investments (over the last 5 years in the study). The rise in knowledge stock is then used to explain the firm-level patents.[2]

$$\dot{k}_{i,t} = \alpha_i + \beta_t + \sum_{g=0}^{5} \gamma_g r_{i,t-g} + \epsilon_{i,t} \quad \textbf{(4)}$$

The change in knowledge stock is then used to explain the number of firm’s patents.

$$p_{i,t} = \delta_0 t + \delta_1 \dot{k}_{i,t} + \varepsilon^*_{i,t} \quad \textbf{(5)}$$

[2] α_i stands for firm fixed effects and since they are time-invariant, the equation above, which is similar to a law of motion for stock of knowledge, the fixed effects can be re-written in terms of the past R&D stock as below. The firm's fixed effects and error terms are assumed to be uncorrelated with the R&D stock.

$$\alpha_i = \sum_{g=0}^{5} \varphi_g r_{i,-g} + \epsilon_i$$

The error term in the model is assumed to include both a firm-level fixed component and an independent error term. k and $\varepsilon*$ are both assumed to be uncorrelated. This transition from the R&D stock to knowledge production constitutes the underlying structure of more contemporary models that rely on the distinction between innovation input and output.

On the other hand, endogenous growth theories suggest that economic growth can be achieved by modifying endogenous factors, such as the technological level and human capital, within the economy. Technology is an explicit input in these models that is nonrival and partially excludable. In this respect, it can be stated that the "A" term in the Cobb-Douglas function is now disturbed, and knowledge production is regarded as another dynamic factor in the production function. As the pioneering economist in endogenous growth theory, Romer (1990) describes his model as a combination of the Solow (1956) model with technological change, which emerges as a result of the intentional decisions of economic agents and is postulated to trigger more capital accumulation. Market incentives play a crucial role in driving technological change that is closely tied to the profit-maximisation objective of private firms. He also notes that the initial stages of a technological change, such as the work done by an academic, might not reflect market incentives. Still, the fact that there is an opportunity for the change to be introduced into the market creates an environment that automatically provides incentives for translating a researcher's knowledge into practical value (Romer, 1990). Technological change refers to the alteration in the set of instructions used to process raw materials, and once they become publicised, their marginal cost is zero. However, the constant need (or competition) to improve them might equal a fixed cost.

Romer (1990) defines four inputs for the production function: capital, labour, human capital, and an index referring to the level of technology. Capital is measured in consumption goods, and labor refers to the basic skills needed to work from a healthy person. Human capital refers to the combined effect of formal education and on-the-job training. While human capital refers to a rival good, that is embedded in the specific individual, the technological component, A, refers to a non-rival good that can persist beyond the individual's life. "A" is measured by the count of designs.

Romer divides the economy into 3 sectors: research, intermediate goods and final goods. While the research sector produces designs for new producer durables, the intermediate goods sector combines these designs with capital to produce the final goods. The final goods sector combines all labor, human capital and durable goods to produce the final output. The research sector employs human capital and the accumulated level of knowledge, i.e., the accumulated level of all technological changes that are also publicly known, to produce designs. One of the most striking findings of Romer's model is that larger markets induce more research and faster growth.[3]

Highlighting endogenous growth theory is significant because it demonstrates the importance of innovation in economic growth, indicating that countries do not necessarily remain stuck on doomed paths dictated by exogenous factors imposed upon them. All these approaches and theories suggest a relationship between innovative activities and economic growth, although it is modelled differently and with varying variables. The following section describes prominent theories that are specifically concentrated on the dynamics of innovation. The reasons behind doing innovation and factors affecting its course are also discussed in these studies.

2.3 Innovation and Standardisation of New Definitions

The use of R&D and innovative activities in economic growth models has highlighted the need for creating standardised terminology and principles in data-gathering processes. In this respect, the OECD published the Frascati Manual in 1956 as the first international guideline for research and development (R&D) activities. In its latest version published in 2015, the manual describes R&D activity as follows:[4]

> Research and experimental development (R&D) comprise creative and systematic work undertaken to increase the stock of knowledge –including

[3] Considering the possible market expansions to be created by the Belt and Road Initiative, Romer's conclusion is a point that needs to be kept in mind throughout this study

[4] The most recent version is available on the OECD’s official website for the *Frascati Manual*: https://www.oecd.org/en/publications/2015/10/frascati-manual-2015_g1g57dcb.html

> knowledge of humankind, culture and society – and to devise new applications of available knowledge (OECD, 2015, p.44)

The Frascati Manual places a significant emphasis on determining whether an activity can be classified as R&D or not. By presenting the definitions above, it outlines the principles of data collection and classification. The coverage of the Frascati Manual falls within the first block of the CDM framework, as R&D activities are regarded as an input to innovation.

Similar to the Frascati Manual, the OECD published the Oslo Manual in 1992, with its latest fourth edition published in 2018.[5] The Oslo Manual aims to provide international guidelines for collecting and evaluating innovation data. It provides the baseline for countries to revise their data collection systems on innovation. The Oslo Manual 2018 describes innovation as follows:

> An **innovation** is a new or improved product or process (or combination thereof) that differs significantly from the unit's previous products or processes and that has been made available to potential users (product) or brought into use by the unit (process). (OECD, 2018, p.20)

This last version includes a significant update in the scope of process innovation. Marketing and organizational innovations were gathered under business process innovations. Yet, the basic distinction between innovation output and product/process innovations has been maintained.

The Community Innovation Surveys (CIS), which constitute the primary dataset used in this thesis, are conducted in tandem with the Oslo and Frascati Manuals. As will be explained in detail in the data section, the survey questions are updated in accordance with updates to the Oslo Manuals. Eurostat is a significant partner of the OECD in the design of manuals due to the experience gained through the conduct of CIS surveys.

It is essential to acknowledge that the echoes of the definitions of product and business process innovations in the latest version of the Oslo Manual are rooted in

[5] The most recent version is available on the OECD's official website for the *Oslo Manual*: https://www.oecd.org/en/publications/2018/10/oslo-manual-2018_g1g9373b.html

historical work. For instance, Schumpeter (1983) describes five types of innovations: the introduction of new products, new production methods, opening up to new markets, provision of a new supply source, and managing a new organisational structure. Freeman and Perez (1988) adopt a different approach, concentrating on the source and future pathways of the innovative process. They define four types of innovations: incremental innovations, which are realised not as a result of R&D efforts but of the feedback collected from customers. Radical innovations are often discovered through an R&D process, but they do not occur continuously; instead, they happen in an ad hoc manner. The third type refers to the changes in technology systems that pave the way for the creation of new sectors. In contrast, the fourth one refers to the techno-economic paradigm change equivalent to the technological revolution.

Under the CDM framework, various measures of innovation output are used. The number of patents (Crepon et al. ,1998) and the share of sales from innovative products (Lööf and Heshmati, 2001) are among the most frequently used measures. However, some caveats are underlined concerning the use of patent data. Pakes and Griliches (1984) warn that patents may fail to reflect the full magnitude of innovative effort, as not all innovative products are patented. Licht and Konrad (1997) suggest that patents may be more effective as intermediate innovation outputs. Due to concerns surrounding the use of patent data, the share of innovative sales is preferred much more frequently than patents as an indicator of innovation output.

2.4. Frameworks on R&D, Innovation and Productivity Nexus

Relying on the three-pillar structure constructed by Pakes and Griliches (1984), which includes the R&D effort, the knowledge production function, and the innovation output produced by exposing the R&D effort to the knowledge production function, Crepon et al. (1998) introduce a sharp distinction between innovation input and output. Pakes and Griliches (1984) do not model the determinants of R&D activity. Still, Crepon et al. (1998) model the decision and the investment level of R&D. They also underline that what affects productivity is the innovation output, not innovation input. The model introduced by Crepon et al.

(1998) is known as the CDM model and is built upon three blocks, as depicted in Figure 1.

2.4.1. CDM Model

The CDM model aims to analyse the relationship between innovative activities and productivity. The model divides the innovative activity into innovation input and output, justifying that the latter affects the firm's productivity using French firm-level data. In the original CDM study, engagement in R&D activities and the level of R&D investment serve as proxies for innovation input, constituting the first block of the model. The number of patents and shares of innovative sales are proxies for the innovation output, corresponding to the second block. Labour productivity is explained in the last block using innovation output as the primary explanatory variable. CDM uses these three blocks to present a chain of causalities from R&D decisions and investment to productivity. Crepon et al. (1998) use the 1990 French survey on innovation in manufacturing industries and the French Annual Firm Survey.

2.4.1.1. Equations of the First Block

Starting with the equations in the first block, CDM posits that firms undertake R&D activities if the expected profit from the innovative activity exceeds a threshold level. The latent threshold level is represented by g_i^* as represented in Eq.6.

$$g_i = \begin{Bmatrix} 1 \; if \; g_i^* = x_{0i}b_0 + \varepsilon_{0i} \quad > 0 \\ 0 \; if \; g_i^* = x_{0i}b_0 + \varepsilon_{0i} \; \leq 0 \end{Bmatrix} \qquad \textbf{(6)}$$

In the second equation of the first block, equation (7), the intensity of the R&D investment is explained by using explanatory variables that are not necessarily the same as those in the first equation.

The R&D intensity modelled in the second equation becomes latent or actual depending on the decision taken by the firm in the first step. If the firm decides to do

R&D in the first step, the level of R&D intensity is postulated to be equal to the observed intensity value. Otherwise, it becomes a latent variable that needs to be estimated.

$$\ln(R\&D)_i^* = k_i^* = x_{1i}b_1 + \varepsilon_{1i} \qquad \textbf{(7)}$$

where

$$(R\&D)_i^* = \ln(R\&D)_i \text{ if } g_i = 1$$
$$(R\&D)_i^* = 0 \text{ if } g_i = 0$$

The generalised Tobit model in the estimation assumes that the error terms in Equations 6 and 7 are normally distributed with a mean of zero.

$$\begin{pmatrix} \varepsilon_{0i} \\ \varepsilon_{1i} \end{pmatrix} \sim \mathrm{N}\left(\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}\right), \begin{bmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix}\right)$$

Like Pakes and Griliches (1984), the CDM model also uses the R&D stock value with a depreciation rate of 15%. The explanatory variables align with the factors suggested by Schumpeter. The number of employees, the firm's market share, and indicators of demand-pull and supply-push factors, as well as the inverse of the Herfindahl index, are among the explanatory variables, in addition to sector fixed effects.

2.4.1.2. Equations of the Second Block

The third and fifth equations refer to the innovation output, proxied by the number of patents (ni) (per employee) and share of innovative sales (ti). Predicted values of the latent R&D intensity (R&D per employee) obtained from the second equation in the first block are added to this model as an explanatory variable.

$$ln\, n_i^* = ln\, E\,(n_i \mid k_i^*, x_2, u_2) = \alpha_K k_i^* + x_{2i}b_2 + u_{2i} \qquad \textbf{(8)}$$

$$t_i^* = \alpha_K\, k_i^* + x_{2i}b_2 + u_{2i} \qquad \textbf{(9)}$$

In this vein, firms' R&D decisions can be modelled as follows, recognising the threshold level as zero in this study. In Equation 7, rd_i* is the latent threshold level estimated using the CIS responses. CDM uses the asymptotic least squares (ALS) technique to estimate the equations in the last two blocks, assuming their error terms are correlated.

Labour productivity is explained by using innovation intensity as an explanatory variable in the last stage.

$$q_i = \alpha_I \ ln\, n_i^* + x_{3i}b_3 + u_{3i} \quad \textbf{(10)}$$

$$q_i = \alpha_I \, t_i^* + x_{3i}b_3 + u_{3i} \quad \textbf{(11)}$$

In analysing the relations among R&D, innovation, and productivity, two problems emerge: selectivity bias and endogeneity of the variables due to simultaneity. Selection bias arises because R&D reporting firms are self-selected. Any analysis involving only these firms would cause non-random bias. Moreover, it cannot be ensured that non-reporters do not conduct R&D activities, as firms might not reveal their R&D efforts below a certain threshold or disguise them (Griffith et al., 2006).

Simultaneity bias, on the other hand, refers to the intrinsic relationship between R&D and productivity. R&D investment in a certain period can affect future output, depicting causality from R&D to productivity. The decision about that R&D investment is made considering both previous output levels and future profits. The lagged productivity level functions as the common factor that drives both the current level of productivity and R&D investment, leading to endogeneity bias. Griliches (1979) states that if the appropriate lag length between the R&D investment and (observation of its impact on the) output could be determined, such endogeneity could be controlled to a certain extent by adding lags of the variables. However, in the same study, estimating such a "lag length" is presented as another issue to be tackled in estimations. Indeed, the cross-sectional nature of the CIS data precludes the inclusion of a time dimension in the analysis. As indicated above, Crepon et al. (1998) also utilise CIS data to construct their 3-step model, which includes no lagged terms. While concerns about selection bias are reserved, those surrounding simultaneity are even more extensive, encompassing the relationships among innovation input (R&D investment), innovation output (innovation intensity), and productivity. They construct their model so that the error terms in the model are assumed to be correlated, acknowledging the possibility of two-way causalities. Crepon et al. (1998) state that their estimation techniques significantly alleviate the bias that could stem from these problems.

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Crepon et al. (1998) state that their estimation techniques significantly alleviate the bias that could stem from these problems.

2.4.1.3. MMK Model

The model developed by Mairesse, Mohnen ve Kremp (MMK, 2005) is a CDM-type model, which was further developed by the inclusion of selection equations in the second block of the CDM framework. In the CDM model, the latent variables of R&D intensity estimated at the end of the first block are added directly as explanatory variables to the equation for innovation output intensity. In the MMK model, whether the firm decides to continue the innovation process (i.e $a_i = 1$ below) by using the innovation input to produce innovation output or scrap it is questioned. This is done by modifying the second block as follows:

$$a_i = \begin{Bmatrix} 1 \; if \; a_i^* = y_{0i}m_0 + y_{1i}g_i^* + s_{0i} & > 0 \\ 0 \; if \; a_i^* = y_{0i}m_0 + y_{1i}g_i^* + s_{0i} & \leq 0 \end{Bmatrix} \text{ where } a_i = 1 \text{ if } a_i^* > 0 \text{ and } a_i = 0 \text{ if } a_i^* \leq 0 \qquad \textbf{(12)}$$

$$ln\, sales_i^* = ln\, E\ (sales_i \mid a_i^*, x_2, s_1) = \alpha_K k_i^* + x_{2i}b_2 + s_{1i} \qquad \textbf{(13)}$$

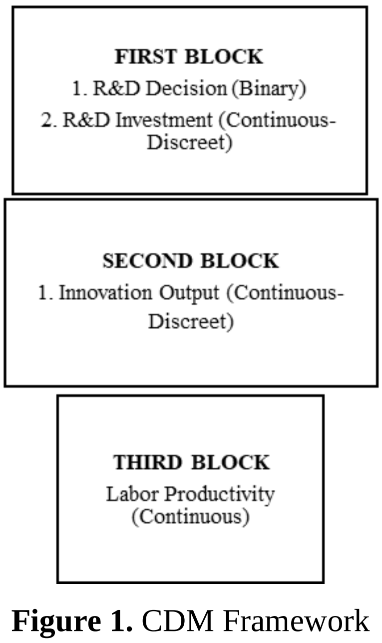


Figure 1. CDM Framework

As seen in Equation (12), the change happens by adding the selection equation for the sales of innovative output, and the predicted value for the decision to engage in intramural R&D activity is added as an explanatory variable to this equation. The second equation is constructed similarly to the first block. Namely, suppose the latent variable of deciding to introduce sales into the new markets is positive. In that case, the intensity of the innovation output is modelled by using the latent innovation input estimated in the first block.

Although the MMK framework is adapted in this thesis's analyses, it is most often used interchangeably with the CDM framework. Due to the similarity in their basic setup, i.e., built on three blocks, there is no harm in using them in that way. The CDM framework is frequently mentioned, as it is the original framework and more widely known than the MMK framework.

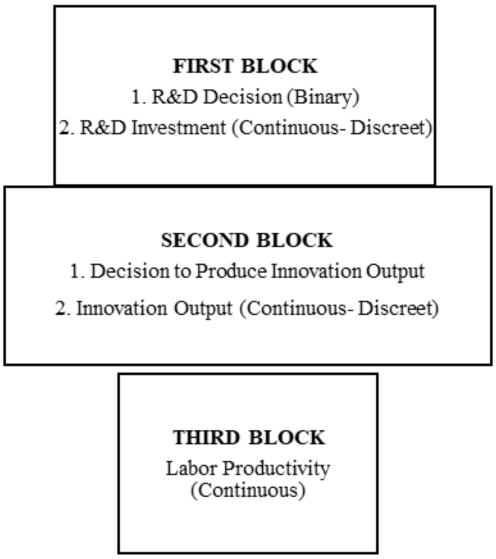


Figure 2. The MMK framework only differs in the second block with the addition of selection equation before modelling the equation for turnover from innovative sales

CHAPTER 3

IMPLICATIONS OF THE CHINESE BRI ON THE EU DYNAMICS

3.1. Contemporary Challenges of the EU

With its no-mincing attitude prevalent throughout the report, The Draghi Report, published in September 2024, marks a significant manifestation of the agony suffered by the European economy, with its roots dating back two decades. The doubling of disposable income in the U.S. compared to the EU, along with the lagging productivity of the EU and its lagging performance in innovation behind China, are presented as the sharp realities that should trigger the EU to take coordinated action if the continent wants not only to maintain but also improve its competitiveness. In other words, the comfort zone of staying still would no longer be an option for the EU in the face of stiff global competition, according to the Report. Draghi (2024) emphasises that the EU should reduce its dependencies, proposing a policy framework built on three pillars. The first of these aims to close the innovation gap between the EU and its competitors, with a primary focus on sectors that utilise advanced technology. Second, the EU's emphasis on decarbonisation is sustained by highlighting the need to integrate it into policies related to competitiveness, as the latter could be prioritised over the former to gain leverage. Third, EU security should be improved, and dependence on countries outside the EU should be reduced. These pillars are interrelated with each other and the Draghi Report explains them in detail.[6]

[6] The report includes two parts, the second of which includes detailed analyses and suggestions. For the report see Draghi, M. (2024). The future of European competitiveness: In-depth analysis and recommendations (Part B). European Commission. https://commission.europa.eu/document/download/ec1409c1-d4b4-4882-8bdd-3519f86bbb92_en?filename=The+future+of+European+competitiveness_+In-depth+analysis+and+recommendations_0.pdf

Although they are interrelated, the focus of this thesis falls under the first pillar of the Draghi Report (2024). By 2024, it is seen that Mr Draghi references the problem of commercialization by stating: "Europe is full of talented researchers and entrepreneurs. It is because innovation often lacks synergies, and because we are failing to translate ideas into commercial success."

In this respect, the illustration comparing the EU's performance to that of the US and China is presented below. The two key points to note are: First, China has performed quite well in the last decade in terms of innovation indicators, threatening the supremacy of the EU. Second, for a long time, the EU's indicators have been above those of China, indicating a broader accumulated knowledge stock in the EU compared to China. That is, the EU had the accumulated power, but commercialisation failed as designated by the EU authorities.

Figure 1 illustrates the relative position of the EU, the U.S., and China in terms of their share of R&D expenditures in total GDP. Although the graph clearly shows that China has surpassed the EU since the beginning of the 2010s, a long-standing supremacy of the EU over China is evident. Figure 3. indicates the relative positions for the innovation output for the three economic regions.

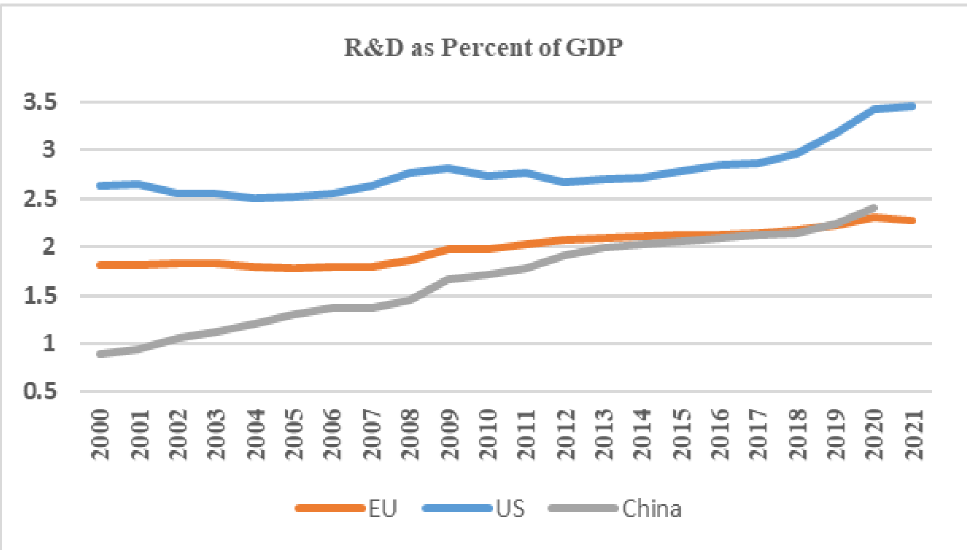


Figure 3. R&D Investment as Ratio of GDP (%)

Source: Science, research and innovation performance of the EU 2024, European Commission

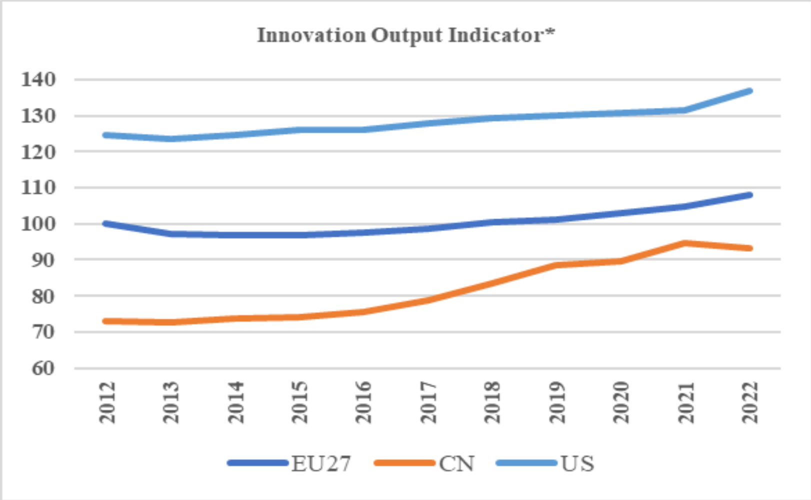


Figure 4. Innovation Output Indicator

Source: Innovation Output Indicator 2023, European Commission.

(*)The values have been normalised to the 2012 figure for the EU-27 region in terms of indexation.

Innovation output scores normalised against the EU27 international score in 2012 indicate that China came very close to the EU by 2021. The U.S., on the other hand, is above both the EU and China for the related periods.

In fact there are different views around the validity of the European paradox. Argyropoulou et al., (2019) review the studies that test for the existence of the "Paradox" and conclude that the paradox is inherently absent since the first condition of the paradox is immediately eliminated when the impact of the research papers is considered.[7] In other words, the numbers are high, but the quality is debated.

Figure 5 below indicates that in 2010 and 2022, the EU has a higher share of scientific publications than the U.S. However, Figure 6 contradicts it when the quality of the publications is considered. In 2010 and 2022, the U.S. had a higher share in top journals and was ahead of the EU, while China overpassed the EU in 2022. This figure eliminates the paradox's first condition, namely that the EU is ahead of the rest of the world in terms of scientific production. Discussion defying

[7] Specifically, Rodríguez-Navarro and Narin (2016) underline the quality of the research published and warn that the number of papers should not be the sole measure of achievement in innovation. Hammadou et al. (2014) indicate that Europe lags behind the U.S. when both quality of the research papers is considered.

the European paradox mostly refer to the measures around the quality of scientific production.

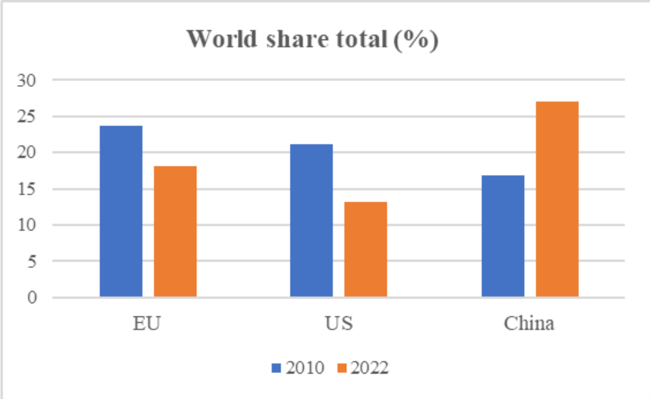


Figure 5. Ratio of Scientific Production to Total World Production (%)
Source: Science, research and innovation performance of the EU 2024, European Commission

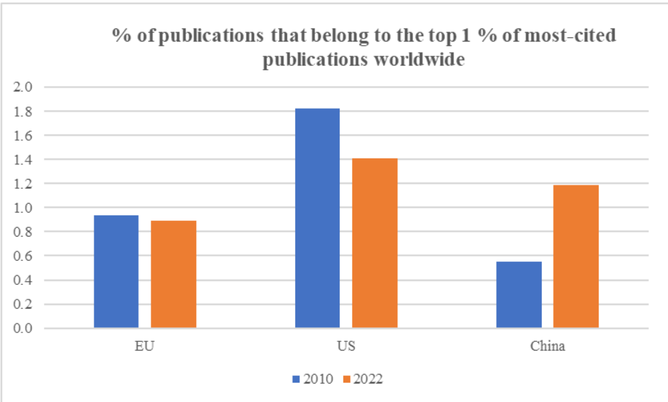


Figure 6. Ratio of Qualified Scientific Production to Total World Production (%)
Source: Science, research and innovation performance of the EU 2024, European Commission

Although the numbers may be satisfactory in terms of R&D investment, the neglect of quality matters. Therefore, policy suggestions focusing solely on the blockages in transforming innovation input into innovation output should also be treated carefully.

Following the Draghi Report (2024), the Commission published the report named " A New Competitiveness Compass for EU" in January 2025. The report outlines a new competitiveness model based on innovation-led productivity improvements in five areas of horizontal enablers, aligning with the priorities highlighted in the Draghi Report (2024). These enablers include the simplification of the regulatory environment, the elimination of remaining barriers within the Single Market, the provision of new financing opportunities under a refocused EU budget, the promotion of skills in the context of social fairness, and the better coordination of policies at both the EU and national levels. A timeline is also added in the report for each enablers.

In addition to the reports published by the EC, there are also studies related to the stagnation in the EU economy with particular reference to what should be done to increase innovation diffusion and productivity. Rodríguez-Pose and Ganau (2022) also note that institutional quality needs to be significantly improved in Europe to enhance the diffusion of high-tech firms to low-tech ones. Completion of the Single Market, accelerated convergence of the new EU members, relaxation of regulatory barriers (such as taxes) that prevent small but productive firms from growing, and protection of patent rights are among the steps that could be taken to increase the diffusion of innovative capabilities. Aghion and Akcigit (2017) state that vertical policies should be implemented in Europe to increase the diffusion of innovative activities. Such policies, the details of which are determined in Brussels, could provide the required subsidies and infrastructure (including digital technologies) that would trigger selected firms in the EU to become the new stars in innovation. Aghion and Akcigit (2017) advocate for vertical support at the supra-national level, as selection at the national level may be susceptible to corruption, and the number of firms may be limited. Regarding the diffusion of knowledge among economic agents, Draghi (2016) notes that large companies with the ability to produce high-tech goods have become reluctant to share their ideas due to their reliance on market power and their reluctance to protect IPRs. He suggests that increased competition should be supported by institutional quality to accelerate the diffusion process.

ECB Report on Productivity (2021) emphasizes the laggardness of the EU against China, stating that even though the export market share of the EU in manufacturing slightly increased between 2012 and 2018, its share in high-tech manufacturing exports declined by 7%, while China increased its share by 10% in the same period.

The policy suggestions presented in recent official reports and related studies aim to improve the European innovation ecosystem, although they may differ in their focal points. The policy suggestions are concentrated on eliminating fragmentation in innovation policy instruments, strategising the Single Market, and taking collective yet localised actions from a systemic perspective. Considering that Jackson (2011) describes an innovation ecosystem as a set of complex relationships formed among economic actors who gather together under the common goal of maintaining technological development and innovation, it is straightforward to observe that the recent policy agenda aims to modify the innovation ecosystem substantially. Economic actors in an innovation ecosystem include material resources, human capital, and research institutions, as well as the relationships among these actors in their own right. From decreasing dependencies on the rest of the world to supporting regional innovation endeavours, the EU signals that the fundamentals of the EU innovation ecosystem will change. The change in the attitude of the EU authorities is also evident in a comparison of the reports in 2010 and 2024.

Key innovation policy frameworks of the EU are Horizon Europe (HE), European Innovation Ecosystems (EIE), European Innovation Council (EIC), Digital Europe Programme, European Institute of Innovation and Technology (EIT), European Regional Development Fund (ERDF) and the Green Deal Innovation Policies.[8]

At the end of the Global Financial Crisis, the EU published the "EUROPE 2020 A Strategy for smart, sustainable and inclusive growth" Report in 2010, including policy suggestions for a smart, sustainable and inclusive growth path for the EU. The Report highlights the ambitious and innovative activities of China and India, and warns that a higher share of GDP should be allocated to innovative activities. The urgency tone in this report, compared to the Draghi Report, is, however, much lower.

The 2010 Report is not focused on the commercialisation of innovative products, as seen in the Draghi Report or the Competitiveness Compass, but rather on improving skills. The Draghi Report also emphasises skills, but more than that, it underlines that

[8] A vast description of the innovation polices can be found on European Commission. Research and innovation. https://research-and-innovation.ec.europa.eu/index_en

the accumulated skills and knowledge cannot be utilised efficiently, calling for more drastic measures that could upset the older innovation ecosystem. There is evidence of focus in the official reports.

In addition, one of the most apparent changes in the EU's approach to the elements of the innovation ecosystem is seen in the level at which policies are formed. In the last decade, innovation policies in the EU have become increasingly localised. Foray (2015) presents four reasons for such a shift : First, regional disparities in the EU have remained persistent despite all efforts to provide cohesion. Policies determined in Brussels lacked designation of region-specific problems and solutions, as well as identification of local opportunities that could be captured. Second, the EU regions possessed skilled labour, research capacity, and successful localised sectors, all of which contributed to the broad statistics of the EU. However, they were not utilised strongly enough by national policies. In other words, the regional advantages of the BRI were the undisclosed parts of the innovation paradox, as they contribute to the broad statistics of the EU but not to the commercialisation process due to the incapacitation in Brussels. Localised policies aim to transfer more power to local agents in their self-discovery process, enabling them to direct innovation investment. The Smart Specialisation Strategy, first introduced in 2010, evolved and gained prominence as the EU became more aware of the need for bottom-up governance.[9] There are six core aspects of the Smart Specialisation Strategy: Entrepreneurial discovery process, evidence-based analysis, a focus on strengths, multi-level governance, targeted investment, monitoring and evaluation, and alignment with sustainability goals. Among them, the Entrepreneurial Discovery Process (EDP) is the most essential aspect of the S3, as it refers to the coming together of regional stakeholders, businesses, researchers, civil society, and authorities, all of which are components of the innovation ecosystem. Place-based innovation is the guiding motto of S3, primarily related to the EDP component. The EU aims to leverage the path dependency and technical relatedness among sectors in the regions by implementing S3 strategies.

[9] The Smart Specialization Strategy was introduced by the European Commission on March 3, 2010. The policy document can be accessed on https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52010DC2020 . This strategy is also known as the S3, where three S's of the words "smart", specialization" and "strategy" are combined.

A third reason that moves the EU towards more localised policies is the waste of resources due to double funding provided under the European Regional Development Fund (ERDF) and the deployment of venture capital to sectors such as nanotechnology or biotechnology without thorough efficiency analyses. Fourth, the EU does not want innovative power to remain in the hands of some regions or sectors. By using localised policies, the EU aims to maintain an even distribution of innovative power and competitiveness. From the perspective of this thesis, understanding S3 is essential not only because it is expected to be the most popular innovation framework in the EU by 2025, but also because the findings in this thesis provide spatial inferences that could be used as policy suggestions for S3. As the S3 enables regions to identify their strategies, the scope could also be defined for strategies addressing global developments while maintaining the principal target of achieving cohesion within the EU along with a strong single market.

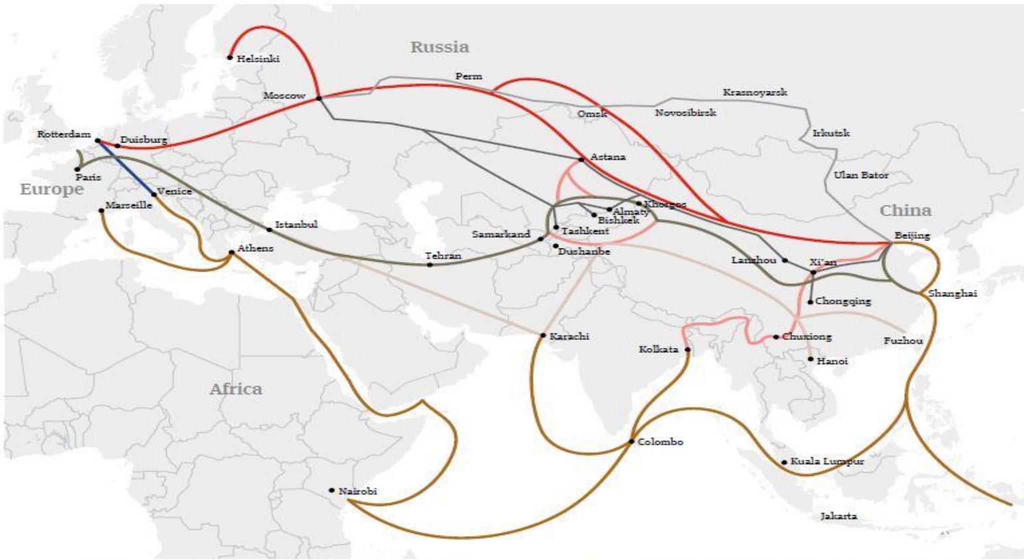
3.2. Chinese Belt and Road Initiative

Xi Ping announced the Belt and Road Initiative (BRI) in October 2013 as the "Going Global" project of China.[10] The BRI is projected along two main routes: the Silk Road Economic Belt and the 21st-century Maritime Silk Road. Through these roads, the BRI aims to promote connectivity, investment, trade volume, consumption, job opportunities, and cultural interactions among the energy clusters across participating countries. The two main roads and the 6 economic corridors on the main paths are indicated in Figure 7.[11] The Silk Road Economic Belt is an overland route encompassing a rail and pipeline network from China to Europe. The 21st Century Maritime Silk Road is a sea route featuring integrated port and coastal infrastructure projects that run from China's east coast to Europe, India, Africa, and the Pacific, traversing the South China Sea and the Indian Ocean. The six economic corridors are

[10] The last few decades have witnessed the establishment of numerous regional and global initiatives aimed at enhancing interregional connectivity through investments in infrastructure and construction. Among similar examples such as the ASEAN Master Plan for Connectivity, the Belt and Road Initiative, Japan's Partnership for Quality Infrastructure, ASEAN-Korea Infrastructure Fund, Russia's Eurasian Economic Union (EAEU), the European Union's "Connecting Europe and Asia", and the PGII as the newest initiative of this kind. The BRI is the most prominent among these due to its vast scale, geographical coverage and geostrategic influence (Yu, 2024).

[11] In its original formation, the BRI was called as One Belt One Road.

the China-Mongolia-Russia Economic Corridor, the New Eurasian Land Bridge, the China–Central Asia–West Asia Economic Corridor, the China–Indochina Peninsula Economic Corridor, the China-Pakistan Economic Corridor, and the Bangladesh-China-India-Myanmar Economic Corridor. The ancient Silk Road was built approximately 2,000 years ago during the Han Dynasty. Its “newer” version is similar to the original one and encompasses an area from China to Eurasia, Southeast Asia, South Asia, Arab Persian Gulf, and the Mediterranean.



Source: The Centre for Geopolitics & Security in Realism Studies'(CGSRS), original source: Tim Summers, "Roadmap to a wider market" in The World Today, October – November 2015

Figure 7. The corridors on the Belt and Road

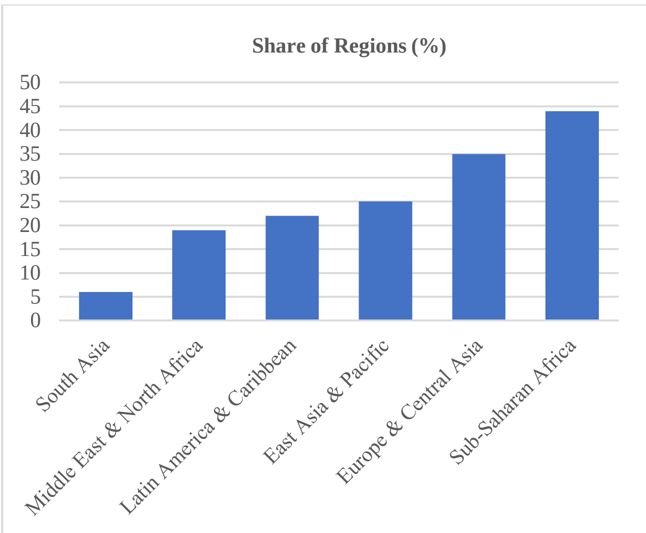


Figure 8. Participant Countries& Regional Distribution

Source: The China Global Investment Tracker (2023)

As Figure 6 indicates, countries in Sub-Saharan Africa have the highest number of projects in the BRI, followed by European and Central Asian countries. The upper-middle-income and lower-middle-income countries receive the highest number of BRI projects. The fact that low-income countries receive the fewest number of projects suggests that China's ambitions may not be as philanthropic as it claims.

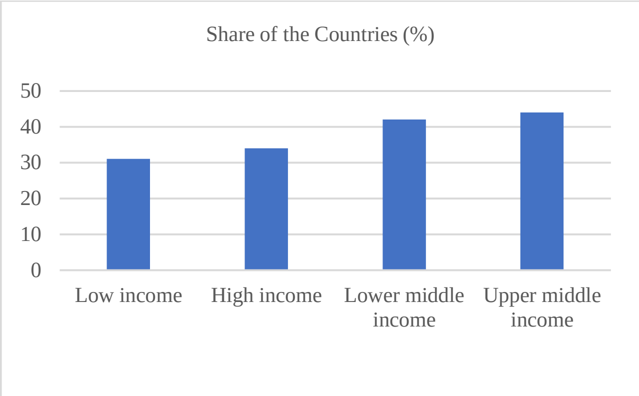


Figure 7. Participant Countries and Income Level
Source: The China Global Investment Tracker (2023)

Figure 8 lists the 10 countries with the highest BRI-related projects. The countries geographically closer to China receive the highest number of projects.

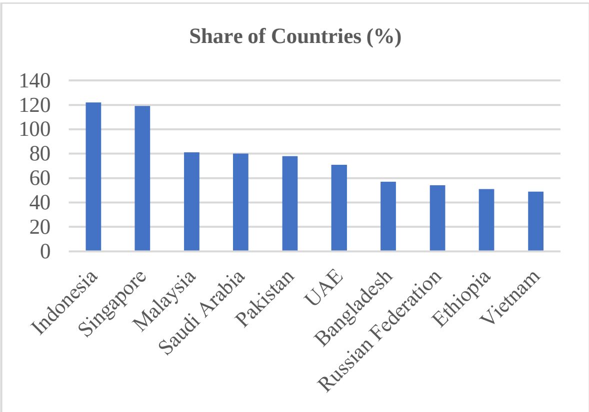


Figure 9. Top 10 Countries with the highest number of projects
Source: The China Global Investment Tracker (2023)

The BRI aims to improve connectivity, trade, financial integration, policy coordination, and exchange among participant countries. Of areas emphasised, the primary focus is on improving physical infrastructure connectivity.[12] By building a massive regional network of roads, railroads, airports, seaports, energy plants and digital communication facilities, China aims to transform the geoeconomic landscape in Asia and beyond. By reviving the ancient Silk Road through both land and maritime routes, China aims to be the leader in achieving an efficient and smooth flow of goods, services, capital, technology, and people. It has embarked upon lending activities to projects outside China and provided loans (at lower rates than the market) to developing or low-income countries since 2013. The Export-Import Bank of China and the State Development Bank are two major financial institutions that provide such loans.[13]

Maintaining a sustainable maritime shipping route is crucial for China, as it requires importing intermediate (semi-finished) inputs and raw materials to support its vast export-oriented manufacturing sectors (De Soyres, 2019; Yu, 2024).

Three fundamental reasons are listed for China to start the BRI initiative (Yu, 2024): China's economic challenges, its desire to gain strategic power and the investment needs of developing and low-income countries.

First, China faces a significant overcapacity problem, necessitating the search for new sources of demand. Despite the evident preference of the Chinese government to increase domestic consumption in recent years, the country's export-led production inevitably requires expansion into new markets. China has reached its limits in

[12] Physical infrastructure involves hard and soft infrastructure: Hard infrastructure refers to a comprehensive network of expressways, railroads, ports, airport, power plants, energy supply, and electricity infrastructure and ICT adoption (information and communications technology), while soft infrastructure refers to institutional quality, trade facilitation mechanisms, efficient and speedy custom procedures, and border controls (Yu, 2023). For the first five year of the BRI, Chinese government announced its plan of directing 5 billion US $ to the projects.

[13] Ray and Simmons (2020) strikingly note that the amount of loans these banks provided in 2008-2019 (US$462 billion) was very close to the amount of development financing (US$472 billion) provided by the World Bank during the same period. Even though the period goes back to the announcement of BRI, the closeness of the figures indicates China's dedication and strength in financing the projects. In addition to these two banks, the Shanghai Cooperation Organization Bank and the Asian Infrastructure Investment Bank (AIIB) are among the institutions supporting the funding mechanisms (Lim,2015). AIIB is mostly funded by Chinese regional or non-regional participants. This Bank is strikingly different from the Bretton-Woods Institution such as the World Bank or Asian Development Bank since it provides loans at much lower rates to borrowers in low-income countries.

reaping the benefits of its comparative advantage in cheap labour for exports to traditional Western markets (Yu, 2024). Due to this limitation and the increasing pressures of the digital age, China also aims to enhance the quality of its exports to these markets. Meanwhile, it needs to relocate its low-quality manufacturing to low-income countries to establish a secure base for exports that is immune to fluctuations in Western destination markets. Hence, developing or low-income countries need to be strengthened and under new and enlarged agreements. Despite challenges in achieving those targets, China's leading position in world exports and its role as a critical hub in supply chains with strong upward and downward linkages have enabled the Chinese government to undertake grand endeavours, the biggest of which is the BRI.

Second, Chinese foreign policy has undergone significant shifts since the reforms and opening-up policy was introduced in the early 1980s. China seeks to consolidate its economic success with a “Going Global” strategy, aiming to establish strategic leverage and influence that encompasses both geopolitical and geoeconomic power. For this purpose, China has joined multiple international organisations and agreements. Admission to the WTO in 2001 and membership in the BRICS, the Shanghai Cooperation Organisation, and the Regional Comprehensive Economic Partnership are examples of China’s efforts to become globally connected. However, none of them gives China the level of control it aims to attain with BRI. At this point, BRI is valuable since it enables China to position itself as the primary decision-maker in selecting, funding, and building BRI projects, leveraging its competitive power in industries such as construction, infrastructure, metallurgical building materials, and communications equipment in these countries. (Khanna, 2016).[14]

Third, the positive response of participant countries has not subsumed in years despite all the arguments about the Sino-centricity of BRI projects. This continuing

[14] According to the Engineering News-Record’s list of “2021 Top 250 Global Contractors”, in the field of technological capacity and infrastructure construction, fourteen Chinese construction firms are listed among the top 20 largest infrastructure contractors in the world. These companies are ranked according to construction revenue, which were generated outside of each company’s home country in 2020. Chinese firms are not merely the leading players; in fact, China structurally dominates the global infrastructure construction industry.

positive attitude can be attributed to the significant gap in infrastructure investment among these countries. According to the ADB's (2017) estimates, the investment needs of South Asian countries are expected to reach 8.8% of their GDPs, whereas this rate is projected to increase to 9.1% for the Pacific countries by 2030. Additionally, infrastructure investment could be considered a significant factor behind the economic growth in developing countries. Despite all the suspicions about China’s attitude, its participation in the WTO and its leading position in the export market have helped the Chinese government create a pro-free trade narrative intended to alleviate concerns.

Despite efforts to standardize tender processes, challenges persist for China in consistently meeting technical standards due to ongoing technical and financial limitations

3.2.1. Critiques and Challenges of the Belt and Road Initiative

After the ambitious start in 2013, there has been a dramatic decline in the growth rate of Chinese investment under the BRI (Figure 9). The annual growth rate of total Chinese funding under the BRI was 244% in 2014, but this rate could not be sustained in the following years. Garcia-Herrero (2017) emphasises that the dramatic decline in Chinese reserves (Figure 10), the slowing down of the Chinese economy (Figure 11), and the share of nonperforming loans in banks’ balance sheets contribute heavily to the decline. The author notes that the $3 billion in reserves has been the lower limit set by the Chinese authorities, and as the reserves decline, less surplus of reserves could be devoted to the BRI.

In addition to slowing China’s ability to finance projects, severe criticism has emerged regarding how China executes these projects. Baltensperger and Dadush (2019) state that despite the BRI’s massive potential, the objectives are not detailed enough and lack transparency and coordination. In addition, China experiences long delays in fields, and the loan repayments of participant countries at remarkably different stages of development cause concerns about the debt-structuring processes. In 2017, when China provided the highest lending amount under the BRI, It was the world's largest official creditor, significantly ahead of the figures provided by the IMF or the World Bank (Yu, 2024). Hurley and Portelance (2019) highlight the disparity in lending practices between China and those of the Paris Club, a club of significant creditors worldwide.[15] This inequality is predicted to oblige the latter group of lenders to initiate debt relief programs for countries with debt overhang problems.[16] China's reluctance to align with the globally accepted "rules of the road" as a creditor poses a crucial problem, as multilateral organisations struggle to pinpoint China's actions in cases of debt repayment failure in low-income countries.[17] China's cancellation of debts for certain countries, such as Sudan, Ethiopia, and Kenya, or its exchange of debt repayment for land allocation or leasing for long periods from indebted countries like Tajikistan and Sri Lanka, are not solutions the Western World is accustomed to. Authors also designate Djibouti, the Kyrgyz Republic (also known as Kyrgyzstan), the Lao People's Democratic Republic (also known as Laos), the Maldives, Mongolia, Montenegro, Pakistan, and Tajikistan as countries with a high risk of debt failure.[18] They also note that there are no European countries with debt repayment risks.

The lack of an official dataset spanning multiple years, with country and sector breakdowns, exacerbates the problems mentioned above regarding the BRI.[19] Garcia-Herrero (2017) suggest more cooperation with the European Banks in co-lending operations. Considering the distance of the Chinese government from Bretton-Woods principles, such an alliance could be a window of opportunity to influence the

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[15] List of the members of the Paris Club can be found on https://en.wikipedia.org/wiki/Paris_Club . China insists on not becoming the member of the Club, but participates in the meetings as observer.

[16] Examples of such initiatives are the Heavily Indebted Poor Country (HIPC) Initiative and the Multilateral Debt Relief Initiative (MDRI) (Hurley & Portelance, 2019).

[17] Authors regard the capacities of the memorandums of understanding (MOU) signed between the Chinese government, The World Bank, ADB, AIIB, and the European Bank for Reconstruction and Development (EBRD) insufficient on shaping the lending terms. The establishment of the China-IMF Capacity Development Center in 2018 was also regarded a crucial step in training the officials of the participant countries to promote the building of certain standards across countries. Further information about this centre can be found on https://www.imfcicdc.org/content/cicdc/en.html

[18] Djibouti is the site of China's only overseas military base (Hurley & Portelance, 2019).

[19] The Chinese government publishes the total investment made under the BRI. Nevertheless, those publications are merely in the form of one-page public announcements. Thankfully, other data sources provide historical data for the BRI, including sector and country breakdowns. These consistent data sources pave the way for BRI-related analyses (Nedopil, 2024).

Chinese government to adopt market principles. Indeed, there is cooperation with institutions such as the European Bank for Reconstruction and Development (EBRD), the World Bank, and the International Monetary Fund (IMF). However, they are not strong enough to have leverage over Chinese authorities.[20]

Although physical infrastructure investment was at the forefront in the early years, projects incorporating green and digital technologies have proliferated over time. Green Silk Road and Digital Silk Road projects were announced as new parts of the BRI. In June 2021, the BRI Green Development Partnership Agreement was established by China and 28 countries to finance projects using renewable energy or low-carbon techniques. The activities of Chinese companies in digital industries, such as 5G communications, e-commerce, big data, and quantum computing, are regarded as part of the Digital Silk Road (DSR), even though state organisations do not directly finance them. Examples include Huawei (the world's leading manufacturer of 5G telecommunication equipment), Alibaba (the leading firm in e-commerce), ByteDance (the owner of the social media platform TikTok), and Tencent (the maker of WeChat). The Chinese government regards these companies as tools to penetrate both developed and developing countries. It is highly possible that favourable lending conditions from Chinese state-owned banks to such companies could be utilised to enhance their business deals overseas. Despite these significant investments, the "small but beautiful" motto announced at the third BRI meeting in October 2023 suggests that China faces the costs of uncertainty and the inefficiencies associated with large-scale investments. The motto emphasises small but effective projects over massive ones. In addition, the COVID pandemic has shown China that export-led growth should not be the sole priority due to problems in supply chains. Therefore, some analysts suggest that projects in China should also be funded by the BRI resources to support domestic development (Yu, 2024).[21]

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[20] In the Belt and Road Forum in 2019, Christine Lagarde also emphasised cooperation in procurement tenders and particularly in risk-assessment periods of the projects. Close monitoring of the loans would necessitate an agreement on shared principles and criteria. The speech can be accessed at https://www.imf.org/en/News/Articles/2019/04/25/sp042619-stronger-frameworks-in-the-new-phase-of-belt-and-road

[21] The increasing rivalry between the U.S and China and the COVID-19 pandemic pushed China to declare "dual-circulation" in 2020. With the duality, development in both domestic and international markets are implied.

Finally, in October 2023, during the 3rd BRI Forum, Chinese President Xi Jinping stated that the revived Silk Road had also become a life-saving road. The extension of the BRI from Eurasia to Latin America, including 151 countries and official agreements with more than 30 international organisations, was a great success. Hydro, wind, and solar energy-based power plants, the Belt and Road Science, Technology, and Innovation Cooperation Action Plan, and the planned Global Initiative for Artificial Intelligence (AI) Governance are highlighted as the hallmarks of the second decade of the BRI, i.e., BRI 2.0.[22]

Despite China's continued ambitious statements, it was notable that Greece, the Czech Republic, Italy, Malaysia, the Philippines, and Switzerland were absent in 2023, despite their attendance at the first two meetings. IMF did not send a director, either (Mardell, 2023).[23] In December 2019, the EU Commission published a report urging member states to make a national risk assessment of the cybersecurity of 5G networks.[24] Even though the Chinese companies Huawei and ZTE were not explicitly named in any of the following statements, the EU authorities emphasised the avoidance of dominant suppliers, which could stem from potential subsidies or dumping activities.[25] The two companies above are the targets of such statements, and by September 2023, 11 countries banned the use of Huawei and ZTE equipment in 5 networks. That Germany (as the biggest trade partner of China in the EU), Romania, Estonia, Latvia, Lithuania, and Portugal are among the banner countries is striking from the viewpoint of this thesis since these countries are (or were) the strong alliances of the BRI in Europe.[26] On the other hand, the Malaysian and Indonesian governments have officially declared their intention to collaborate with

[22] Xi Jinping (2023). The speech can be accessed at http://www.beltandroadforum.org/english/n101/2023/1018/c124-1175.html

[23] The article could be assessed on https://thechinaproject.com/2023/10/19/belt-and-road-forum-round-up/

[24] The report named “EU Coordinated Risk Assessment of the CyberSecurity of 5G Networks”, can be accessed on https://ec.europa.eu/newsroom/dae/document.cfm?doc_id=62132.

[25] https://ec.europa.eu/commission/presscorner/detail/en/qanda_20_127

[26] https://www.reuters.com/technology/european-countries-who-put-curbs-huawei-5g-equipment-2023-09-28/

Chinese companies to enhance their digital economies. In a sense, China tries to balance the influence of Western actors with that of Asian ones.

3.3. EU–China Relations under the Belt and Road Initiative

The EU-China economic relations encounter inevitable setbacks that would exist even without the BRI. Dealing with one of the most significant issues, Herrero and Xu (2017) state that Chinese State-Owned Enterprises (SOEs) pose a considerable hurdle for any bilateral investment agreement between China and the EU. Due to the Chinese government's industrial policy, these companies focus on the manufacturing sector. They could operate with overcapacity and with no risk of bankruptcy due to the non-economic orders from government officials.[27] The subsidisation and the provision of favourable credits from the Chinese government to these firms strengthen Chinese firms' global competitive advantage. In addition, Chinese firms are protected by regulations and special support programs, such as "China Manufacturing 2025", against foreign firms in mainland China. These features of the Chinese state-owned enterprises (SOEs) pose undeniable competitive risks to European firms in Europe and mainland China. To bring the European firms on equal footing, Herrero and Xu (2017) suggest that the EU should not prevent Chinese firms from acquiring European assets or impose restrictions or sanctions on them. Such an action is expected to elicit a more significant response from the Chinese government in support of these firms. Instead, European authorities should find ways to penetrate the preferential market access for Chinese firms in mainland China. The hardship in gaining access to sectors such as energy, infrastructure, utilities and finance leads to the last suggestion: EU authorities are also recommended to put international pressure on Chinese firms to align with global market principles by implementing and encouraging further liberalisation. For instance, supporting China's membership in the OECD could be a practical step, considering that China's WTO accession has

[27] In China, SOEs were enlarged in the 1990s by bringing small SOEs together to create effective and globally competitive corporate giants through the end of 1990s, most of these firms were partially privatized with still strong ties between the private owners and the state. On the other hand, the EU state-owned enterprises are small; by 2016, their share in total employment was below 10%. Most Chinese SOEs do not have profit maximisation objective as they were established in the planning period to correct market failures and provide social justice. Establishment of such enterprises has contributed hugely to the overcapacity problem of China in recent years (Herrero and Xu, 2017).

not been sufficient to alter its policymaking. Considering the influence of the Chinese BRI on the EU, these suggestions imply that the EU should not confront the Chinese government explicitly, but rather use policy instruments in competition policy and dispute resolution frameworks to address the externalities of the projects. As the current disputes between the EU and China are analysed, it is seen that the EU mostly prefers this route while trying to build alternative road maps like the "EU-China Connectivity Platform".

Underlining the requirement for a coherent approach, Mardell (2018) presents three BRI-related risks for the EU. The first relates to the potential political influence China could have on EU members.[28] Such influence is viewed as a significant challenge to the cohesion policies of the EU. The second one is related to a widespread concern, the debt problem frequently discussed in the realm of the BRI. China could take over some of the infrastructure projects in EU members in case of debt repayment problems. This poses another threat to economic unity, which might need financial support from the more vital members of the EU. The third concerns doubt about China's ability to comply with Europe's environmental, social, and economic standards. These risks were proposed in 2018, and as the BRI evolved to include more green projects, technical conformity, as in the Belgrade-Budapest Railway, could still be an issue.

2012, China established a connectivity platform with 16 Central and Eastern European (CEE) countries (CEECs), including 5 Balkan countries and 11 EU members.[29] Before the global financial crisis, the trade volume between China and these countries was growing. In the aftermath of the crisis, there was also interest in these countries' cooperation with China. In 2019, Greece joined the Platform, and it has since expanded to 17+1. In 2022, Estonia, Latvia and Lithuania exited the

[28] Both Greece and Hungary agreed in not criticizing China for its activities in the South China Sea in 2016. It should be recalled that Greece did not participate in the third BRI convention in October 2023, representing a significant shift in attitude. For details, see Mardell (2018) on https://merics.org/en/comment/responding-chinas-belt-and-road-initiative-two-steps-european-strategy

[29] The 16+1 Format refers to 16 countries and China as plus one. The countries were Albania, Bosnia and Herzegovina, Bulgaria, Croatia, the Czech Republic, Greece, Hungary, Montenegro, North Macedonia, Poland, Romania, Serbia, Slovakia, and Slovenia.

Platform, which is currently known as the 14+1 Connectivity Platform. China's focus on CEE countries also stems from their ordinary communist past and the acquisition of assets by Chinese companies at low prices during the crisis (Garcia-Herrero & Hu, 2017). EU Commission (2018) also declares that China's dealings could reverse EU cohesion policies.[30] More precisely, China's lending practices, pressure on these countries during public tenders, and insistence on using Chinese labour and inputs imported from China, as well as negotiating the terms and conditions of the projects with the participant countries, rather than with EU headquarters in Brussels, are listed as sources of potential problems.

Figure 12 shows that the share of the BRI projects coming to Europe (not only to the members of the 14+1 Cooperation Platform) has evolved significantly, particularly in the aftermath of the COVID-19 pandemic. In Figures 13 and 14, the shares are presented at the country level. Serbia is the leader in attracting BRI-related investment projects. As stated above, Serbia is not a member of the EU, which has facilitated the inflow of BRI projects. Despite the failure in the Hungarian section of the Budapest-Belgrade railway, Hungary is still the second destination for the BRI in Europe. The third position of Portugal is not surprising, considering the historical relations between Portugal and China in Macau, which Portugal handed over to China peacefully in 1999. On a sectoral basis, investments in transport and energy account for the two largest shares of Chinese investment in Europe (Figure 10).

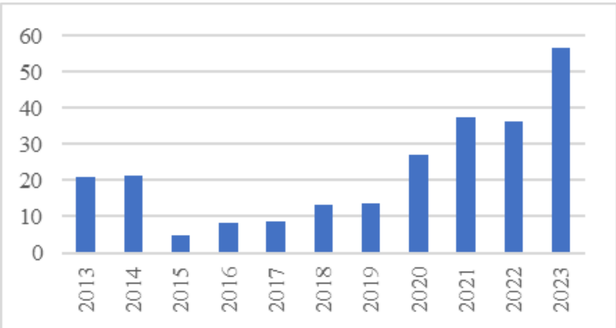

Figure 10. Share of BRI-Related Investment in total FDI to Europe (%)

Source: The China Global Investment Tracker (2023)

[30] The related EU Commission Report is available on https://www.europarl.europa.eu/RegData/etudes/BRIE/2018/625173/EPRS_BRI(2018)625173_EN.pdf .

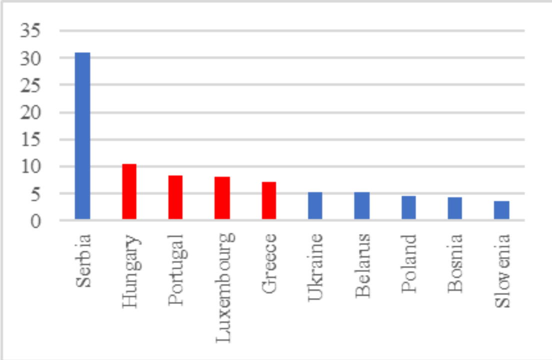

Figure 11. Share of Investment in total BRI-Related Investment to Europe

*The countries also in this thesis's sample are coloured in red.

Source: The China Global Investment Tracker (2023)

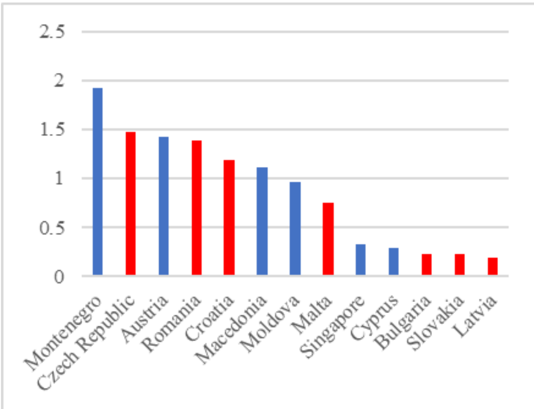

Figure 12. Share of Investment in total BRI-Related Investment to Europe

*The countries also in this thesis's sample are coloured in red.

Source: The China Global Investment Tracker (2023)

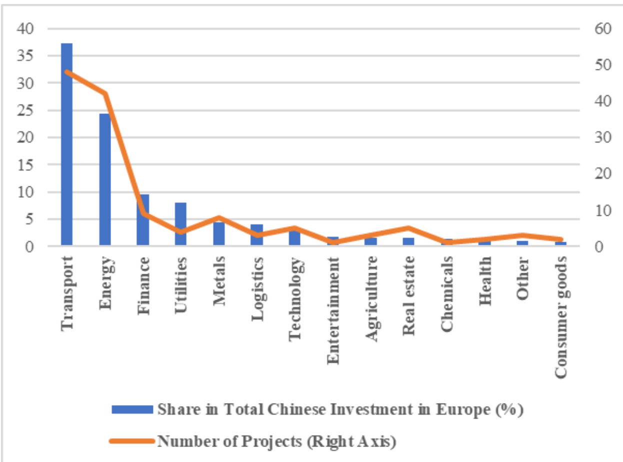

Figure 13. Sectoral Shares in total Chinese Investment to Europe (%)

Source: The China Global Investment Tracker (2023)

There are also BRI-related initiatives between China and the E.U. A Connectivity Platform was established in 2015 between the European Commission (DG MOVE) and the National Development and Reform Commission of China (NDRC) to improve transport connectivity. This platform aims to eliminate the conflicting interests between the Trans-European Transport Network (TEN-T) and the OBOR by maintaining a level playing field and enhancing transparency and reciprocity in market access and transport infrastructure.

Although the BRI-related investment is directed at all European countries, some studies focus solely on the European Union (E.U.) countries. Fardella and Prodi (2017) focus on the impact of the Piraeus Port in Greece, built as part of the BRI Project, on the Italian ports by the Adriatic Sea. They claim that the construction of the Piraeus Port challenges the significance of Italian ports. This risk would be amplified by the construction of railways in Greece, as well as the development of new ports in Egypt and Algeria. Verlare and van der Putten (2015) state that, in response to the penetration of BRI projects into E.U. regions, a unified approach agreed upon by E.U. states would yield higher benefits for them compared to individual responses and stances.[31]

While there are many challenges on the road, initiatives are also working to bring the EU and China together in collaborative research and innovation activities, the most recent of which are under the Horizon Programme (2021-2027). China and the EU aim to cooperate in food, agriculture, biotechnology, and climate change. A co-funding mechanism was established between the Horizon Europe and China's Ministry of Science and Technology.

[31] There are also BRI-related initiatives between China and the E.U. A Connectivity Platform was established in 2015 between the European Commission (DG MOVE) and the National Development and Reform Commission of China (NDRC) to improve transport connectivity. This platform aims to eliminate the conflicting interests between the Trans-European Transport Network (TEN-T) and the OBOR by maintaining a level playing field and enhancing transparency and reciprocity in market access and transport infrastructure.

CHAPTER 4

LITERATURE REVIEW

In this chapter, the studies focusing on the use of the CDM framework across different country groups are presented first. Following that, studies investigating the relations among enhanced infrastructure, trade, and innovation are presented. As the BRI was initially presented as an infrastructure project, understanding the pathway from infrastructure to enhance trade and innovation is crucial. Lastly, studies on the impact of knowledge spillovers and proximity are presented as the second approach, as the analyses rely on extending the traditional MMK framework to incorporate spatial dependence.

4.1. Literature Review on R&D, Innovation and Productivity Nexus

In their pioneering study, Pakes and Griliches (1984) argue that the direct inclusion of R&D expenditures in the Cobb-Douglas production function as input leads to the significant neglect of the link between innovation inputs and innovation outputs that the knowledge production function should capture. They focus on the incremental changes to economically valuable technological knowledge at the firm level, proxied by patent applications. Using data from 121 large U.S. firms for the 1968-1975 period, they explain the firm's knowledge production using research expenditures from the last five years, a firm-fixed effect, and a time trend. The change in knowledge is then used in the patent equation as regressors, which ultimately results in research expenditures being included as regressors for patent applications when the two equations are combined in the final model.[32] It is observed that, although

[32] Since firms make their research efforts explicit by applying for patents, a threshold level of future benefits is postulated beyond which the application is made. Pakes and Griliches position the patent's application as a midpoint between the inputs and the benefits.

only the first and fifth lags of research expenditure are significant, approximately 85% of the variance in patents is associated with variance in research expenditure. This high association is found to stem from the between-firm variance in research expenditures.

On the other hand, the within-variance in firms' patents corresponds to at most 25% of the variation in firms' research expenditures. This finding suggests that differences such as technological opportunities or managerial ability could lead to significant variations in the productivity of the research effort and patent applications under the model considered. This study primarily involves the research effort and knowledge production associated with the research and development (R&D) process.

On the other hand, it is seen that since 1950s, there have been studies focussing on the impact of R&D effort on economic growth and productivity.[33] Pakes and Griliches (1984) was indeed built on the groundwork of previous studies. The focus of the studies on R&D also triggered the need to establish international standards and guidelines for the correct measurement and interpretation of R&D figures. In this respect, the Frascati Manual was published in 1963 by the OECD as a guideline defining fundamental concepts related to R&D activities, leading data-gathering processes and presenting classifications of the R&D statistics. The distinctions between basic research, applied research, and experimental development are highlighted in the Manual, shedding light on what should be recorded as R&D and under which category. The Frascati Manual has been updated six times, the most recent update published in 2005.[34]

The counterpart of the Frascati Manual on the innovation side is the Oslo Manual, which is closely related to the primary data used in this study. The first Oslo Manual

[33] A detailed sketch of such studies is presented in the section for theoretical background.

[34] The original name of the report is "The Proposed Standard Practice for Surveys of Research and Experimental Development". Other updates of the Manual were published in 1970, 1976, 1981, 1993, and 2002.
Detailed information about the Frascati Manual can be found on the OECD Publications, which is available on https://www.oecd.org/en/publications/frascati-man ual-2015_9789264239012-en.html. Other updates of the Manual were published in 1970, 1976, 1981, 1993, and 2002.

was published in 1992 and has been revised thrice since then.[35] The latest version was published in 2018 as the 4th edition. The Oslo Manuals provide information about definitions, types of innovation, and guidelines that pave the way for the construction of a common language among statisticians and innovation policymakers worldwide. The Oslo Manuals have evolved considerably, both in terms of sectoral and functional coverage, since 1992. In the first edition, only manufacturing industries were covered, which was expanded by the inclusion of service sectors in the second edition, published in 1997. The third edition, introduced in 2005, incorporated marketing and organisational innovations in addition to the then-existing product and process innovations. However, with the latest edition in 2018, the dispersity in definitions was eliminated. With the integration of processes, marketing and organizational innovations, a new category was created as "business process innovation". Since 2018, all innovation statistics that comply with the criteria of the Oslo Manual have been categorised into two types of innovations: product innovation and business process innovation.

The idea that the production function should not directly include R&D investment but rather that there should be a step that stands to produce innovation is established in a neat framework by the pioneering work of Crepon et al. (1998), known as the CDM framework. The study's main contribution is a 4-step model that rests on the idea that innovation output, rather than innovation input — i.e., R&D investment — promotes productivity. In this vein, the first two equations model the R&D decision and the level of R&D capital, respectively. The third link connects R&D capital to innovation output, and the last link connects innovation output to productivity.[36]

In the first equation, they model the firm's decision to conduct R&D. By using a generalised Tobit model, a latent decision criterion is explained in terms of variables such as market share, firm differentiation, and firm size.[37] These variables are

[35] Detailed information about the Oslo Manuals can be found on the OECD Publications, which is available on https://www.oecd.org/en/publications/2018/10/oslo-manual-2018_g1g9373b.html

[36] Depending on data availability, it is seen that R&D expenditure is also widely used in studies that apply the CDM framework.

[37] This decision criterion is the expected present value of the firm profit accruing to research investment.

computed from the French Firm Annual Survey, using the firms' sales decomposition by lines of business, product lines, or industry segments. Market share is the weighted average of the firm's share in each industry segment, where the weighting is determined by the share of the related industry in the firm's total sales. The diversification index is the inverse of the firm's Herfindahl index. Using these explanatory variables, it is postulated that the firm conducts R&D activities above a threshold level, which might be industry-specific or common to all firms in the sample. In the second equation, the same explanatory variables explain the R&D capital per employee, which might be latent or actual (depending on the firm's decision in the first stage). The disturbances are assumed to be jointly normally distributed, and the research capital is used as a stock variable. However, the experimentation with the flow measure provides almost the same results.

In the third equation, the innovation output of the firm, proxied by either the number of patents or the share of innovative sales, is explained using the R&D capital calculated in the second equation.[38] Market share and diversification indicators are not included in the innovation output equation, although size remains a factor. CDM (1998) envisions a basic and extended model, where the extended model comprises the demand-pull and technology-push indicators in the first three equations and the skill composition indicators in the fourth equation. The fourth equation links innovation output, measured by the expected number of patents or the latent share of innovative sales, to labour productivity, measured by the value-added per employee. In addition to innovation output, the model also includes physical capital per employee, the shares of engineers and administrators in the total number of employees, and size. In CDM (1998), the R&D investment, patent and the share of innovative sales are continuous, count and interval data, respectively. Such differences in the data structure necessitate the use of Tobit, heterogeneous count data, and ordered probit specifications in the estimation. Additionally, two significant problems are noted in the analyses, specifically focusing on the relationships between R&D, innovation, and productivity. The first is the selectivity bias, stemming from the fact that only a subset of firms engage in R&D activities, and any model relying on these firms would introduce biases. Second, there are two-

[38] Both variables are added as latent variables.

way causalities among R&D, innovation and productivity, leading to the simultaneity bias and endogeneity problems. To address the endogeneity, CDM (1998) employs a two-stage estimation approach, which involves converting all the equations to the reduced form and then applying the methods of moments in the first stage. This is followed by the second stage's asymptotic least squares (ALS) estimation. The ALS model is favoured since it facilitates estimation by requiring minor assumptions about the disturbances, which are expected to be highly correlated.

Starting with the estimations of the basic model, it is seen that doubling the firm's market share and diversification variable increase the firm's odds of engaging in R&D activities by 8.6% and 5%, respectively.[39] CDM emphasises the importance of these two factors, even when size and sector are controlled for. The effects of the market share and diversification variables on the R&D intensity reach 25% and 20%, respectively. At the same time, no significant impact on the firm's size is obtained for the R&D intensity equation. The innovation intensity, measured either by the number of patents or sales-weighted innovations, is not affected by firm size; however, a negative impact is observed when the sample is restricted to patent owners only. The considerable effect on innovation intensity stems from R&D intensity. A 1% increase in R&D intensity results in a 0.9% increase in the number of patents, whereas this effect is 0.4% for innovative sales. Coming to the final part, the productivity equation indicates that a substantial impact on productivity comes from physical capital, with a 20% increase observed upon doubling physical capital. The impact of knowledge capital also yields promising results, with 13% and 10% increases achieved by doubling the number of patents and sales-weighted innovations, respectively. In the extended model, the findings regarding firm size,

[39] Schumpeter's "creative destruction" concept stands as a significant pillar in the evolutionary and endogenous growth theory. According to the theory of "creative destruction"; new goods, new methods of production, the opening of new markets, the discovery of new sources of supply, and new organizational forms lead to the destruction of existing economic structures and their replacement with new ones. In the first stages of Schumpeter's theory, the entrepreneur was the centre of the innovative activity due to his/her uninterrupted desire to go beyond boundaries and alter (or overhaul) the existing organizational forms. In the succeeding studies, he claims that larger firms operating in concentrated industries are the prominent leaders of innovative activity. Such a shift stems from the observation that innovation has to be built upon the accumulated knowledge and financial sources evidenced by the vast R&D laboratories using strong human and physical capital. The reference given by Schumpeter to the economies of scale is highlighted in the studies, mainly when the coefficient for the size of the firm is found positive and significant.

market share, and differentiation are nearly identical. Among these variables, moderate and strong technology push dummies significantly increase the odds of conducting R&D, as well as the intensity of R&D and innovation.

In contrast, strong demand has a positive impact on the decision to conduct R&D. When innovation output is proxied by patents, even negative and significant coefficients can be obtained for supply-side factors. However, more plausible findings, such as significant demand and various supply conditions, are found when innovative sales are considered. A significant change is observed in the productivity equation's coefficient of knowledge capital when supply and demand conditions are taken into account. Skill composition variables are also found significant in the productivity equation.

CDM (1998) also acknowledge that the cross-sectional structure of their data prevents them from testing the validity of the assumptions (such as full correlation among the error terms of the equations) made on the structure of the models. As shall be seen below, the CIS survey's structure does not allow for full utilization of panel data techniques, and studies focus on finding solutions to this drawback by using a supplementary source of data that allows for the use of lags, using sophisticated estimation techniques or trying different assumptions about the correlations of the error terms.

Mairesse et al. (2005) investigate the RIP relation using the French Annual Survey of Enterprises and the CIS for the 1998-2000 period, focusing on manufacturing firms with a clear distinction between high-tech and low-tech sectors. With no feedback from productivity, latent variables for R&D and innovation occurrence and intensity are used in the recursive estimation, with correlations among equations acknowledged but not considered.[40] Size, the weighted average of the market shares in different industry segments, Herfindahl index, being part of a French or foreign group, recognition of the international market as the primary market, existence of

[40] Share of innovative sales and sales per employee are used to proxy for innovation occurrence and productivity, respectively. Also, since R&D expenditure only relates to the last year of the CIS survey, the innovation definition of the OSLO Manual is considered. So, firms in the sample could report no R&D investment even though they are "innovators".

government support, cooperation, sources of information, physical capital stock and materials, industry fixed effects are used as firm-level explanatory variables in the equations with both binary and continuous dependent variables. Like the CDM (1998), recognising the latent R&D variables as instruments in the innovation equations reduces the number of explanatory variables from the first to the last. The study presents mostly expected results and notable differences among firms with varying technology levels. Even considering only the new-to-the-firm product innovations, it is evident that being an R&D performer increases the odds of being a product innovator by 46% and 35%, respectively.In contrast, doubling innovation (intensity) raises productivity by 22.5% and 4.8% for high-tech and low-tech firms, respectively.[41] The most significant contribution of the study, however, relies on the separate estimations made by correcting for selectivity only, for endogeneity only, for neither, and for both.[42] The comparisons among the models reveal the presence of significant downward biases in the productivity equation when the endogeneity of product innovation is overlooked. It is emphasised that if the source of possible endogeneity were the simultaneity between the innovation and productivity equations, i.e., the expectation that more innovative firms would be more productive, the results would present upward biases. Therefore, endogeneity could stem from measurement errors, casting doubt on the correct qualification of the firms' activities in responding to the surveys. Random measurement errors in self-reported indicators are primarily detected for binary R&D indicators and among low-tech firms. The binary response for R&D is less informative than the R&D intensity variable. In contrast, the binary innovation variable is more informative than its intensity counterpart, as the variances stemming from measurement errors are directly comparable.

Klump and Leeuwen (2001) investigate the RIP relation using the Netherlands's CIS2 and Production Survey data for the period 1994-1996. They present a

[41] Also, size and diversification affect only R&D occurrence for the whole sample, whereas market share influences only R&D intensity. Recognition of the international markets as the primary market has no influence beyond the R&D section of the system, and the coefficients are positive.

[42] The results mentioned in the previous sentence belong to the model for which both endogeneity and selectivity are corrected. The contributive estimations are separately made for the two sub-samples by introducing continuous R&D per employee, product innovation new-to-the-firm, new-to-the-market, process innovation and patent holdings.

framework in which economic performance indicators impact innovation input and output.[43] Instead of using R&D expenditures as an innovation input, they use innovation expenditures as an input, along with the share of new or improved products, to measure innovation output. Instead of productivity, total sales and employment growth are selected as economic performance indicators. Klump and Leeuwen establish three models for each innovation input and output, such that the first one refers to an OLS estimation disregarding selectivity issues. In contrast, the second refers to the model obtained by Heckman's 2-step selection procedure. The third equation enables the simultaneous estimation of innovation input and output equations, both of which incorporate Mill's ratio, reminiscent of Heckman's procedure. The third equation allows for the correlation among the errors, which differs from the first two models. The findings indicate that correcting for selectivity converts the previously insignificant feedback effect of sales growth on innovation input into a significant one.

Furthermore, simultaneous estimation (with FMLS, still including the Mills' ratio) increases feedback on innovation input, while it becomes insignificant for innovation output. The single and simultaneous equation estimates for economic performance indicators indicate that the joint estimation of total sales and employment growth equations increases the contribution of innovation output to total sales growth, while the unidirectional impact of total sales growth on employment growth becomes insignificant. These findings suggest that selection and simultaneity issues are relevant even when using alternative economic indicators. Another important finding of the study is the significant coefficient obtained for the process innovation not only in the innovation output equation but also in the sales growth equation.

Griffith et al. (2006) examine the relationships among innovation effort, knowledge production, and productivity in France, Germany, Spain, and the U.K. using the third wave of the CIS data, which covers the period from 1998 to 2000. The descriptive analysis of the data presents interesting results: Even if French firms surpass the

[43] The feedback effect from the economic performance to the input stage requires dynamic solutions, which cannot be satisfied due to the limited longitudinal structure of the CIS data. As in similar studies, they try to capture the feedback effects by acknowledging the interdependencies among the equations.

U.K. and Spanish firms in R&D intensity, they fall behind the three countries in converting innovation into increased sales. Also, French firms have the highest average labour productivity in the manufacturing sector, while Spanish firms incur the highest investment per employee (i.e., training). The fact that some R&D efforts may not be reported is highlighted, particularly in the daily conversations among workers on a typical working day, which are not classified as R&D activities.[44] Due to this deficiency in reporting, the R&D decision and effort (intensity per se) is modelled relying on the data of reporter firms. Nonetheless, the results of the CDM model apply to the entire sample, as the parameters obtained for the reporting firms are used to predict the R&D intensity of all firms, resulting in the use of a limited set of variables in the R&D intensity equation. The obligations resulting from environmental, health, or safety standards are added as demand-pull indicators, along with the appropriability conditions. For process innovation, investment per employee is added to the model due to the complementarity observed in between. Sales per employee refer to productivity, and the incompleteness of the capital stock data renders the use of the investment in physical capital in the productivity equation. Separate models are estimated for each country, including fixed industry effects and firm size, except for the R&D intensity equation, which excludes firm size as an explanatory variable. According to the estimations of the probit model, the more firms engage in international markets, protect their innovations, receive government funding, and hire employees, the higher the probability of conducting R&D. Yet, some of these factors are not significant in the R&D intensity equation, such as protection measures, clarifying the distinction between the decision for and the intensity of R&D. The estimations for the knowledge production function (i.e. the innovation equation in the CDM model) indicate that R&D intensity has similar effects on product and process innovations for Germany and Spain. For France and the U.K., however, product innovation is more sensitive to changes in R&D intensity than process innovation. Protection methods are more effective on product innovation. At the same time, they have no impact on either type of innovation in the UK. Both types of innovations, however, are affected by environmental regulations in France. In contrast, German firms primarily consider them for process

[44] Those talks might include significant points related to the enhancement of processes.

innovations. Enlarging the firms' sizes improves process innovation in all countries, although its impact on product innovation is only observed in countries except the U.K.

On the other hand, the contribution of investment in employees is found to be highest for process innovation in the U.K. Nevertheless, the findings are mostly similar before the productivity equation. The productivity equations indicate that process innovation is significant only in France, which is explained using the sales per employee as the productivity measure. A significant association is found, surprisingly, for product innovation in all countries except Germany. Griffith et al. (2006) note that, despite the vast range of indicators included, the cross-sectional structure of the data should be considered with caution when interpreting the results as causal relations.

Using the CIS data for Sweden for the 1996-1998 period and the business register data from Statistics Sweden, Lööf and Heshmati (2001) employ eight different categories of innovation engagement as innovation inputs.[45] Unlike the original CDM study, latent variables are estimated only for the innovation input (R&D investment) and the inverse Mill's ratio obtained from this equation is inserted into the innovation output. Loof and Hesmati divide the four equations into two parts: the first two equations are estimated using Tobit models, and the last two are estimated using instrumental variables under 3SLS estimation. They criticise the CDM (1998) for assuming full correlation among all the errors, as full correlation implies that productivity in the last part could affect the R&D propensity at the first stage. However, such interaction would also require dynamic structure and lags of the variables, which are not possible under the cross-sectional structure of the CIS data.

[45] The study aims to make sensitivity analyses using different models, estimation methods, measures of firm performance, subpopulations of business sectors, different data sources, different specifications of innovation, and level and growth rate dimensions.
Measures are R&D-based products, services or processes, innovations within the firm, non-R&D based innovation activities, purchase of services for innovation activities, purchase of machinery and equipment related to products, services and process innovations, other non-machinery and equipment related innovation activities, industrial design or other preparations for production of new or improved products, education directly related to innovation activities, and introduction of innovations to the market. Authors also define a firm as innovative only if it has positive innovation investment and innovative sales.

By dividing the whole model into 2 and allowing for limited correlation, they end up with an estimation procedure at the mid-point of those in CDM (1998) and Pakes and Griliches (1980). The number of performance indicators in the last stage is also remarkable, with the use of value-added per employee, sales per employee, profit before and after depreciation per employee, and sales margin, all in logarithmic form.[46] In addition to the basic version explained above, alternative estimations include variations ignoring selectivity, simultaneity, and neither. It is seen that ignorance of selectivity produces negative bias, whereas ignorance of simultaneity produces upward biases.[47] A comparison of the impact of innovation output on economic performances indicates that the highest two coefficients for firms in both manufacturing and service sectors are found for profit after and before depreciation, respectively. However, since firms with negative profits are omitted from the sample, profit-related indicators are not found reliable. The innovation output elasticity for the sales per employee is 0.16 and 0.20 for the manufacturing and services sectors, both of which are regarded as too high in light of the findings in the literature. The elasticities for the value added per employee are 0.12 and 0.09 for the manufacturing and service sectors, respectively, which are more reliable in comparison to the CDM (1998) findings of 0.07 and 0.10. Additionally, the inclusion of new-to-the-firm innovations in the analyses yields more significant results in the productivity equation (across all definitions) than new-to-market innovations. Overall, such trials of alternative models are conducted to compensate for the dynamics that cannot be captured with the cross-sectional structure of the CIS data.

Studies also investigate whether there are any changes in the storyline among the firms concerning their functioning in global markets. Janz et al. (2003) investigate

[46] As an alternative, the growth versions of these variables and employment growth are also used as dependent variables in the last stage.

[47] Selectivity is ignored by the exclusion of Mill's ratio in the innovation output equation. In the version which ignores simultaneity, only the simultaneity between innovation output and productivity is ignored. The endogeneity of the explanatory variables is maintained since the recursive estimation is still maintained. In one of the alternatives, the CDM model is updated to five equations with the addition of productivity as the third dependent variable to the framework. The equations until the fourth are estimated using innovating and non-innovating firms. The fourth equation includes Mill's Ratio and the estimated productivity in the third step. Following Tobit model estimation, the third and fourth equations are estimated with OLS. In the fifth equation, productivity is still estimated using the predicted innovation output in the fourth stage. Such trials of alternative models are mostly done to compensate for the dynamics that could not be captured with the cross-sectional structure of the CIS data.

the existence of a shared story between Swedish and German firms using responses from manufacturing firms in the CIS3 survey. The manufacturing firms in the analysis are classified as "knowledge-intensive" because they possess high R&D intensity, human capital intensity, and a strong focus on global markets. Functioning on such a scale requires the conduct of innovative activities to maintain competitive productivity levels. Janz et al. (2003) employ a modified version of the CDM model to incorporate the productivity variable into the innovation model, acknowledging the simultaneity between the two variables.[48] Additionally, process innovation is included in both the R&D investment and innovation output equations, whereas more recent studies regard such innovation as a separate dependent variable.

Antonietti and Cainelli (2009) extend the CDM framework by incorporating exports and agglomeration economies into models using data from a survey conducted on Italian manufacturing firms from 1998 to 2003. Although evidence for these relations is mixed, the possible effects of agglomeration economies and the two-way causality that could be detected between productivity and exports justify the inclusion of such factors in the CDM model.[49] Variables related to agglomeration economies are added to every equation in the new CDM model, including the block of export equations added to the framework following the productivity block. Agglomeration economies are incorporated into the model using four variables that represent local externalities: a specialisation index, related and unrelated variety indexes, and population density. These variables are calculated and added to every equation.[50] The extended model's

[48] In line with this, the last two equations in the CDM model are estimated in a simultaneous equation system. The last two equations are estimated only for the innovative firms implying that innovation input (i.e. R&D investment) remains the sole latent variable. The study also assumes that the error terms of the equations are not fully correlated. The analysis starts with a Tobit model representing the decision to conduct R&D investment, and the rest is similar.

[49] The authors present studies from the literature that focus on the relations among agglomeration economies, productivity and exports to justify their choice of framework[49]. It is suggested that productivity affects export behaviour by reducing fixed costs associated with entry to new markets.

[50] The rest of the explanatory variables are mostly similar to the widely used indicators in the literature. The extended model adds three types of local externalities to each equation. The first one is the localization economies, which refers to the spatial concentration of firms in the same industry. The second is related to Jacobs' externalities, which refer to the increase in variety that is strengthened by knowledge spillovers among the firms in the geographically close firms in the same or related industries. The third one focuses on urbanization economies that regard information spillovers as local public goods mainly directed by the market and density of the urban area apart from the firms' and industries' dynamics.

export block includes the firm's propensity to export, the share of 2003 export sales and the number of macro-areas in which firms exported in 2003.[51] The findings suggest that agglomeration economies have no effect on firms' R&D decisions, whereas related variety and population density have a positive impact on R&D intensity, in contrast to the negative impact of unrelated variety. The knowledge spillovers among firms in different but complementary activities could explain the positive impact. The negative impact can be explained by the decrease in expected R&D returns resulting from knowledge spillovers that may exceed the desired level. The agglomeration terms in the innovation equation are mostly insignificant, whereas the R&D intensity is highly significant in this equation. Specialization affects productivity using either product or process innovation. Finally, productivity is highly significant in the propensity to export, along with the urbanisation (population density) term. Similar results are found for the export intensity equation. For the number of macro-areas, it is seen that unrelated variety contributes to the complementary role of urbanization and productivity. These findings suggest that agglomeration economies may play a significant role in understanding the relationship between the RIP and exports, as evidenced by the coefficients in the R&D and export equations.

Goya et al. (2012) investigate the impact of inter and intra-industry spillovers of R&D expenditures on the productivity level of individual firms using the Spanish Technological Innovation Panel (PITEC) data and the CDM model. The inter- and intra-industry spillovers refer to the weighted sum of all R&D expenditures incurred by firms in all other sectors and the same sector, respectively. Both the determinants in the CDM model and the impact of spillovers are evaluated by considering the technology level of the firms.[52] Both product and process innovations positively impact productivity, with the highest impact felt by high-tech firms that undertake process innovations. Low-tech firms mostly experience intra-industry spillovers on

[51] Instead of a reduced form setting, a structural model is estimated using the 3-year lagged explanatory models in the equations that tackle simultaneity issues.

[52] In the study, both the first and the third equations include binary dependent variables and are estimated as probit models. Product and process innovation models are estimated separately and with a similar set of explanatory variables except for the investment in capital stock to the model of process innovation.

productivity, whereas inter-industry spillovers are more prevalent among high-tech firms.

Baum et al. (2016) utilise the CIS data of 7,000 Swedish firms for 2008-2012, employing a modified version of the CDM model. They differ significantly from the prior studies: First, they estimate all steps of the traditional CDM model in a single process using the general structural equation model. Like CDM (1998), they begin by modelling the firm's decision to engage in R&D activities, but do not hypothesise a threshold beyond which the firm's decision is affirmative. Instead, they use the probit model to model the determinants of that decision using variables such as a dummy for location in Stockholm, imports per employee, market share, capital stock and presence in foreign markets. The explanatory variables do not change dramatically across the equations. However, including lagged productivity, the lagged count of patents, the share of imports to the G7 countries as an innovation input (R&D intensity) in the equation, and the human capital and ownership variables in the productivity equation yield distinctive findings.[53] While most studies focus on finding the best estimation technique to deal with endogeneity, this study introduces a latent variable to the first three equations, suggesting that there may be unobserved factors that simultaneously affect R&D decisions, their intensity, and innovation output, which are captured by this variable.[54] Following the probit model estimation, the full-information maximum likelihood model (FIML) is used in the remaining equations to address the missing data problem.[55] Possible correlations of error terms in the CDM model's recursive structure are also considered with the full-information maximum likelihood estimation. Most studies attempt to capture sector-specific effects by using sector-fixed effects or estimating sectors separately. This study allows the coefficients to vary by sector, utilising firm-level data.

[53] It should be noted that the study uses supplementary data on patents, human capital and firm characteristics.

[54] This latent variable is estimated by factor analytical methods and used in every equation except the productivity equation.

[55] The authors state that the recursive structure of the CDM model with possible correlated errors paves the way for making estimations by the "Seemingly Unrelated Regression" technique. However, since the FIML already handles the cross-correlation among the errors, they prefer the latter to deal with the missing data problem, too.

The findings suggest considerable heterogeneity across the sectors: The propensity to do R&D is highest in high-tech manufacturing. At the same time, the number of lagged patents has the highest impact on the R&D intensity of the firms in the knowledge and information sector (KIS). Being in Stockholm only affects the R&D intensity of high-tech firms, whereas the increase in imports from the G7 countries only impacts the intensity of high-to-medium-tech manufacturing firms. Imports from the G7 countries are considered a source of external knowledge carried by global spillovers. Lagged labour productivity affects only the R&D intensity in the other services sector. The R&D intensity is significant in innovation output for all sectors, with the highest impact in the KIS sector. An increase in capital intensity solidifies the process of creating innovation output for low-tech firms but weakens it for firms in other-services sectors.

Contrary to the second equation, being in Stockholm does not impact innovation output in high-tech firms. The innovation input has the highest coefficient in the high-tech and KIS sectors, with significant coefficients obtained for all sectors. An increase in human capital significantly enhances productivity in all sectors, except high-tech firms, a finding attributed to the already high level of human capital in that sector. On the other hand, being affiliated with a multinational enterprise (MNE) (either domestic or foreign) has the most substantial impact on high-tech firms, with significant effects observed across all sectors, except for the KIS sector's affiliation with domestic MNEs. Unobserved components captured with latent variables are significant for all sectors in every model included. Tests for homogeneity of the coefficients across sectors are mostly rejected, although it could not be done for factors such as the impact of the lagged number of patents on the R&D decision. Considering the recursive structure, however, it is evident that the sequential effects of R&D decisions on productivity differ across sectors.

Hashi and Stojcic (2013) evaluate the RIP relation using data from the CIS4 survey across 16 European countries, including seven that joined the E.U. in 2004 and two that are not E.U. members. Following the CDM approach, firm size, market orientation, cost or knowledge factors that hinder innovation, type of subsidy, type of source of information, and type of cooperation are used as explanatory variables, along with productivity and Mill's ratio, in the equation for innovation output.[56] The findings present heterogeneity among the results. Organisational innovations decrease productivity in Western European (WE) countries, implying the inability of firms to convert innovation output into profits for their firm in the short run. Additionally, the firms in the WE rely solely on internal sources when transforming innovation input into innovation output. Being in a trading firm increases R&D investment, while it decreases innovation output in WE countries. In the CE EC countries, there is negative feedback from productivity to innovation output, which is explained by the deployment of gains in efficiency to the production of existing products in a more competitive manner. At the same time, they could also be deployed to introduce new ones. As it is also considered that cost concerns significantly decrease investment in R&D in these countries, it can be concluded that a risk-averse behaviour is observed in these countries, from investment in R&D to productivity gains.

For Turkey, Bacanlı (2014) utilises the three waves of CIS surveys (CIS 2004, CIS 2006, and CIS 2008) for Turkish manufacturing firms and analyses the relationship between R&D, innovation, and productivity using the CDM model. His study is the first to make a distinction between process and product innovation for Turkey within a CDM framework. Engagement in international competition, source of funding for the R&D project, cooperation with other firms, source of information needed for R&D projects (such as customers, suppliers, universities or governments), size of the firm, investment intensity on tangible goods and R&D intensity measured by the R&D expenditures per employee are among the explanatory variables used in at least one of the stages. He finds that involvement in international competition and national funding of projects increases the likelihood of conducting R&D. Product innovation has a significant impact on productivity only between 2004 and 2006, whereas process innovation has a significant effect only between 2006 and 2008. The results show that involvement in international competition and securing funding from the central government increase a firm’s probability of conducting R&D. Additionally, utilising suppliers as a source of information increases the likelihood of engaging in process innovation.

[56] The innovation input in the study includes intramural and extramural R&D expenditures and the acquisition of machinery, equipment and software that are not R&D related.

In contrast, firms that obtain information from consumers primarily focus on product innovation. In the final model, investment in tangible goods increases labour productivity in all years. In addition to these consistent results, some of his findings are mixed. For instance, the positive impact of E.U. funding on R&D engagement in 2004-2006 vanishes when the model is estimated for the 2006-2008 period. Additionally, the positive impact of R&D expenditure on both product and process innovation during 2002-2004 and 2006-2008 is not observed during 2004-2006. Finally, the positive impact of product innovation on productivity is observed only during 2004-2006, but not in other years.[57]

Henriquez et al. (2023) investigate the impact of R&D investment and product and process innovations using microdata in Latin countries.[58] Due to a lack of proper data on R&D investment in most developing countries, they often use the World Bank's 2010 Enterprise Survey, which includes targeted questions about R&D and innovation-related activities. The authors highlight that the determinants of R&D investment may differ significantly from those in other (mostly developed) countries, particularly in terms of institutional instability, difficulty in accessing finance, an underdeveloped level of digitisation, high rates of informal competition, and unsatisfactory levels of cooperation among firms with more prominent roles.[59] The analyses focus on both product and process innovations, utilising the CDM and Lasso models. The latter approach, which utilises machine-learning techniques, eliminates irrelevant variables from the model by assigning a zero coefficient. The CDM model is the traditional version, which utilises the first three equations, while omitting the one for productivity. The comparison made by confusion matrices notes higher performance for the CDM model. The findings suggest that size influences the likelihood of both types of innovation across all countries. The findings also indicate a negative contribution of R&D intensity in Bolivia, Chile, and Colombia to

[57] Studies mostly concentrate on product and process innovation. While process innovation refers to improvements in production processes as implied, product innovation is observed when a firm has introduced brand-new or considerably modified products.

[58] The countries included in the sample are Argentina, Bolivia, Chile, Colombia, Guatemala, Peru and Uruguay.

[59] Even though the study highlights the importance of alternative factors, only the source of finance, bank vs non-bank, is included in the model.

the probabilities of product and process innovations. In contrast, it is positive for the rest of the countries. Being an exporter increases the odds for either type of innovation only in Chile, while it has a diminishing effect on the rest. The finding that exporters are more likely to be successful is attributed to possible differences in the technological level of traded goods or services and the geographical range of destination markets. Non-bank financing plays a significant role in the probability of process innovation in Argentina and Bolivia, whereas bank financing is significant in both types of innovation in Chile and Guatemala. Remarkably, the coefficients for the financing variables are significantly smaller than those for other variables.

Raymond et al. (2015) utilise the French and Dutch CIS data from the periods 1994-1996, 1998-2000, and 2002-2004, focusing on the manufacturing sector, except for the food industry. The study includes only the firms that have introduced at least one product innovation in the three years of the survey, an innovation that is not necessarily new to the market.[60] They stress that dynamics should be added to the CDM models due to inherent features of the innovation process, such as "time to build", opportunity cost and uncertainty surrounding the investment. Additionally, the observation that “success breeds success,” the better economic performance of innovators in terms of productivity persistence, and the availability of less-restrained resources for R&D investment, as represented by higher retained earnings, are listed as reasons for such inclusion in the models. They construct four models that rely on both observed and latent variables to predict the occurrence and intensity of product innovation. Latent variables are explained with the first lags of observed innovation and productivity, past R&D expenditure, R&D per employee, market share, size group, and industry and time dummies.[61] The productivity equation is modelled with both observed and latent innovation variables, as well as lagged productivity, firm size, physical investment per employee, sector, and firm fixed effects.[62] In the CIS surveys, the responses to qualitative questions, such as the occurrence of innovation,

[60] Such a preference renders the first equation of the CDM structure irrelevant, and they start with the innovation output equation in the CDM model.

[61] Size group indicators are constructed since the relation between size and innovation could be non-linear.

[62] Including the firm size in the productivity equation indicates that the assumption of constant scale elasticity is abandoned.

refer to the three years preceding the survey, whereas the responses to quantitative questions, including innovation sales, R&D intensity, and the number of employees, pertain to the last year of the survey period. In both countries, firms that undertake R&D in the previous two to four years (i.e., in a persistent manner) exhibit a higher propensity to conduct innovation and achieve higher innovative sales, with a greater impact noted for Dutch firms. The larger firms are also found to be more innovative in France, with no difference in propensity noted for Dutch firms. In both countries, decreasing returns to scale are noted. In productivity analysis, statistically significant differences in the coefficients are found only between the two countries for models with observed innovation. Being a product innovator raises labour productivity by 20% and 6% in French and Dutch manufacturing, respectively. Both observed and latent variables are found equally close to the "true" model, providing no superior choice between them. It is also highlighted that innovation output is insignificant in the productivity equation when the errors in the innovation output and productivity are assumed to be uncorrelated. In other words, no significant effect is obtained when the endogeneity between innovation output and productivity is ignored. The study concludes with a uni-directional causality from R&D to innovation and innovation to productivity, presenting that the firms closer to the production frontier are not necessarily the top R&D investors in future periods. Vancauteren et al. (2017) analyse the RIP relation for Dutch firms using patent application data from the 2000-2006 period.[63] They underline that the decision of firms to conduct R&D investment is related to possible gains in the future. When combined with the uncertainty (or unforeseen randomness) of investments, more extended periods may be needed better to understand the impact of R&D activities on productivity.[64] They also state that the endogeneity in the CDM model, which primarily stems from the impact of unobserved firm characteristics, is significantly alleviated by using firm fixed effects and including lags in the models.[65] The inclusion of dynamics has no

[63] Firms that report zero R&D (in surveys such as the CIS) actually apply for patents, and there might be a tendency for firms to refrain from reporting their activities due to insufficient protection mechanisms.

[64] For a broader discussion around the requirement for lags, the authors reference Mansfield (1980).

[65] It is important to note that despite a lengthy discussion around the importance of lags in the CDM model, only one lag of the variables could be added to the equations since the R&D expenditure data is gathered from the CIS survey.

significant impact on either the probability of obtaining a patent or the number of patents. However, past R&D expenditures affect current R&D expenditures, and having applied for at least one patent increases the odds of making an R&D investment. The number of patents or citations is found to have a significant and positive effect on productivity, with no significant impact on past research and development (R&D) expenditures. The smaller firms are found to be more R&D intensive and productive, whereas size has no impact on innovation output.

Dai et al. (2022) employ spatial estimation techniques to examine the relationship between R&D investment and production efficiency, utilising firm-year data from Shanghai technological enterprises for the period 2009-2017. They introduce the concept of "effective" R&D capital, the sum of the firm's internal R&D expenditures and its collaborations with other firms. Capital stock, labour, internal R&D expenditures, the stock of cooperative benefits and the accessible knowledge pool explain production at the firm level.[66] The TFP in this model then represents the total impact of the last three variables. They emphasise cooperation among firms due to the cost increases triggered by patent protections, uncertainty, and innovation-related risks. Additionally, it is emphasised that economies of scale in R&D activities enhance efficiency by utilising cheaper complementary factors and reducing the need for repeated trials. Scale economies also support the ability of firms to expand into new markets and reap the benefits of innovative output. In addition to deliberate R&D cooperation, knowledge spillovers serve as external factors that either hinder or enhance the firms' productivity. While knowledge spillovers are generally expected to increase efficiency, competitive pressures may also decrease firms' productivity. They test the existence of spatial dependence among the productivity of economic units and conclude that spatial models should be used to account for technological proximity. Both static and dynamic spatial models are estimated. Productivity and knowledge spillovers are multiplied with the weight matrix, which is based on the number of patents in different classifications and can be time-varying.[67] In both static and dynamic

[66] Control variables such as trade openness, education level, and government subsidies are also inserted into the model.

[67] The possible endogeneity of the weight matrix is also discussed since unobservable factors might impact the weight and productivity simultaneously. This problem is tackled by using a control function approach.

models, the highest elasticity is found for knowledge spillovers, followed by internal R&D stock and R&D cooperation. The elasticities of the first two indicators are almost 5 times higher than that of R&D cooperation. For every 10% increase in the knowledge capital of neighbouring firms, productivity is expected to increase by 1.91%. The low coefficient found for the R&D cooperation indicates that science and technology firms in Shanghai have yet to reach a high level of efficiency. It is suggested that R&D across firms' boundaries may require additional coordination, monitoring, unexpected costs, and potential information asymmetry problems.

Recent studies employing the CDM approach or focusing on the RIP relation have implemented modifications to the model by incorporating dynamic spatial effects or utilising different sets of explanatory variables tailored to the sample countries. For instance, Fedyunina and Rodasevic (2022) analyze the RIP relation in CEECs, CIS countries, and Turkey, stating that the original CDM model has limitations in emerging economies.[68] They criticise the use of a broad notion of innovation that includes both R&D and machinery and equipment expenditures (M&E) in CDM models, as absorbing M&E effectively requires an initial production capability level with no direct and widely accepted proxy.[69] Production capability is hypothesised to affect both innovation intensity and productivity. No significant effect is found on the former, whereas a significant effect is observed for the latter. Production capability and investment in maintenance and engineering (M&E) have a significant impact on productivity, whereas innovation intensity does not. This finding is crucial to understanding the importance of absorptive capacity in emerging countries. In summary, the studies investigating the R&D, innovation, and productivity framework primarily employ the CDM model developed by Crépon et al. (1998). The innovation surveys of countries are used to obtain firm-level findings, which are based on the EU Commission’s Community Innovation Survey for Europe (also implemented by EFTA and some candidate countries). The export shares of countries mainly capture the impact of trade volumes.

[68] Since countries (except Turkey) do not have CIS data, the Business Environment and Enterprise Performance Survey dataset constructed by the World Bank and EBRD are used in the analyses.

[69] Production capability is defined as a dummy variable which takes the value of one if the firm has an international quality certificate and the share of full-time employees who received formal training in the previous year is above 10%.

Table 1. Summary of the Studies in the CDM Literature

Study	Sample	Dependent Variable	Explanatory Variables	Econometric Method	Key Findings	Key Result Summary
Pakes & Griliches (1984)	US manufacturing firms (panel)	Patent counts	R&D expenditures (current and lagged), firm fixed effects	Poisson, Negative Binomial, Panel Fixed Effects	Positive R&D-patent link with firm heterogeneity	R&D expenditures are positively associated with patent counts, exhibiting firm-specific effects.
Crépon et al. (1998)	French manufacturing firms (1990 CIS)	R&D decision, Innovation output, Labor productivity	Firm size, R&D intensity, industry dummies	CDM Model (Heckman, Tobit, Probit, OLS)	R&D boosts innovation, which improves productivity	R&D investment stimulates innovation output, which subsequently enhances labor productivity.
Mairesse & Mohnen (2005)	French CIS data	Product & process innovation, Productivity	R&D intensity, size, collaboration	Probit, OLS with endogeneity correction	R&D and collaboration enhance innovation and productivity	R&D intensity and collaborative efforts positively influence both product/process innovation and productivity.
Klump & van Leeuwen (2001)	Dutch manufacturing firms	Labor productivity	R&D intensity, capital intensity	Panel regression	R&D intensity improves productivity	Increased R&D intensity leads to improvements in labor productivity.
Griffith et al. (2006)	Firms from France, Germany, Spain, UK	Labor productivity	Innovation output, R&D intensity	CDM Model	Innovation boosts productivity with cross-country differences	Innovation output positively impacts labor productivity, with variations observed across countries.
Lööf & Heshmati (2001)	Swedish manufacturing firms	Labor productivity	Innovation indicators, firm size, capital intensity	Sensitivity analysis using various econometric models	Innovation has a positive impact on firm performance, with robust results across various model specifications.	Innovation indicators consistently show a positive effect on firm performance, robust to different model specifications.
Janz et al. (2003)	Firms from Germany, Sweden, the UK, and France	Labor productivity	Innovation activities, R&D intensity, firm characteristics	Comparative analysis using firm-level data	A positive relationship exists between innovation and productivity across countries, although the strength varies.	Innovation activities are positively linked to labor productivity across multiple countries, though the strength of this relationship varies.
Antonietti & Cainelli (2009)	Italian manufacturing firms	Innovation output	Spatial agglomeration, technological capabilities	Spatial econometric models	Firms in agglomerated areas with higher technological capabilities are more likely to innovate.	Spatial agglomeration and technological capabilities increase a firm's likelihood of innovation.
Goya et al. (2012)	Firms from Latin American countries	Product and process innovation	R&D investment, firm size, sector	Machine learning methods and traditional econometric models	R&D investment significantly influences both product and process innovations in Latin American firms.	R&D investment is a significant determinant of both product and process innovations.
Baum et al. (2016)	Firms from multiple countries	Productivity	R&D investment, innovation output	Generalized structural equation modeling (GSEM)	GSEM provides a comprehensive framework to understand the R&D-innovation-productivity nexus.	Generalized Structural Equation Modeling (GSEM) offers a robust framework for analyzing the R&D-innovation-productivity relationship.
Hashi & Stojčić (2013)	Firms from Western and Eastern Europe	Firm performance metrics	Innovation activities, firm characteristics	Multi-stage econometric modeling	Innovation activities have a positive impact on firm performance, with variations between Western and Eastern Europe.	Innovation activities positively affect firm performance, with notable differences between Western and Eastern European contexts.
Bacanlı (2014)	Turkish manufacturing firms	Labor productivity	R&D activities, innovation output	Structural modeling based on the CDM framework	Innovation significantly contributes to labor productivity in Turkish manufacturing firms.	Innovation output significantly enhances labor productivity in Turkish manufacturing firms.
Henriquez et al. (2023)	Urban regions in Chile	Land use conflicts	Urban planning scenarios, spatial data	Spatial analysis and scenario modeling	Different urban planning scenarios result in varying degrees of land use conflicts; spatial planning can help mitigate these conflicts.	Urban planning scenarios influence land use conflicts; spatial planning can mitigate these conflicts.
Raymond et al. (2015)	Dutch and French manufacturing firms	Productivity	R&D investment, innovation output	Dynamic panel data models	There is a unidirectional causality from R&D to innovation and from innovation to productivity.	Unidirectional causality is established from R&D to innovation and subsequently from innovation to productivity.
Vancauteren et al. (2017)	Dutch firms	Productivity	Innovation activities, R&D investment	Panel data econometric models	Innovation activities are positively associated with productivity growth in Dutch firms.	Innovation activities demonstrate a positive association with productivity growth.
Dai et al. (2022)	Firms from various countries	Total factor productivity	Effective R&D capital measures	Econometric analysis using firm-level data	Effective R&D capital is positively related to total factor productivity across firms.	Effective R&D capital measures are positively correlated with total factor productivity.
Fedyunina & Radosevic (2022)	Firms from emerging economies	Productivity	R&D investment, innovation output	CDM model and alternative econometric approaches	The CDM model effectively captures the relationship between R&D, innovation, and productivity in emerging economies.	The CDM model effectively captures the R&D-innovation-productivity relationship, particularly in emerging economies.

4.2. Studies on the Impact of Infrastructure Investment on Trade and Innovation

There is a significant interest in analysing the impact of transport infrastructure on trade dynamics at both global and regional levels. In line with the objectives of this thesis, the effects on trade, productivity and innovative activity are discussed in this section.

There is a global consensus that investment in transport infrastructure can enhance the capacity of businesses to reach their goods and services to existing or new markets safely and on time, while directing the regional labour force to the most appropriate jobs (World Economic Forum, 2016).[70] In addition to enhanced trade capacity, firms can reach supply chains with lower costs and safer procurement. The increasing demand could also necessitate hiring new employees or enhancing the productivity of existing ones, which may also prompt innovative activities. In parallel, the World Bank declares that the BRI transport projects could enhance trade and foreign direct investment (FDI) and reduce poverty by lowering transport costs, a significant component of trade costs (World Bank, 2019).[71]

Four aspects of transport costs are valuable in analysing their impacts on trade volumes. First, they inform firms about the exact cost of a particular mode of transport, thereby eliminating one source of uncertainty for them.[72] Second, transport costs involve the quality of the infrastructure. Clark et al. (2004) demonstrate that reducing the quality of ports in the U.S. from the third quartile to the first quartile results in a 12% increase in shipping costs. The BRI focuses on improving the efficiency of ports through modernisation and enhancements in their connections by railways to inland areas. Third, the close relationship between the optimal mode of transportation and delivery times is significant for companies that operate just-in-

[70] The report can be accessed on
https://www3.weforum.org/docs/WEF_Technology_in_Infrastructure.pdf

[71] The report can be accessed on https://www.worldbank.org/en/topic/regional-integration/publication/belt-and-road-economics-opportunities-and-risks-of-transport-corridors.

[72] There is a secular decline in transport costs in the 20th century due to technological developments as stated by Redding and Turner (2015).

time practices and rely on an international supply network (Lu et al., 2018). The influence of that relation is not confined to certain types of companies.

Hummels et al. (2007) note that average import tariffs declined from 8.6% to 3.2% between 1960 and 1995; however, by 2004, one-quarter of world trade still occurred between countries with common borders. Authors warn that the trade capacity at further lengths had not improved sufficiently, drawing attention to the non-tariff trade barriers. Time delays are acknowledged as important parts in non-tariff barriers. Goods' sensitivity to rapid depreciation in terms of their content and the demand for them brings forth the importance of delivery times, the length of which could function as a non-tariff trade barrier. Not only fruits and vegetables, but also electronic items that have a slightly upgraded version that could easily replace the one on the market, require quick deliveries. During periods of global uncertainty, shorter delivery times would increase the scope for firms to have longer periods of consideration for making well-adjusted production plans. Such production plans might even involve producing at plants with lower labour costs and could permanently eliminate the markets in regions with lower competitiveness. When small regions are connected to larger ones, lower prices, higher quality, and a variety of goods in the larger regions could attract consumers and employees, ultimately resulting in a remarkable shrinkage in the size of the small region. Considering the competitiveness of Chinese firms, certain regions (countries) may encounter significant losses if their factors of production are left outside production or captured by other countries. Due to the objectives of higher mobilisation of labour and capital across BRI participants, this scenario is not far-fetched.[73] In short, the BRI could provide welfare gains for countries, but not without hurting some sectors.

In their pioneering work, Limão and Venables (2001) investigate the determinants of trade costs and the extent of their effects on trade volume. Infrastructure and geography are possible determinants of trade (transport) costs. Regarding the transport cost data, they utilise company quotes for transporting a standard container

[73] Even though China emphasizes that the aim of the BRI is not to undermine but to develop underdeveloped countries, it remains a viable question to what extent and how China could prevent the evaporation of business in specific sectors in BRI participants.

from Baltimore to selected destinations, including information on the cities of departure, arrival, and final destination, as well as the land and sea legs of the journey.[74] The geography of the countries is represented by using distances among them, the existence of a common border between them, and their location as landlocked, coastal, or island.[75] The infrastructure variable is constructed as an average of the density of roads, the paved road network, the rail network, and the number of telephone main lines per person.[76] This average is calculated for both the origin and transit countries. The results obtained using the gravity model provide insights that could shed further light on the effects of the BRI.

First, being a landlocked country incurs costs that are 75% higher compared to non-landlocked countries. The breakdown of the straight-line distance between countries into sea and land portions ends up with higher coefficients in models than the one obtained by using the straight-line distance. Therefore, the possibility of a considerable underestimation of trade costs (in many studies in the literature) is underlined. Additionally, incorporating land distance into the model does not eliminate the significance of being landlocked, which is attributed to border delays, transportation coordination problems, higher insurance costs due to delays, and inevitable transit costs. Infrastructure terms (of origin and transit countries) are both found significant, with the higher impact noted for transit infrastructure on landlocked countries. Breaking down distance into sea and land still improves the

[74] The second data source is the ratio of the CIF and FOB values for bilateral trade between countries. This dataset provided by the IMF, however, lacks in providing sectoral breakdown.

[75] They highlight that including the distance variable along with the border variable is significant for three reasons: First, the number of shipments might be significantly lower due to the possible integration of transport networks allowing the use of the same transport mode across countries. Second, neighbours might have particular customs agreements lowering shipping and insurance costs. Third, the possibility of easier backhauling allows the firms not to refrain from making high-volume trade agreements.

[76] Measuring the impact of transport infrastructure investment on related regions is not a straightforward task, primarily due to the selection bias in the choice of investment's location. If the investment targets connecting economic hubs with already high growth potential (that could also be across countries), dissecting the factors that could add up to the ultimate growth figures would need special identification techniques to obtain the true level of causality. Historical transport networks, geographical features of the areas or previous decisions related to the area could be used to gauge the counterfactual growth figures and compare the ones obtained after the investment. Yet, such instruments might not directly provide sufficient relevance to the initial research question, which might need some sacrifice on the content of the original research question.

model while making the impact of transit infrastructure insignificant.[77][78] These findings suggest that establishing overland and maritime roads, as well as infrastructure improvements, under the BRI could significantly reduce trade costs. In particular, such investments could help landlocked countries avoid the high transit costs associated with reaching ports.

In addition to its impact on trade, investment in infrastructure can catalyze the dissemination innovative ideas, from the local to the regional level, and enhance productivity in related areas. The impact of infrastructure investment on regions with improved connectivity is closely related to the productivity levels of the existing firms. If firms in a region operate with low productivity and cost efficiency, they will likely be replaced by more productive and competitive firms that are still in the distance.[79] Unless firms' products are sophisticated enough, their market share will inevitably be captured by more competitive firms that are still distant but can be accessed in the new setting (Frusawa, 2017). Concerns about allocative efficiency should also be considered when evaluating productivity outcomes. If governments deploy resources to meet the requirements of the new “constructed” demand for labour in supported regions instead of regions with greater potential for productivity growth, the allocative efficiency of the investment would be diminished. Therefore, it would be valuable for local or general governments to analyse the results at a macro level and measure the peculiar effect of the investment, as mentioned above (Venables et al., 2014).

Farhadi (2015) investigates the effects of public investment in core infrastructure on both labour and total factor productivity in countries, using a historical dataset from 1870 to 2009 for 18 OECD countries. He states that measuring the impact on economic growth through production or cost functions indicates the direct effect by

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[77] Land distance as a separate variable is suspected as the variable behind the conversion to insignificance.

[78] The analyses are repeated by using the CIF/FOB ratios as trade costs and similar findings are obtained.

[79] How the accessibility of a region changes after the investment is of significant importance. Instead of the lengths of the km, of the roads or railways are built, one of the most used measures is the average income level of the new markets that are accessible by the region after the investment.

considering public investment as an input. However, there is also an “indirect” effect through productivity observed due to accelerated access to the services, increased market mobility, saving time, and reduced business costs. The core infrastructure term includes roads, highways, airports, railways, and inland waterways, i.e. the transport infrastructure.[80] The share of public transport investment in GDP is used as an explanatory variable in a model that includes variables such as innovation intensity and stock of national and international knowledge to explain productivity. Their results indicate that both types of productivity are affected positively by the increase in the share of public investment, albeit at lower levels than other variables. The findings are significant from the perspective of BRI projects as they show the potential impact on the productivity levels of the related countries.

In a study similar to Farhadi (2015) and Limão and Venables (2001), Yang et al. (2020) first demonstrate the productivity-enhancing effect of infrastructure investment under the BRI framework. They initially made separate predictions about the investment that could be made by 31 countries in Southeast Asia, South Asia, and Greater Central Asia for the 2010-2015 and 2016-2020 periods. Using the data of investment demand estimated by the ADB (2009) and Bhattacharya (2010) for the 2010-2020 period and subtracting the predictions for investment realisation by countries themselves in the 2016-2020 period, they obtain figures of investment need that are regarded as a void to be filled by the BRI projects. Considering these figures as infrastructure investment in these countries, positive effects on total factor productivity are also noted, with the highest impact in low-income countries. Using Limão and Venables (2001) parameters, they find that a 1% increase in the (obtained) investment figures in coastal countries leads to higher trade cost declines for landlocked and coastal countries than increases in merely landlocked countries. It is also observed that the decline in trade costs associated with infrastructure is evident for countries in the lower quartile of their former infrastructure levels. The diminishing marginal effect of infrastructure investment is also noted here.

The more intense interaction of innovative ideas might lead to higher innovation outputs. Agrawal, Galasso and Oettl (2017) investigated the impact of a 10%

[80] In doing so, however, there is no particular reference to the quality of the investment.

increase in the stock of highways in the United States on the number of patents, finding that in 5 years, the number of patents increased by 1.7%. In market structures where increased competition incentivises innovation, lower transport costs would increase the tendency to innovate through higher competition (Aghion et al., 2015).

4.2.1. Effects of the Belt and Road Initiative on Trade

Using trade data from 2013 for 71 countries along the BRI, Baniya et al. (2019) employ the gravity model to assess the impact of BRI infrastructure projects on trade volumes, after calculating potential decreases in trading times under various scenarios, including the strengthening of trade agreements. They also emphasise that sectoral heterogeneity is evident in the findings, suggesting that using time-sensitive goods not only as final but also as intermediate goods facilitates the transfer of considerable benefits to countries heavily engaged in global value chains.[81] Indeed, their most striking contribution is the acknowledgement of possible endogeneity between infrastructure and trade volumes, as the most important investments that could benefit China's trade capacity may be prioritised in BRI projects. They tackle such endogeneity in three ways: First, they exclude the countries at the end of the BRI path (i.e., nodal countries) and the energy sector from the analysis, as China could mainly target large markets in destination countries or gain control of energy supplies. Second, they introduce two instruments: The first focuses on the percentages of moderately to highly mountainous areas and the land area within 100 km of the nearest ice-free coastline in the transit countries. The estimations from using this instrument as a proxy for the pre-BRI trading times indicate that a 1-day decrease in trading time would increase trade volume by 12%.

In comparison, it was only 5.2% in the baseline gravity model, ignoring endogeneity. Third, the difference-in-difference approach is applied to the delivery times of two sectors: sensitive and insensitive. This approach also calculates direct and indirect effects regarding the goods' final or intermediate goods (or both). The trade of goods,

[81] The strengthening of trade agreements, i.e. border facilitation, can decrease the trading times by at least 7.4% when only introducing better infrastructure by the BRI could lead to a 2.8% gain in trading times. Baniya et al. (2023) mostly follow the methodology of De Soyres et al. (2019), and they also pay attention to the sectoral heterogeneity following Hummels and Schaur (2013).

which is more oriented towards final use, is less affected by the decrease in trading times compared to the trade of goods, which requires using time-sensitive goods as inputs. This result indicates that indirect effects (through inputs) could overpass the direct effects (mainly observed through final goods), and the countries' location in the global value chain matter in reaping possible gains.

Herrero and Xu (2016) compare the gains that could be obtained under two scenarios: establishing a free trade agreement (FTA) between China and the 63 countries participating in the BRI, and the execution of the BRI project. While the former refers to the decreases in tariffs, the latter refers to the decline in transportation costs. Using a gravity model that considers the multilateral resistance effect of trade costs on bilateral trade data from 137 countries in 2014, they compare the aforementioned effects by examining the coefficients of tariffs and trade costs.[82] The study indicates that reduced transportation costs primarily benefit the landlocked European Union countries, followed by the rest of the European Union. On the contrary, if China establishes an FTA, it is evident that the benefits are more widely diffused among Asian countries, while non-Western European Union countries still reap significant benefits. Under this scenario, the E.U.'s disadvantageous trade position stems from the deployment of E.U. trade to countries in the BRI, resulting from the elimination of tariffs. They conclude that the BRI benefits mainly the E.U. countries.

Like Baniya et al. (2019), in their study covering 65 BRI and 28 EU countries, Lu et al. (2018) investigate the trade implications of the infrastructure investment under the BRI. Starting with the gravity equations, they find a positive and significant relationship between transport infrastructure and bilateral trade. Due to possible endogeneity in the models, they emphasise that the relation should be considered just as a correlation. They also include indicators related to the service quality of the infrastructure and find positive contributions. However, it is striking to see that the quality of infrastructure does not render the exact “distance” between trade partners insignificant. Even though the infrastructure becomes more qualified, for instance,

[82] They use a model recognizing that reducing bilateral transportation costs can have spillover effects for a third country.

through better practices at borders, the distance between two points still matters for cities within the same country. This is particularly important for landlocked countries. The authors also compare the investments in railways, roads, airports, and maritime logistics.[83] The results indicate that the most substantial contribution to trade stems from increasing railway intensity. Road, airport and maritime logistics improvements follow the railway intensity, respectively.

Kohl (2019) investigates the impact of the BRI on supply-chain trade for 64 economies from 2002 to 2011. Using a structural gravity equation, he estimates the declines in distances and trade costs due to the BRI. It is postulated that the vast amount of infrastructure investment and possible FTAs to be established in the BRI would lead to such declines. Following the literature and related reports, they postulate that the BRI infrastructure leads to a decline in distances between destinations by 15%, 30% and 50%, respectively. They find that declines in distances lead to higher gains in trade than possible free trade agreements (FTAs) could bring about. Also, using general equilibrium, the effects of those declines on trade flows between destinations are calculated. Since a general equilibrium approach is used, the ultimate effect on a bilateral trade flow includes not only the direct effect of the BRI but also the indirect effect coming from other destinations. Unlike Herrero and Xu (2016), Kohl (2019) concludes that the enhanced market access to the E.U. would benefit Russia and China more than the E.U., with possible disruptions to the E.U. cohesion policy. He also notes that the study assumes a uniform mode of transportation, and the costs would change significantly if the mode of transportation were to change.

Many studies incorporate the infrastructure into the production function as public capital without considering the regional dimension.[84] Wang et al. (2020) investigate the impact of transport infrastructure on economic growth in BRI countries from 2007 to 2016 at both national and regional levels.[85] They consider geographical

[83] They construct series of indices to measure the transport infrastructure and connectivity.

[84] See Ansar et al. (2016) and Maroto and Zofio (2016) for evidence from China and Spain, respectively.

[85] Economic growth is measured by the per capita GDP measured in constant 2010 U.S. dollars.

distance, as well as cultural, economic, and institutional distance, to create a spatial weight matrix. The transport infrastructure is measured by road and railway lengths.[86] Since infrastructure maintenance costs are not easily separable from maintenance costs, infrastructure investment is measured by the physical measurement of railways and roads, not by monetary value. Tests for the spatial autocorrelation (S.A.) indicate that the per capita GDP of the countries that are close to each other concerning any distance measure (in the matrix) exhibit mutually positive effects on economic growth.[87] The S.A. figures for the railway measure indicate that S.A. is among the geographically and institutionally close countries. However, institutional proximity is the only significant S.A. for the road variable.

Furthermore, they show that the geographical agglomeration of railway infrastructure is declining over time, indicating that countries are seeking railway technology transfer from countries other than their neighbours due to breakthroughs in railway technology. These findings, along with those for per capita GDP, are crucial from the perspective of the BRI, as the BRI projects involve a vast coverage of countries that are mostly not China's neighbours.[88] As explanatory variables, labour, urbanisation rate, trade openness and physical capital are added to the regressions.[89] It is underlined in the study that the quality of the roads and railways is essential in interpreting the results of the analysis. The regional direct effects of infrastructure investment suggest that in Southeast Asia and Central and Eastern Europe, the increase in railway and road use has a significant impact on economic growth. In South Asia, a positive impact is detected only for railway infrastructure. No significant impact is noted for the East and Central Asia and CIS countries for either

[86] Due to a lack of data, the analyses do not include data on ports and airports. Roads and railways per 1000 km2 of land are used in the models.

[87] Both global and local Moran's I tests are conducted. The results of the global Moran's I are presented above.

[88] Also, BRI aims to increase geographical connectedness and cultural and institutional ones, underlining the necessity of using spatial models in related studies.

[89] Labour and urbanization variables refer to the ratio of labourers and the urban population to the total population. Trade openness is expected to increase economic growth through goods and services exchanges, technology transfer, scale economies, resource allocation and knowledge dissemination (Wang et al., 2020). All the variables in the regressions are normalized by the BRI average of the related variable to reduce dimensional effects and capture more stable results.

type of infrastructure. For West Asia and North Africa, railway infrastructure has a negative impact on economic growth, with no significant effect from road infrastructure. The indirect effects on railway infrastructure, indicating spatial spillover effects, are adverse for East and Central Asia and the CIS countries. This result is attributed to the fact that these countries already have low connectivity and poor infrastructure, which necessitate the deployment of high levels of productive resources to construct new railways. Such deployment would lessen the resources shared with neighbouring countries and generate regional polarisation. On the other hand, the positive indirect effect of the railway infrastructure in Central and Eastern European countries is attributed to the easiness of enhancing connectivity built on the already rich infrastructure level. As connectivity increases, development in a region is diffused to the neighbouring areas.

Villafuerte et al. (2016) use the GTAP model to measure the impact of the BRI project on the GDP, welfare, and exports of the Asian countries involved.[90] The GTAP is a global computable general equilibrium (CGE) model that is comparative and static and operates under perfect competition with constant returns to scale. It also takes bilateral trade relations for all countries/regions into consideration. They found that China was the primary beneficiary among the Asian countries, followed by Mongolia and Pakistan. Regions such as Central and Southeast Asia also obtain huge benefits from the BRI project. Extending the sample of countries significantly and capturing the effects observed in the E.U., the USA, Japan and Australia individually, Zhai (2018) uses the exact version of the GTAP model in Villafuerte et al. (2016) to understand the effects of BRI under three possible scenarios.

Nevertheless, Zhai (2018) differs from the study of Villafuerte et al. (2016) in three ways: First, a dynamic version of the CGE model is employed to incorporate the time-dependent structure of BRI-driven investments and related capital accumulation into the analysis. Second, firm heterogeneity is included in the analysis to observe inter-firm resource allocation and the variations in the extensive margin of trade. Third, empirical evidence rests on the relationship to declines in trade costs and

[90] They used the GTAP 9A version in 2011.

infrastructure. Refraining from assumptions about that relationship is significant, as infrastructure investment relies on the core of the BRI project and follows a flexible pattern. Zhai (2018) focuses on three scenarios that operate cumulatively. In the first scenario, only the effects of the investment change caused by the BRI are evaluated. The second introduces the reduction in trade costs in addition to the first scenario. The third postulates the full implementation of the BRI project, including the positive externalities from energy infrastructure investment projected under the BRI. All scenarios are projected for the period from 2015 to 2029. Like Villafuerte et al. (2016), Zhai (2018) notes huge benefits for Southeast Asian countries, with the highest increase in exports gained by Vietnam, followed by Singapore. Pakistan is also noted for the increase in exports, calculated under the third scenario. Contrary to Herrero and Xu (2016), the benefits accrued by the E.U. appear dim compared to the gains of other countries in the sample.[91]

4.2.2. Impact of Trade on Innovation

As stated above, the primary effect of infrastructure investments under the BRI is expected to be on trading costs, calculated as the equivalent of an ad valorem tariff on imports, as described in De Doyres et al. (2018) below. Therefore, in evaluating the relationship between trade and innovation dynamics, the scope can be expanded to cover the impact of countries' tariffs and trade policies on firms' innovation decisions.

Bloom et al. (2016) evaluate the impact of Chinese import competition on the patenting, IT, and total factor productivity (TFP) of 12 European countries from 1996 to 2007.[92] As the BRI-related trade cost declines are expected to increase competition among firms globally, analysing how European firms are affected by the influx of imports from China is valuable. This study highlights the endogeneity between changes in the technological level of European firms and Chinese imports, as an increase on the European side, for instance, could lead to a decrease in Chinese

[91] While the exports of Vietnam are expected to increase by 34.2 % under scenario 3, exports of the E.U. are found to increase by 0.9%.

[92] The countries included are the developed countries in Europe.

imports over time. The abolition of quotas on Chinese imports, following China's accession to the WTO in 2001, is used as an indicator that if European firms can survive under higher import competition from China, they exhibit higher figures for patents, IT, and R&D expenditure per employee, as well as better management practices. Survival is observed mostly among high-tech firms, as low-tech firms often exit or shrink in size due to stiffer competition. Bloom et al. (2016) also investigate the anticipation effect of China’s WTO accession on firms, suggesting that firms may have deliberately frozen their innovation activities until China’s accession, leading to an overestimation of the coefficients. They find no evidence for such anticipatory behaviour, which is explained mainly by a new specialisation in production on the European side. Recalling the technological supremacy of European firms over Chinese ones, they conclude that European countries enjoy the benefits of obtaining intermediate inputs at lower costs and an enlarged market size in China, supported by the quality of their products. In the meantime, low-tech and less productive European firms are eliminated due to profit losses in line with the Schumpeterian view. On the other hand, high-tech firms increase their patent filings because they innovate more, driven by an enlarged market size and lower input costs. OECD (2009) presents that exporters are more innovative and productive. There are debates on the direction of causality, as some studies claim that the self-selection of more productive firms into international markets is a factor. In contrast, others argue that exporting may provide new learning opportunities for firms, thereby enhancing their initial level of productivity.[93] The latter view, i.e., learning-by-exporting, includes the possibility of technical assistance from overseas buyers, facilitated access to knowledge related to improved production techniques, elevated quality standards in foreign markets, and sales-driven increases in capacity utilisation (Park et al., 2010). The OECD Report also highlights that entering foreign markets can increase R&D tendencies and expenditures due to higher profits in certain sectors, such as the pharmaceutical industry.

Geng and Kali (2021) define the increased market size as trade's "exogenous" effect on innovation. They claim that enhanced export markets could lead to higher

[93] The famous study belonging to the first strand is Melitz (2003). Wagner (2007) presents a detailed analysis of studies showing causalities in both directions between exports and productivity.

profitability and more financial opportunities for innovation. The type of innovation would also vary depending on the market entry requirements. Entrance into new markets requiring product differentiation would enhance product innovation rather than process innovation. Exports to similar markets would still require quality upgrading under stiff competition. Increased competition in international markets could promote domestic innovation if the industry structure is neck-and-neck, resources have been distributed inefficiently, and consumers value the brands' sizes. It is also emphasised that the marginal innovation effect triggered by international trade is heterogeneous across firms, with significant geographic dependence being detected. Import competition is found to enhance innovation in Europe and developing countries but reduce it in North America.

Additionally, import competition is found to have a greater impact on process innovation than on product innovation. Existing productivity levels also affect innovation, such that less productive firms tend to decrease their innovation in the face of stricter competition. Lastly, foreign sourcing is found to have an ambiguous effect on innovation. It can increase innovation by providing increased financial opportunities that support cost reduction, knowledge spillovers, and improvement in absorptive capacity. On the other hand, it might hinder the desire for innovation, as it allows sourcing firms to obtain inputs rather than develop them through in-house R&D.

Aghion et al. (2018) analyse the impact of export shocks on firms' innovative activities using French firm-level data. They also attribute different responses of firms to export demand shocks to productivity differentials among them. The increase in market size supports innovative activities, whereas increased competition hampers the innovative capacity of firms with particularly low productivity. In such a setting, the impact on firms with higher productivity is inevitably enlarged. They highlight the possibility of an endogenous relationship between export and innovation. To address this issue, they develop firm-level export proxies that respond to changes in aggregate demand conditions in a firm's export destinations, which are beyond the firm's direct control. In other words, they observe the changes in import demand from the exporters to the export destination, specifically the French firm in focus. Starting with those changes and then weighting them by the shares of the good and the export destination in the firm's total exports, they obtain an indicator for the dynamics in the export destination that the French firm cannot influence. Analyses relying on patent data, which is used as a proxy for innovative activity, support the widespread notion that more productive firms benefit from increased export capacity. In contrast, less productive ones are condemned to the hazardous effects of increased competition.

Zaman and Tanewski (2024) empirically test the simultaneous relationship among R&D, innovation, and exports, using firm-level data with a specific focus on the role of firm size. They find that for large firms, innovation mediates a two-way relationship between R&D and exports: R&D influences exports through innovation, and exports influence R&D via enhanced innovation. This supports both "learning-to-export" and "learning-by-exporting" effects. In contrast, for SMEs, no such simultaneity is observed. This implies that small firms neither innovate as a precursor to exporting nor significantly enhance their innovation outcomes through exporting activities, supporting the argument of neck-to-neck competition above. In other words, more productive and competitive firms exhibit a higher propensity to alter their innovative behaviour under enhanced trade dynamics. The study highlights the need for differentiated innovation and export policies based on firm size, suggesting that larger firms benefit more from the dynamics between technological capability and internationalisation.

In short, increased market size, intensified market competition, product switching, offshoring, and learning through imports are among the channels suggested to function between trade and innovation; however, there is no consensus about the direction and significance of this relationship. The impact of the enlarged trade opportunities relies on the initial positions of the firms in the market they function, their productivity and competitiveness.

So far, the background of the thesis has been established to provide the context for the main analysis. This thesis investigates the impact of China’s Belt and Road Initiative (BRI) on the European innovation ecosystem. Specifically, it examines how the BRI affects the nexus of R&D, innovation, and productivity, using the Initiative's influence on trade dynamics as a mediating channel.

To this end, before presenting the analytical framework dedicated to analysing the nexus of R&D, innovation, and productivity, the thesis first addresses the EU's long-standing innovation challenge, widely referred to as the European Innovation Paradox. This is followed by an introduction to the Chinese Belt and Road Initiative (BRI), outlining its motivations, key practices, and associated challenges. The EU's policy responses to the BRI's implications are also presented, including example projects and official reports.

Given that the BRI initially emphasised enhancing connectivity through large-scale infrastructure investments, the preceding section has described how infrastructure developments affect trade, innovation, and productivity, with a particular focus on the bidirectional relationships among them. The relations outlined here are reflected in the MMK framework, which utilises a novel dataset created to proxy the BRI's impact.

4.3. Studies on the Impact of Knowledge Spillovers on R&D, Innovation and Productivity Nexus

The innovation capacity of a firm is determined not only by its own innovative efforts, but also affected by the knowledge production processes of nearby firms. Knowledge spillovers, in this respect, refer to the use of knowledge produced by a firm for free (Venuvinod, 2011, as cited in Doyar (2023)). The OECD (2015, 2018) defines three types of knowledge: codified, tacit, and embodied knowledge. Codified knowledge refers to the knowledge that can be *articulated and transmitted in formal, systematic language*. Codification involves data collection through publications, patents, databases, and knowledge outputs from R&D. In contrast, tacit knowledge relies on perception. It refers to personal, experience-based knowledge, *and hard to communicate or transfer without direct interaction*. Technology transfer is underscored through learning-by-doing, as the mobility of skilled labour and networks among firms are highly intertwined with tacit knowledge flows.

There are three types of knowledge spillovers in the literature. The first is known as the "MAR" externality, following the names of Marshall, Arrow, and Romer.[94] The MAR externalities primarily refer to monopolistic market structures and within-industry localisation and specialisation. The second type of spillovers, introduced by Jacobs (1969), is more relevant to industries where complementarity is important. Diversification prompts firms to innovate, which is more easily achieved under competitive market structures. The complementarity aspect relates to the knowledge spillovers between industries. The third type of knowledge spillover, developed by Porter (1990), combines the elements of the first two types. Namely, they emphasise the within-sector knowledge spillovers that benefit from specialisation, albeit under high competition.

As the transmission of knowledge spillovers requires minimal interaction between economic actors, measuring and defining proximity among the actors becomes a crucial part of the related analyses. The question of which type of proximity has the greatest multiplier effect in the transmission of knowledge is extensively discussed in the literature.

Boschma (2005) introduces five types of proximity. These refer to the geographical, cognitive, organizational, social, and institutional structures in which the firms operate. Indeed, the discussions of Boschma (2005) around cognitive proximity lay the ground above which the success of all other types of proximities would be determined. They suggest that cognitive proximity entails firms (or people) with a similar knowledge base and experience engaging in a learning process more easily than those that diverge from them in these circumstances. This expectation is closely related to the concept of absorptive capacity, as proposed by Cohen and Levinthal (1990). They define absorptive capacity as "the ability of a firm to recognize the value of new, external information, assimilate it, and apply it to commercial ends," emphasizing its dynamic nature. The knowledge level of a firm, which encompasses skill sets, a shared language, and information about the latest scientific or technological developments, is a significant factor that shapes whether the firm can

[94] This types of externality was first developed by Marshall (1890), and developed by Arrow (1962) and Romer (1980), respectively.

discern the value of new knowledge and, if so, how it will behave and internalise this external knowledge. The extent to which firms can comprehend and convert this knowledge into commercial use can be further improved by investing in their capacity. Any innovative activity that the firm carries out has an inevitable progressive effect on this capacity, in line with the cumulative structure of knowledge. His focus on cognitive proximity is significant, as firms' cognitive proximity can also change over time. Cognitive proximity is the key to other types of proximities functioning, while it is also the end result of the success of different types of proximities.

The type of knowledge is also a critical factor in the proximity required for dissemination. Kaygalak and Reid (2016) state that the spillover of codified knowledge is predominantly affected by institutional and industrial proximity, whereas tacit knowledge is more easily disseminated as economic agents get closer in geographic and social terms. Therefore, a broad view covering both types of knowledge should also focus beyond geographical proximity.

According to Baschma (2005), the search of firms around their familiar vicinity, which is measured not only by geographical proximity but also by other factors, could have adverse effects, sending them into a hypothetical lock-in. Habits or routines might be irrelevant in the face of new knowledge and firms might operate under a self-imposed "competency trap".[95] Therefore, an optimal distance is suggested that would avoid this trap while maintaining effective communication lines.

As Baschma (2005) outlined, the importance of proximity in innovative processes is closely linked to the cautious behaviour of firms when they are exposed to uncertainty. Since uncertainty is inherent in creating new knowledge, firms prefer to initiate their efforts based on the knowledge base they already possess. This attitude results in routinized behaviour, as described by Nelson and Winter (1982). The caution about wandering into new ventures could also lead to localised results that

[95] Lambooy and Boschma (2001) as cited in Boschma (2005).

cannot be measured explicitly due to the tacit feature of cognitive abilities. As knowledge accumulates and becomes localised, persistent differences among firms may emerge.

Bashcma (2005) also underlines that different types of proximity can function in a complementary manner and compensate for the possible ineffeciencies stemming from another proximity type. For instance, cognitive lock-in can be compensated by the establishment of geographic clusters. Such clusters built upon a common knowledge base with different and complementary resources are suggested as the optimal solutions.

This thesis focuses on the geographical and technical proximity among firms as catalysts for knowledge spillovers among innovative actors. Below are presented the discussions on the pros and cons of both elevated geographical and technical proximity.

The importance of geographical proximity and the fact that firms in the same sectors could be located in a particular region was first proposed by Alfred Marshall in his book *Principles of Economics* (1890). 'Marshall's identification of such a concentration was supported by two concepts: Economies of scale stemming from outside firm factors and knowledge spillovers. Marshall states that firms benefit from the capabilities and sources of nearby firms. In this respect, he defines the Marshallian externalities as a shared labour supply, source of inputs, and knowledge spillovers.[96] The shared labour supply and source of inputs, the first two externalities, result in lower hiring and training costs for workers and input suppliers, as well as the freedom for small firms to set their own terms, thereby mitigating vertical integration pressures. The famous quote by Marshall, "*The mysteries of the trade become no mysteries; but are as it were in the air.*", is related to the spread of tacit knowledge, which he regards as the mysteries of trade. In Marshall's conceptualization, knowledge is primarily tacit, and workers learn from one another through interaction and mutual exchange of information.

[96] Marshall (1890) does not use the term “externality”,but defines these three points as external economies of scale. His student, Pigou (1920) later describes them as externality. These are non-excludable, non-rivalrous, locaed and tacit and self-reinforcing.

Beccatini (1990) develops the Marshallian concepts and defines the "Marshallian industrial district" not only as the agglomeration of economic units, but also extends that by including social life, culture, and identity. In this respect, not only the workers but also their families, social connections, values, and characteristics of the local communities are encompassed within the industrial district, forming a territorial, living socio-economic organism. The analysis of Beccatini (1990) focuses on traditional industries, such as textiles and ceramics, where the interactions promote the spread of tacit knowledge. Strong local connections are found to be indispensable for a competitive advantage in sectors where innovation is not radical.

Due to its undeniable impact on the spread of tacit knowledge through face-to-face interactions, causal knowledge exchange, trust-building, and collaborative learning, there is a strong focus on the benefits of geographical proximity in both the academic literature and policymakers' policy agendas (Gertler, 2003). It is noted that for small and medium-sized firms and sectors where the input structure is dominated by accumulated knowledge, i.e., benefits from path dependency without falling into the trap of getting locked in, such interaction is critical (Tödtling & Trippl, 2005). Such proximity is also postulated to help policymakers disseminate public funds in a more coordinated manner, as firms learn from one another through learning-by-doing (Broekel & Boschma, 2012).

On the other hand, while acknowledging the significance of geographical proximity, Audretsch and Feldman (1996) emphasise the existence of industrial clusters, which are also supported by geographical proximity. They analyze the relationship between the geographic location of the firms and industry characteristics, with a particular focus on controlling for the geographic location of production. The commercial innovations data from the U.S. Small Business Administration Innovation Database in 1982 are analysed, and innovations are found to cluster in some regions. However, the concentration of innovation is not found to coincide with the geographical concentration of production.[97] This observation leads them to reconsider the

[97] States like Ohio and Michigan are found to lag in innovative activity even if they were traditional manufacturing belts of the U.S. In addition, sectors such as primary metals, transportation equipment, textiles, food and beverages, leather and chemicals exhibit geographical cluster of production, but

formation of these industrial clusters of innovation (which are not overlapping with the location of production) as there may be other factors influencing them. Understanding the dynamics behind industrial concentration requires controlling for the impact of geographical concentration of production on industrial concentration as the first step of an analysis. However, the problem of endogeneity arises here, as knowledge spillovers stand as the latent factor behind the scenes, affecting both the geographical concentration of production and industrial clusters.[98] Audretsch and Feldman (1996) also rely on Arrow's (1962) assumption, which associates the importance of knowledge spillovers for an industry with its R&D intensity. After calculating the Gini coefficients for innovation and production, they employ regressions that include measures for the significance of knowledge spillover as factors affecting both geographical and industry clusters, including industrial R&D, skilled labour, and university research data relevant to the industry field. Their results indicate that even after controlling for the Gini coefficient of production orientation and factors such as the sector's natural resource dependency, which are hypothesised to propagate that orientation, the three knowledge spillover measures remain significant. This suggests that an industry cluster of innovation persists even after controlling for the impact of geographical concentration and its sensitivity to knowledge spillover measures.[99] Innovative activities are found to cluster in the industry dimension, too, and this is particularly true in industries where knowledge spillovers play a significant role. Their study is critical in reminding us that geographical proximity is not the sole driver behind innovative success stories.

Some studies indicate the benefits of geographical clustering may erode over time as industries expand in a specific region. Pouder and John (1996) state that economies of agglomeration, which initially attract firms to a region, eventually fade over time, leading to a decline in the innovative activities of firms located in that region. They provide the example of hot spots, which refer to regional clusters of firms, including

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innovation clusters are found to exist in sectors such as transport equipment, instruments and electronics.

[98] Therefore, the impact of knowledge spillovers on industrial clusters occurs both directly and indirectly through the geographical cluster of production.

[99] They also present results that indicate that geographical concentration of a sector is significantly affected by the sector’s susceptibility to knowledge spillover.

rivals in the same sector, start-ups in the initial stages of their establishment, and firms restricted by the physical resources of that region. In the early stages of a firm's establishment in a certain region, successful new firms attract qualified suppliers, skilled workers, and informed investors, further decreasing costs and intensifying agglomeration economies. As new firms are attracted, diseconomies of agglomeration starts to be observed. What Pouder and John (1996) mainly highlight is that, despite the warning signals sent by the diseconomies of agglomeration, managers of these hotspots remain locked in their circles and have difficulty benefiting from knowledge sources other than their own cluster. This situation of being "locked-in" ultimately results in a decrease in the innovative activities of firms in the cluster.

The findings of Pouder and John (1996) are important in designating that firms in a geographic cluster eventually face the problem of competition for resources and stagnant cognitive abilities. In other words, geographical proximity might not result in accelerated innovation activity, particularly if a long time horizon is allowed.

Chauvin (2019) states that increasing physical proximity between firms is a double-edged sword concerning firm performance.[100] She states that while increasing proximity provides agglomeration benefits, it also creates adverse spatial competition effects. In line with the Marshallian externalities, as firms locate close to each other, they benefit from positive externalities, such as access to human capital, inputs, and ideas. On the other hand, as firms are located close to each other, they are claimed to have less room to differentiate their products within their limited geographical borders, exemplifying the adverse effects of competition. The competition effect leads to the exit of the least productive firms in the region, triggering a series of selection and reallocation as more firms are located in the same area (Melitz, 2003; Syverson, 2004).

Highlighting that there is not a consensus in the literature about which effect would dominate, firms' decision to collocate is defined as a balancing act between these two effects, the result of which depends on firm-level characteristics. In this respect,

[100] Firm performance is measured by productivity and survival rate in the study.

the market orientation and the sizes of firms are presented as factors that determine the ultimate decision of the firm. It is also found that for industries focusing on local markets, collocation expels the smallest firms while increasing the survival rates of the largest firms, which are also local market-oriented. Competition is local and it may hurt some firms. As small firms are expelled, they can either fully exit the market, relocate elsewhere, or switch to another sector. For sectors that focus on national markets, i.e. not dependent on a localised market, collocation is found to increase the survival rates of firms, highlighting the positive agglomeration effects.[101] These findings indicate that the merits of physical proximity are closely related to the market orientation of firms. Wang and Shaver (2014) state, on the other hand, that a firm’s tendency to relocate decreases as customers are concentrated in a region. Even though the newcomers harden the firms to the region, they might not relocate due to high opportunity costs. Breschi and Lissoni (2001) criticise the R&D spillover literature in three aspects. First, they claim that knowledge externalities are not free and mostly rely on compensation. Second, the involuntary knowledge spillovers are not “involuntary”, but instead transferred through events organised by institutions and firms. They also state that knowledge spillovers do not increase the innovation opportunities of firms but rather increase their capacity to absorb the new knowledge they acquire.

Concerning the impact of economic proximity, as measured by input-output tables, Albert O. Hirschman's seminal work, The Strategy of Economic Development (1958) stands as the starting point of all analyses using input-output tables to understand the dynamics of knowledge diffusion. the greatest contribution of the study is the introduction of the concepts of backwards **and forward linkages**. He states that investments in specific sectors could stimulate economic growth by creating demand for inputs (backward linkages) and supplying outputs to other sectors (forward linkages). His framework highlights the importance of identifying sectors with strong linkage potentials to maximize the diffusion of innovation and economic benefits.

[101] Chauvin (2019) examines the impact of road infrastructure improvement on Brazilian firms’ collocation decisions. As the BRI was initially an infrastructure project, the findings of this study are remarkable.

Hidalgo and Hausman (2009) create a product space network by linking products based on their similarity in input requirements, which are not only tangible but also encompass knowledge. They show that countries tend to build industries that are proximate to the ones they already possess, as it allows them to utilise existing capabilities multiple times. Stressing that innovation is path-dependent, they advocate for innovation policies focusing on sectors with high relatedness to the existing one.

Taalbi (2018) investigates the dynamics of the Swedish innovation system between 1970 and 2013 and calculates the extent to which innovation patterns depend on backwards and forward inter-industry linkages. It is demonstrated that 30% of innovation patterns can be attributed to factors related to backwards and forward inter-industry linkages. Taalbi states that innovation is path-dependent and not isolated and evolves within structured systems of demand, supply, and technological familiarity. Zhu et al. (2015) uses the World Input-Output Database (WIOD) to quantify global economic proximity as a measure of the potential for knowledge spillovers. They show that sectors positioned similarly in global value chains are more likely to experience shared innovation dynamics. This finding is also related to indirect knowledge flows, referring to knowledge gained from providers of providers in the supply chain.

Fons-Rosen et al. (2017) analyse the impact of foreign FDI on total productivity levels measured for six countries. They find that knowledge spillovers from foreign firms become significant and positive if the sectors to which the investment is oriented are technologically close to the dominant sectors in the host country, highlighting the importance of economic proximity in facilitating knowledge transfer. Piermartini (2014) evaluates whether international supply chains can function as a transmitter between R&D in foreign and domestic countries. Using international input-output tables and patent data for 29 countries as indicators of innovation, it is found that increased engagement in global supply chains leads to greater knowledge transfer, as measured by the number of patents. Liu et al. (2021) use the World Input-Output Database to model economic proximity.

A summary of the studies covering knowledge spillovers and their sensitivity to measures of proximity, geographical and technical (economical) proximity in particular, indicates that even though proximity accelerates knowledge spillovers and innovation in many cases, it is also highly viable that too much proximity could cause problems such as lock-in, competition for new markets or sources that might lead to the exit of firms from the industry or stagnated periods of innovation indicators. A definitive answer to the direction of proximity, therefore, is hard to conclude.

In the next section, the datasets used in the analyses under both approaches are presented.

CHAPTER 5

DATA

As stated above, this thesis involves two approaches to analyzing the impact of the BRI on the European innovation ecosystem. The first approach involves models that rely on the traditional MMK framework without considering spatial dependence. The second type of analysis, on the other hand, is constructed by extending the models in the first approach with spatial dependence. In this chapter of the thesis, the data used in both types of analyses are presented respectively.

5.1. Description of the Data Used in Models Without Spatial Dependence

5.1.1. Sample Countries: Innovation Indicators and the BRI

As shall be presented below in detail, the primary data set used in this thesis is the firm-level responses of the "Community Innovation Survey ", provided by Eurostat. Although data from all the countries that provided data was requested from Eurostat, only 14 of them were provided. Of the countries listed below, 12 have satisfied data for all periods, ensuring that fundamental variables are not missing.[102]The list of countries analysed, along with their corresponding country codes, is presented in Table 2.

Most of the sample countries in the study are members of the CEEC (Cooperation between China and Central and Eastern European Countries) Initiative, led by the Chinese Ministry of Foreign Affairs, which aims to enhance business and investment

[102] The CIS responses of Malta were available only for 2014 and 2018 data. The CIS data of Romania, on the other hand, lacks the sectoral information for 2016 CIS. Therefore, both of these countries were not included in the analyses.

relations between China and countries in Central and Eastern Europe. When it was first established in 2012, the format included 16 Central and Eastern European (CEE) countries and China, known as the 16+1 format.[103] In 2019, Greece joined the platform. However, in 2022, Estonia, Latvia, and Lithuania withdrew from the platform, and the Initiative has been converted to 14+1 since then.

Table 2. Sample Countries

Country Name	Country Code*	Participation in CEEC
Bulgaria	100	+
Czech Republic	203	+
Germany	276	-
Estonia	233	Until 2022
Greece	300	+
Spain	724	-
Croatia	191	+
Hungary	348	+
Latvia	440	Until 2022
Lithuania	428	Until 2022
Portugal	620	-
Slovak Republic	703	+

Source: UN Comtrade Database and Belt and Road Portal

The data provided included only the above 12 countries, which is still satisfactory since it contains 9 of the 17+1 CEEC format in 2019. The inclusion of Spain and Portugal in the sample is significant, as they encompass ports that can help capture the implications of cost changes in marine transportation. As one of the strongest innovators with the highest GDP in the EU, Germany's inclusion in the analyses also contributes significantly to the analysis.[104] Eurostat has provided data on the sample countries since 2004, but the data from 2014 has been used since the BRI was first announced in 2013. It is investigated that the impact of declining trade costs will be felt as the survey period progresses. The following section presents the performance of countries in terms of innovation variables and productivity.

Since the ultimate purpose of this thesis is to understand the implications of the BRI-led trade cost declines on the innovativeness of sample countries, it would be

[103] These 16 countries were Albania, Bosnia and Herzegovina, Bulgaria, Croatia, the Czech Republic, Hungary, Montenegro, North Macedonia, Poland, Romania, Serbia, Slovakia, Slovenia, Estonia, Latvia and Lithuania. In 2019, it increased to 17 with the participation of Greece.

[104] According to the European Innovation Scoreboard figures since 2012, Germany is among the top innovators in the EU.

enlightening to see the relative positions of these countries in terms of R&D expenditure, innovation and productivity, which stands as the last block in the above mentioned CDM structure.

The sample countries' per capita expenses on R&D activities between 2013 and 2023 indicate that Germany is the leading country in allocating budget to R&D activities (Figure 14). The Czech Republic and Spain follow it. Bulgaria has the least expenditure per capita in R&D activities.

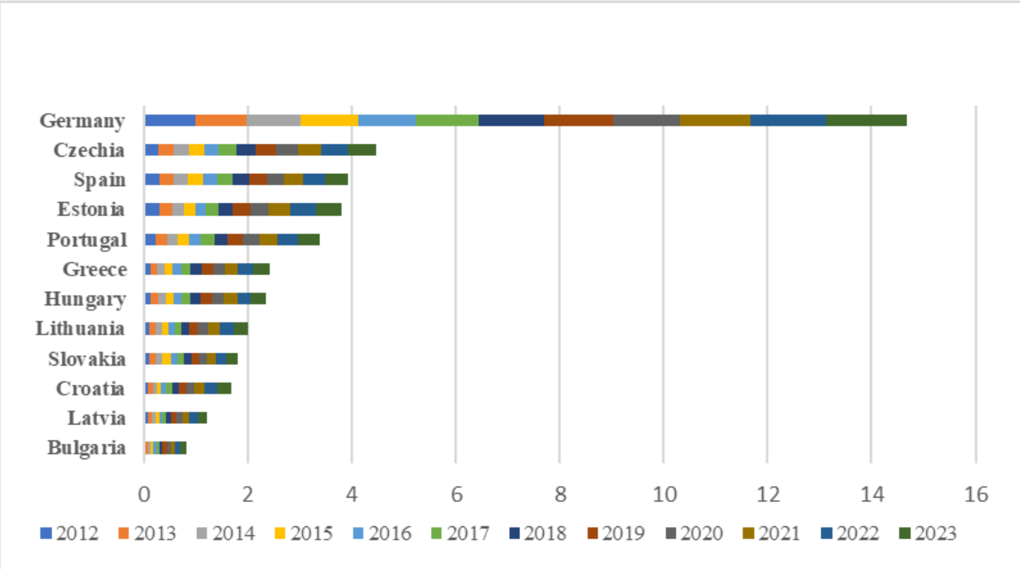

Figure 14. R&D Expenditure Per Capita in the Sample Countries (2012-2023)

Source: Eurostat

Figure 15 indicates the share of the BRI investment in total Chinese FDI inflows to Europe. The figure shows a significant increase in the ratio of BRI-related investment to Europe since 2019. The BRI investment at the country level is depicted in Figure 16. Unlike the figure in the first section, this figure only reflects the BRI investment allocated to the sample countries in this thesis. It is seen that Hungary receives the highest BRI investment in line with its close relations with China. The investment in this country focuses on transport through the construction of railways or the production of electric autos. Portugal has the second-highest BRI investment, with a primary focus on the finance sector (Figure 17). Greece, like Hungary, also has the highest investment in the energy and transportation sectors.

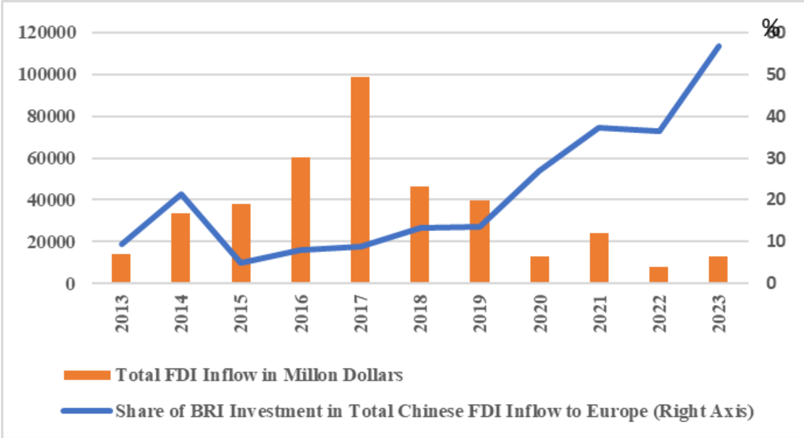

Figure 15. Shares of the BRI Investment in Total Chinese FDI Flow to Europe

Source: American Enterprise Institute: China Global Investment Tracker

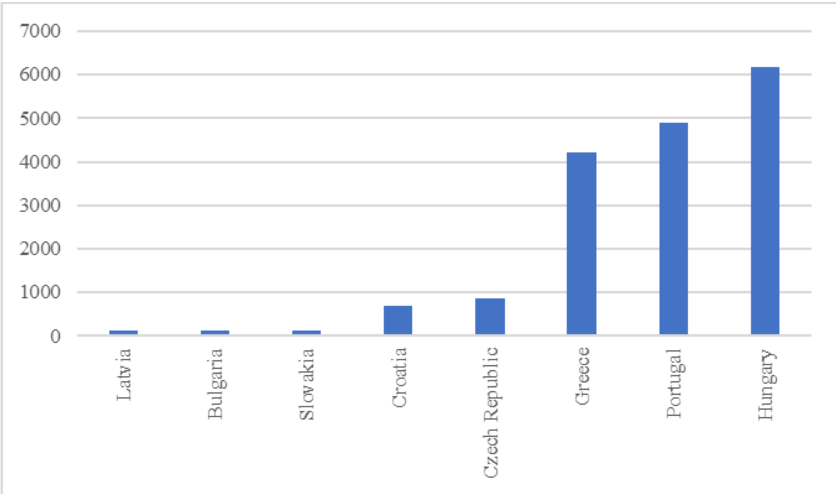

Figure 16. BRI Investment in Sample Countries (in Million Dollars) (2013-2023)

Source: American Enterprise Institute: China Global Investment Tracker

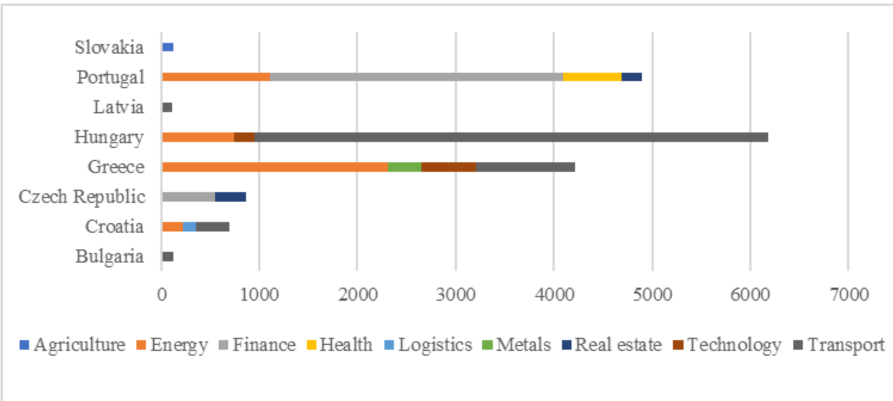

Figure 17. BRI Investment in Sample Countries (in Million Dollars) (2013-2023)

Source: American Enterprise Institute: China Global Investment Tracker

5.1.2. Datasets Used in the Analyses & EEVC Construction

In line with the purpose of this thesis, we establish a connection between the anticipated change in trade volumes resulting from the BRI projects and the trio of R&D, innovation and productivity performance of selected European firms, modelled by the CDM framework. This link is built by creating a series indicating sample countries' "expected export volume changes" (EEVC). The EEVC figures, which represent the expected changes in export volume for import partners, are organized by country-sector pairs and exclude service sectors.[105] The construction of this dataset relies on three other datasets, as outlined below.

The datasets used in this chapter are presented first in the following section. Following their introduction, the steps of the EEVC construction are explained, along with a comparative sketch of the obtained series.

As stated above, an endogenous relationship exists between the firm's innovative effort and export dynamics. Therefore, an instrumental variable is required to capture the changes in the imports of the sample countries' export partners in relevant sectors (Aghion et al.,2018).

EEVC is the instrumental variable indicating the effect of the decline in BRI-led trade costs on the innovative capacity of European firms. It is the sum of the changes in imports of the destination markets to which the sample countries export their goods, except the change in the imports originating from the sample country. Suppose Bulgaria exports goods in sector X to a destination market A. We first calculate the change in the total imports of country A in sector X as a (expected) result of the BRI-led cost changes but then deduct the anticipated changes in imports to be made from Bulgaria. By doing this for every exporting sector and destination market of Bulgaria and excluding Bulgaria from the total figures of destination markets, we obtain an indicator that could function like a demand shock to the

[105] The CDM model is constructed by using the data of the firms in manufacturing, mining and quarrel and forestry and agriculture sectors. We add these figures to each stage of the CDM model but ultimately decide on using them in the first stage since they provide the most robust coefficients.

destination markets of Bulgaria. It stands as an exogenous shock to Bulgaria. It allows Bulgarian exporters to be regarded as bystanders since the demand shock does not originate from or include Bulgarian exporters. In more casual terms, it postulates a scenario in which Bulgarian producers suddenly face a "more-demanding customer" with no apparent reason that can be attributed to the Bulgarian market or producers, which is the main argument supporting the exogeneity of the instrumental variable.

In the first stage of the EEVC construction, we calculate the change in imported volumes resulting from a 1% decline in trade costs. For trade figures, we utilized the bulk BACI data from CEPII for 2011, with a primary focus on import data for goods.[106] We only consider the import of goods, as trade dynamics in service sectors differ significantly from those in goods trade.

In the second step, we combine these figures with the expected decline in trade (transport) costs presented in the World Bank's BRI Global database on a sectoral level. By multiplying the statistics from the first step with those in this dataset, we obtain the expected import volumes for each origin-destination pair. In the third step, we aggregate the import demand shock for each destination and deduct the amount related to the origin country in our sample. Then, we change the perspective from the destination (importer) markets to exporters and aggregate the expected import demand changes in destination markets by weighting them according to their shares in the total sectoral exports of the origin country. In the fourth and final step, we combine the EEVC, the weighted import demand shock variable, with the CIS survey data.

The following section presents the datasets used in constructing the EEVC and the CDM framework. Next, we describe the steps of constructing the EEVC and solutions for the sectoral misalignment problems. In the final section, we summarise the features of the EEVC dataset and present a comparative analysis with similar studies in the literature.

[106] As stated before, the COMTRADE data does not function as a mirror data. We also exclude the services trade.

5.1.3. The Product Elasticity Database

This study uses the product-level elasticities estimated by Fontaine et al. (2019) and provided by the CEPII.[107] Fontaine et al. (2019) estimate the tariff elasticities of 5000 products in HS6 codes using the bilateral trade flows of 152 importing countries in a structural gravity equation. The models are estimated for the years 2001, 2004, 2007, 2010, 2013, and 2016. They claim that the tariff variation constitutes a significant share of import variation. The product-level elasticities are calculated for the HS6 and HS4 categories in the study. Following Baniya et al. (2019), the decline in trade (transport) cost is multiplied by product-level elasticities.[108] Using elasticities at sector levels is reasonable since the impact of shipping times on total trade volume is closely related to the durability of the traded product. Fresh food and wood products are sensitive to delays in delivery times, a fact that is universal, allowing for the use of the same elasticities in the calculations of all BRI participants. The overall mean of the sectoral means is 10.13%, and 74% of the sectoral means lie below the mean (Figure 23). The sectors above the mean are iron and steel production, manufacture of paper and paper products, transport equipment, wool, non-ferrous metals, petroleum and coke products, fibres crops, electricity production, gas manufacture, distribution and coal mining. This suggests that the sectors most susceptible to changes in trade costs are primarily related to natural resources. On the other hand, the sectors with the lowest elasticity are primarily agricultural sectors, while most manufacturing sectors fluctuate between natural resource-based and agricultural sectors. These elasticities may suggest that countries with high export shares in natural resources could benefit from expected cost declines resulting from the Belt and Road Initiative (BRI). The result is not straightforward, as the ultimate effect also depends on the importers (particularly their proximity to the exporter) and the change in their demand resulting from BRI facilitation.

[107]The product-level elasticities are accessed on https://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele_item.asp?id=35.

[108] Since the BRI Global dataset is published at the sectoral level, the initial choice in this study would be to work with elasticities that have been calculated at the country and sector levels. However, it was recognized that Baniya et al. (2019) also estimate elasticities at sector level and apply these elasticities to **all BRI participants’** trade volume calculations.

5.1.4. The BACI Database

The insertion of the BRI-led trade cost declines into the CDM framework requires using countries' export and import figures on a sectoral level. This study utilizes the bilateral trade figures presented in the BACI Database, which the CEPII (Centre d'Études Prospectives et d'Informations Internationales) maintains.109 As described above, the EEVC calculation requires trade cost elasticities, which the CEPII also provides at the product level in HS-4 codes. The BACI (Base pour l'Analyse du Commerce International) dataset is constructed using HS classification, facilitating the use of product elasticities without requiring sectoral matching at the first stage of EEVC construction. On the other hand, the UN Comtrade database, which is classified according to the Harmonised System (HS) classification, serves as the primary dataset behind most available databases, including the BACI set.[110] However, this study still prefers using the BACI database since it has advantages over the UN COMTRADE raw data. Gaulier and Zignago (2010) list some of them as follows in their study introducing the BACI dataset:

1. The UN COMTRADE data contains inconsistencies concerning bilateral trade figures between countries. Partner countries might report different values for the same type of trade flow. The BACI data reconciles these differences, providing a single, consistent figure. This consistency matters, particularly when trade shares are used to estimate the instrument in this thesis.
2. Import values are generally reported in CIF form, including cost, insurance and freight. On the other hand, export values are reported in FOB form, meaning "free on board," which reflects only the cost of the goods, excluding any additional costs incurred during transportation. Therefore, transport costs should be deducted from the CIF figures to provide consistency between import and export values. Detailed data on transport costs are mostly

[109] Gaulier and Zignago (2010) is the study on the construction of the BACI database. The database can be accessed on https://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele_item.asp?id=37

[110] Although most international organisations, such as the OECD, IMF and the World Bank, publish trade data, their data uses ISIC or NACE classifications, which do not comply with the sectoral classification of product elasticity data provided by the CEPII.

unavailable, leading to the estimation of CIF rates by a gravity estimation. These are performed during the dataset preparation, providing significant practicality for data users.

3. In constructing the BACI dataset, reliability indexes are calculated for countries by considering the extent to which their reporting diverges from that of their trade partners. These reliability indices are used as weights in the averaging of mirror flows. The BACI database is not biased toward a specific country or region. Instead, countries' reporting is examined historically, and their performance vis-à-vis the trade partners is the benchmark of their reliability.

In this study, the shares of exports and imports are used to calculate the EEVC, an indicator constructed to capture changes in BRI-led trade volumes. The latest version of the BACI was released in January 2025.[111] This study uses 2011 data, two years before the (public) inception of BRI and one year before the coverage period of the CIS 2014. The 2011 data includes information on 225 countries and 5,047 products in the HS6 categories. These categories are aggregated at the HS4 level before being merged with the product elasticity data, which CEPII continues to provide in HS4 codes.

5.1.5. The BRI Global Data

This study utilizes the BRI Global Database, published by the World Bank, as a basis for the study conducted by De Soyres et al. (2018).[112] Relying on data on completed and planned Belt and Road transport projects, the shipment times before and after the Belt and Road Initiative are calculated using the Geographic Information System analysis. The World Bank's database on BRI-related costs involves both a global and a regional database. The global database includes expected cost declines for bilateral trade in 191 countries and 47 sectors. In contrast, the regional database includes

[111] The latest release contains series between 2007 and 2023. The historical BACI database is also updated regularly.

[112] The database can be accessed through https://datacatalog.worldbank.org/search/dataset/0038706/Belt-and-Road-Initiative-Trade-Costs-Database

estimates for trade between 1,818 cities in 71 countries, which are also included in the global dataset. Moreover, the global database includes changes in time-to-trade and the associated cost declines, calculated by considering the ad valorem value of a shipment per *day* at the sectoral level. The regional dataset only provides the changes in shipping times. The datasets are compiled according to GTAP 10 classification, covering 47 sectors, excluding the 10 service sectors.[113] The GTAP sectors in the BRI Global Dataset are presented in Table 3.

Table 3. Sectors Included in the BRI Dataset

BRI Dataset Sectors			
atp	Air transport	pfb	Plant-based fibers
b_t	Beverages and tobacco products	gdt	Gas manufacture, distribution
c_b	Sugar cane, sugar beet	gro	Cereal grains nec
cmt	Bovine meat products	i_s	Ferrous metals
cns	Construction	lea	Leather products
coa	Coal	lum	Wood products
crp	Chemical, rubber, plastic	mil	Dairy products
ctl	Bovine cattle, sheep and goats, horses	mvh	Motor vehicles and parts
ele	Computer, electronic and optical products	nfm	Metals nec
fmp	Metal products	nmm	Mineral products nec
frs	Forestry	oap	Animal products nec
fsh	Fishing	ocr	Crops nec
ofd	Food products nec	ppp	Paper products, publishing
ome	Machinery and equipment nec	rmk	Raw milk
omf	Manufactures nec	sgr	Sugar
omn	Other mining	tex	Textiles
omt	Meat products nec	trd	Trade
osd	Oil seeds	v_f	Vegetables, fruit, nuts
otn	Transport equipment nec	vol	Vegetable oils and fats
otp	Transport nec	wap	Wearing apparel
p_c	Petroleum, coal products	wht	Wheat
pcr	Processed rice	wol	Wool, silk-worm cocoons
		wtp	Water transport
		wtr	Water

Source: De Soyres et al. (2018)

The ad valorem values are equivalent to the value of time, i.e. the nominal value of an increase in trade cost due to a 1-day delay in shipment. These values are derived from the study by Hummels and Schaur (2013), which utilizes U.S. data and provides data in HS2 and HS4 codes. De Soyres et al. (2018) underline some drawbacks of using the parameters in Hummels and Schaur (2013). First, the parameters are calculated for the U.S. economy and the sectors in which the U.S. has

[113] The latest version of the GTAP 10 database covers 65 sectors. The version of the GTAP covering 57 sectors is also linked on the latest version's address. The latest list can be accessed on https://www.gtap.agecon.purdue.edu/databases/contribute/detailedsector.asp

zero imports (considering trade at a granular level). This approach would introduce bias, as the missing values in these sectors would need to be imputed by taking averages.

Additionally, the value of time can be inherently country-specific, and delays in shipment times could be alleviated by country-specific solutions, depending on the storage capacity or local taste preferences observed in different countries. Although De Soyres et al. (2018) highlight these drawbacks, they still employ the parameters from Hummels and Schaur (2013) due to their perceived strength in the estimation process. A significant contribution of De Soyres et al. (2018) is their aggregation of the value of time parameters presented in HS categories in Hummels and Schaur (2013) into GTAP categories. This is achieved using the trade shares calculated from the UN COMTRADE data, which also relies on the Harmonised System (HS) codes. They impute the value of time parameters for the missing values in the HS categories that take place in the COMTRADE data, but not in the data of Hummels and Schaur (2018). In such a case, if a category H1 is not found in the latter data but has a counterpart in the GTAP sectoral list, the missing values of H1 are imputed by taking the average of the value of time parameters observed for the sectors that are in the same GTAP sector as H1.[114]

Due to their share's dominance in global trade, only trade carried out with maritime and rail transportation is included in the analysis. In addition, the study uses two baseline scenarios upon which further improvements are made possible. The first scenario, i.e., the lower bound, refers to the case in which the exporters do not change their modes of transportation after the BRI infrastructure is implemented. In the upper scenario, exporters can switch their mode of transportation, mostly from long maritime routes to shorter rail connections.

In addition to the basic upper and lower bound scenarios, De Soyres et al. (2018) elaborate on the data, suggesting that focusing solely on physical transport

[114] As highlighted below, this study combines the trade cost elasticities calculated for the HS sectors with the BRI data in the GTAP classification. Unlike De Soyres et al, there is no imputation for the missing values of GTAP sectors with no counterpart in the elasticity list. This study has no imputation until the use of the CIS data.

infrastructure improvement may underestimate the potential effect of the BRI. They state that trade facilitation policies, such as reducing border processing times and improving corridor management, including increased railway speeds along all economic corridors or a decrease in congestion, could further impact shipping times. The list of variables in the dataset, with their descriptions, is presented in Table 4.

Table 4. Variables for Trade Cost Declines in the BRI Global Dataset

Change_Cost_Lower	% decrease in trade costs – No change in transportation mode is allowed.
Change_Cost_Lower_bdred	% decrease in trade costs – No change in transportation mode + Reduction in the border processing time
Change_Cost_Lower_Corridors	% decrease in trade costs – No change in transportation mode + Enhanced corridor management and speed increase all along economic corridors
Change_Cost_Upper	% decrease in trade costs – Changes in transportation mode allowed for.
Change_Cost_Upper_bdred	% decrease in trade costs – Changes in transportation mode + Reduction in the border processing time
Change_Cost_Upper_Corridors	% decrease in trade costs – Changes in transportation mode + Enhanced corridor management and speed increase all along economic corridors

Source: De Soyres et al. (2018)

In this study, the "change-cost-upper" series represents the cost declines resulting from the BRI infrastructure projects. Figure 18 below depicts the sectoral means across all trade partners. The maximum change in transport costs is less than 2.5%, while the costs remain above 1.5%.

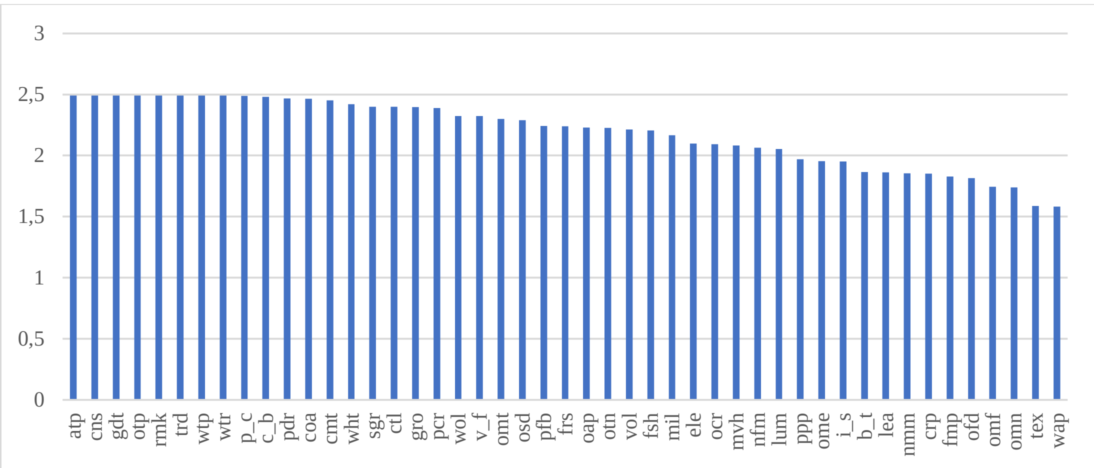

Figure 18. Sectoral Upper Trade Cost Changes in the BRI Global Dataset (%)

Source: De Soyres et al. (2018)

5.1.6. Community Innovation Survey

The Community Innovation Survey (CIS) is a survey that examines innovation activities within enterprises. It is based on the guidance of the Oslo Manual, the first edition of which was published in 1992. The first CIS was conducted in 1993 and has been carried out every two years across the European Union, EFTA countries and EU candidate countries since 2005. Face-to-face interaction, emails, and web-based participation are data gathering methods used in the survey. The content of the survey covers, but not limited to, the innovativeness of firms by type of innovative activity, level of expenditures at different stages, novelty of the products (such as being new to the firm or market), incentives and hampering factors for innovation, sources and financing of activities, level and counterpart of cooperation, patent applications and turnover from innovative output. The methodology of the survey is based on the Oslo Manuals, which serve as the international guidelines for conceptualizing and gathering data on innovation. Following its introduction in 1992, three periods of revision were observed for the OSLO Manual, in 1997, 2005, and 2018. These revisions were inevitably reflected in the framework of the CIS surveys.

Since this study utilizes the CIS data from the 2014, 2016, and 2018 periods, the repercussions of the revisions are also reflected in the analyses. Eurostat warns the data users about a possible break in the analysis and tremendous effort is made in this study to reconcile the first two and the last surveys in terms of concepts and country coverage. The prominent changes between the 2016 and 2018 CIS periods can be listed as follows:

1. The 2018 CIS categorizes subgroups of innovation into fewer categories. Namely, four types of innovation were used in the Oslo 2018 Manual: product, marketing, and organizational innovation. In the 2018 CIS, these are gathered under the title of business process innovation.
2. The 2018 CIS places greater emphasis on digitalization. The coverage of the product innovation is extended to include digital goods and services. In the section on business process innovation, a question is introduced regarding new or improved methods for information processing and communication. This was not clearly stated in the 2016 and 2014 CIS, as they were included in supporting activities vaguely.

3. The 2018 CIS also includes some new questions. These relate to customization and co-creation, patents and IP rights, purchasing technical services, innovative purchases, utilizing information channels, organizing work, and expectations from innovation.

A standard core questionnaire form is used, although modifications are occasionally allowed, provided the countries explicitly document them. The mandatory target population of the survey includes enterprises with at least 10 employees in the Core NACE sections and divisions. Sampling mostly uses the Business Register data of countries as the sampling frame.

This study utilizes the firm-level CIS responses from 12 countries, provided by Eurostat in scientific-use format. Access to CIS firm-level data is provided in two formats: scientific use files (SUF) and secure use files (SC). The first format includes partially anonymized data and is shared with the researcher on CD-ROMs under specified terms and conditions. The secure-use files in the second format are not subject to any perturbation. They are provided in the Safe Centre (SC) at Eurostat's premises in Luxembourg or remotely via accredited endpoints. While the data in SC format allows for the indirect identification of firms, the SUC files are shared after considerable changes have been made to the data to minimise the risk of indirect identification. Eurostat conducts anonymization by recording sector and employee information in broader categories, perturbing quantitative figures, and using ratios and growth rates instead of presenting explicit Euro values. The difference in data presentation between the two formats is presented in detail in Table 5.

Table 5. Availability of CIS Microdata Under Both Types of Dissemination

Variables	Scientific Use File – SUF DATA	Secure Use File- Available in Luxembourg
NUTS	NUTS 0: all survey rounds	NUTS 0: CIS3 to CIS2012
		NUTS 1: CIS2014 (majority of countries) / CIS2016 and CIS2018 (all countries)
NACE	2 digits or groups of 2-digits	4 digits
Number of employees/persons employed	4 broad size classes: 10-49, 50-249, 250-500, over 500	No perturbation / recoding
	Employment growth	
Country of head office of enterprise	Home country	No perturbation / recoding
	other EU, EFTA or candidate country	
	rest of the world	
Turnover	Absolute values perturbed (microaggregation within NACE*size class category)	No perturbation / recoding
	Turnover growth	

Table 5. (continued)

Expenditure on innovation and other activities	Values expressed as a share of turnover	No perturbation / recoding
Remaining variables	No perturbation / recoding	No perturbation / recoding

Source: Eurostat

A significant feature of the CIS data is that it is not longitudinal, i.e. panel data analyses cannot be done with the available data. Therefore, only cross-sectional analyses can be done, and the time-varying implications of the BRI are captured by using three different survey periods: 2014, 2016, and 2018. The 2014 CIS data is postulated to capture the impact at the initial stages of BRI, as it was announced in 2013. Data from 2016 and 2018 are utilized to capture the implications of its evolution.

The list of the countries and their share in the raw CIS data are presented in Table 6. The table shows that Spain has the largest share of data for all survey periods. Bulgaria, Hungary, Poland and the Czech Republic follow it, respectively.

Table 6. Shares of Country Data in Raw CIS SUF Data (%)

	2014	2016	2018
Bulgaria	16.9	16.4	17.2
Czech Republic	6.2	6.3	6.4
Germany	7.5	7.1	6.9
Estonia	2.1	1.7	1.2
Greece	3	4.1	4.4
Spain	36	35.7	34.5
Croatia	3.9	3.7	2.9
Hungary	8.1	7.9	8.2
Latvia	2.9	2.7	2.6
Lithuania	1.8	3.3	3.1
Portugal	8.4	7.6	9.1
Slovak Republic	3.3	3.7	3.6
Total Number of Observations	84212	89391	90235

Source: CIS Data and Author's Calculations

5.1.7. Properties of the CIS Survey

Every CIS survey at time t covers the periods t-2, t-1, and t. Most questions and indicators are based on these three years. Only the indicators for innovation expenditures related to product and process innovations pertain to the last year. In the scientific use format, growth rates of employment and turnover are included in the data, calculated using the figures in t and t-2.

The loss of significant information, such as the firm's location or the exact number of employees, is the drawback of using data in scientific use format. The CIS survey's cross-sectional structure is a primary drawback of the data, widely acknowledged in the literature under both formats. The fact that the firms cannot be tracked leads to the inability to obtain the lags required to observe the impact of an R&D investment on productivity. In the CIS context, there are certain concepts and definitions that a good comprehension of would facilitate a more accurate evaluation of the results obtained from the empirical analyses.

As stated above, the questions in the CIS surveys differ in the 2014, 2016 and 2018 CIS questionnaire forms. Despite the differentiation in the coverage of questions related to innovative activity, some remain constant and provide a basis for analyses that use the same dependent variable across these survey periods.

For the first block of equations in the MMK framework, these questions concern the existence of intramural and extramural R&D activities, along with their ratios to the final year's turnover. Intramural R&D activity refers to the R&D activities performed within a firm by its in-house staff, utilizing the facilities and resources owned by the firm. Extramural R&D activity, on the other hand, refers to R&D activities performed outside the firm and acquired by the firm in exchange for payment (OECD Frascati Manual, 2015). In this thesis, responses related to the intramural activity are selected as the benchmark variable in the first block equations, since adding the purchase of R&D activities from outside sources to the dependent variable could necessitate the dissection of purchases that the BRI could trigger. The ratios for the intramural R&D activity (rdintraratio) are multiplied by the turnover of firms to obtain their intramural R&D expenditure.

For the second block of equations in the MMK framework, variables related to the innovation output are utilized. Three questions in the surveys come to the forefront as candidates for dependent variables: the shares of innovative sales (of innovation output) that are new to the market, new to the firm, and of the output that is unchanged or only marginally modified. In line with the literature, ratio of the innovative sales of the innovation output new to the market is used as the benchmark measure in the second block of the MMK framework. Similar to the first block, the ratios of innovative sales new to the market are multiplied by the firm's turnover to calculate total turnover from such sales.

As stated above, despite modifications to the survey structure across years, the CIS data still provides variables to proxy for innovation input and output in a continuous manner across models.

The CIS surveys use the NACE Rev. 2 sectoral classification to record the firms' main economic activity. The SUF (Scientific Use Files) data is, however, provided under narrower (NACE A) and broader (NACE B) versions of the NACE Rev. 2 two-digit sectors. Even though the primary classification is maintained, some two-digit sectors can be combined as indicated in Table 7. This aggregation in the sectoral codes is closely related to the number of employees at the firm. Although there is an effort to maintain utmost sectoral detail, the country's responses may be coded using the broader definition provided by Eurostat in case the use of NACE_A might lead to the disclosure of the identity of enterprises in sectors with few firms. Eurostat selects an appropriate NACE-SIZE combination for each country, declaring a combination valid if the rare domains under this combination account for less than 10% of the country's survey responses. The NACE-SIZE combinations can change over time, as seen in the case of Bulgaria, where the fourth size group was used in 2014 and 2018, whereas in 2016, size group three was preferred. It is not surprising to see that for countries using the NACE_B (broader) sector classification, there is no observation of size_4 being used. In other words, broadening the scope of sector classification involves using size definitions with larger ranges of employees. The size groups used in the raw CIS data, along with their descriptions, are presented in Table 8. As evident in Table 8, the coverage of the size groups varies across different survey periods. For instance, while size group 1 refers to the absence of employee information in the 2014 CIS, a firm’s reporting under size group 1 in the 2016 CIS indicates that this firm has 10 or more employees. Since each firm is noted in either of these groups, the size information does not overlap. Some countries might be reported under size group 1, while others could be reported under size group 2. As stated above, Eurostat determines which size group definition to use, taking into account the confidentiality of the firms.

Table 7. Nace Rev.2 Classifications Used in the SUF data of the CIS

nace_a	nace_b	nace_a	nace_b
01-03	01-03	24	24-25
05-09	05-09	25	
10-12	10-12	26	26-28
13	13-15	27	
14-15		28	
16	16-17	29	29-30
17		30	
18	18	31	31-32
19-20	16-17	32	
21		33	33
22	22-23	35	35
23			

Source: The manuals provided with the SUF data by Eurostat.

Table 8. Definitions of Size Groups Across Surveys

	2014	**2016**	**2018**
size_1	No employee information	10 and more	10 employees and more, no employee information
size_2	10-249, 250+	Under 50, 50 and more	Under 50, 50 and more
size_3	10-49, 50-249, 250+	10-49, 50-249, 250+	10-49, 50-249, 250+
size_4	10-49, 50-249, 250-499, 500+	10-49, 50-249, 250-499, 500+	10-49, 50-249, 250-499, 500+

Source: CIS Data and Author's Calculations

The final list of the sectors included in the analyses are presented in Table 9. Sectoral definitions are presented in Appendix Table 1.

Table 9. Sectors Used in the Analyses

nace_a		**nace_b**
01-03	24	05-09
05-09	25	10-12
10-12	26	13-15
13	27	16-17
14-15	28	18
16	29	19-21
17	30	22-23
18	31	24-25
19-20	32	26-28
21	33	29-30
22	35	31-32
23		35

This thesis focuses on the initial years of the BRI, when the infrastructure investment was also limited. A more extended sample period would be needed to observe the BRI's full impact on firms' behaviour. As the BRI was announced in 2013, the five years till the end of 2018 would mostly reflect the change in expectations and the "news effect" of the BRI. This period could also be considered as the pondering and waiting process for the firms. Therefore, variables that indicate the motivations of firms, as well as what they target through innovative activity, would be enlightening for the analyses in this thesis. The 2016 CIS has five questions on this issue, focusing on whether companies aim to improve existing goods or services, introduce brand-new goods or services, reach new customer groups, provide customer-specific solutions, or offer low prices. However, while the 2018 CIS surveys provide more detailed responses to such questions, there are no questions in the 2014 CIS related to the firm's motivations. Therefore, responses related to motivations are dropped entirely from the analyses for consistency. The list of variables discussed below and used in the analyses is presented in Table 9 along with their explanations.

Table 10. Description of the Variables Used in the Thesis

co	Cooperation arrangements on innovation activities
empud	Percentage of Employees with Tertiary Education
size	Size group of the Firm
BRI	Expected Export Increase of the Country-Sector combination that the firm belongs to.
larmar	Largest market in terms of turnover between the starting and ending year of the survey period.
marloc	Firm sells to local/regional market (within country)
marnat	Firm sells to national market (referring to other regions of the country)
mareur	Firm sells to the EU-EFTA region
maroth	Firm sells to the regions outside the EU-EFTA region.
largest	The new variable constructed to proxy the largest market in terms of turnover, using the larmar, maroth, mareur, marnat and marloc variables.
rdintrayes	Existence of Intramural R&D Activity
R&Dexp	R&D Expenditure in Euros
newmkt	Introduction of innovation output new to the market
turn	Turnover from the sale of innovative output new to the market
rd*	Predicted probability of the existence of R&D activity
ird*	Predicted value of the R&D Investment from the First Block
mac	The expenditure on acqusitions of machinery and equipment
innopcsprd	Introduction of new methods for producing goods or providing services (including methods for developing goods or services)
inpspd	Introduction of a new or significantly improved method of production
inpslg	Introduction of a new or significantly improved logistic, delivery or distribution system
inpssu	Introduction of a new or significantly improved supporting activities
largest	Largest Market of Turnover of the Firm in the Survey Period
fungmt	Existence of Funding from Government
funeur	Funding from the EU Horizon Programmes
funloc	Funding from Local Authorities
prod_growth	Productivity Growth

The CDM literature also focuses on the sources behind the innovative activity. Customers, competitors, and input suppliers can all inspire or compel firms to engage in innovative activities. However, observations related to the source of innovative activity are largely missing from the provided data.

The variables referring to the funding source for the innovative activity are also widely used in the literature. Fortunately, the three CIS surveys used in this thesis mostly provide responses for the sources of funding. There are four variables related to funding source in the 2014 and 2016 surveys. These indicate funding from the central government, local government funding, EU funding, and the EU's framework programme. The 2018 CIS offers a significantly broader range of funding variables. The funding opportunities from debt financing, equities, and tax credits are also included in the questionnaire.

Additionally, the funding allocated solely for R&D activities is reported. The 2018 CIS distinguishes the sources of EU funding by reporting funding from Horizon Programmes (HP; EU 2020 was valid for the 2018 CIS period) and other EU sources separately. Funding from HP is included in the analyses.

The existence of cooperation activities, the country and sector of the cooperation partner, and the most significant cooperation partner are among the most used variables in the literature. In all survey periods, the existence of the cooperation partner is available in the data, and the share of missing observations is considerably lower than other cooperation variables, indicating the location and sector of the cooperation partner. The strength of the cooperation partner is not consistent across the surveys, either. Variables proxying the existence of cooperation partners, such as customers or suppliers in the EU-EFTA region, China, or India, are mostly missing in the surveys despite being systematically asked in each survey period. As a result, in all models, the co variable, which merely represents the existence of cooperation, is used.

The information on the percentage of employees with tertiary education is also widely used in the studies. The categories of the empud variable are presented in

Table 11. This variable also exhibits discrepancies at the country level across survey periods.

Table 11. Categories of the *empud* Variable

Percentage of employees with tertiary degree	0	0%
	1	1% to 4%
	2	5% to 9%
	3	10% to 24%
	4	25% to 49%
	5	50% to 74%
	6	75% to 100%

Source: Community Innovation Surveys

For instance, Latvia does not provide the firms' tertiary education information (empud) in any period. The Czech Republic provides the data in the 2016 CIS but not in other surveys. Spain and Lithuania do not provide the information in the 2018 CIS. Since empud is a crucial variable in the CDM models, and no other variable could substitute the same information, this variable is not omitted from the analyses, leading to different sample coverages for different survey periods.

The empud variable is also recorded with different formats across survey periods. The variable is in categorical form in the 2014 and 2016 CIS. In the 2018 CIS, each subgroup is asked separately. For continuity, responses in the 2018 CIS are regrouped and presented in the same format as the 2014 and 2016 surveys. Fortunately, the definitions of degrees are the same for all survey periods.

Table 12. Percentage of Missing Observations in the Territorial Education of the Employees

	% of Missing Observations in *empud*		
	2014	**2016**	**2018**
Bulgaria	0	0	0
Czech Republic	100	0	100
Germany	16.8	13.1	15.5
Estonia	0.3	1.1	0
Greece	0	0	0
Spain	0	0	100
Croatia	0	0	0
Hungary	0	0	0.1
Latvia	100	100	100
Lithuania	4.3	0	100
Portugal	0	0	0
Slovak Republic	0	0	11.4

Source: CIS Data and Author's Calculations

The discontinuity in data availability prevails in another significant variable, the firm's largest market. This variable, larmar, in the raw data is presented in four categories in the CIS 2014 and 2016 surveys. The categories are local, national, EU-EFTA, and non-EU-nonEFTA markets. In the 2018 CIS, there is no larmar (firm's largest market) variable. Instead, the shares of each market in total turnover are presented with their ratios. Also, the larmar variable is missing for Spain's 2014 and 2016 CIS data. Since the largest market share information is of utmost significance for the analysis, and Spain's data accounts for a large share of the total data, the missing rows for Spain are imputed using auxiliary data from the surveys. This imputation and the transformation of the 2018 CUS variables are described in the next section.

This thesis examines the impact of the decline in BRI-led trade costs on the R&D-innovation-productivity framework of selected European firms, with a focus on product innovation. The BRI-related cost declines are calculated by the World Bank only for goods, excluding the service sector. In line with this, service innovation is excluded. Process innovations are also excluded as dependent variables to be explained in the analysis, considering that the BRI global dataset primarily focuses on goods trade. However, process innovations such as the introduction of a new or significantly improved method of production, are used as explanatory variables.

As stated above, in the 2018 CIS, there is a significant change in how the process innovations are reported from the 2016 to 2018 CIS periods. The practices reported under marketing and organizational innovation are categorized under business process innovations in the 2018 CIS. Two new elements are added to the survey under business process innovations: new or improved methods related to developing products, services, or processes, and new or improved methods in after-sales services. On the other hand, the responses about the existence of change in design is dropped from the survey. This removal is significant as firms might change the design of their good after innovative activity. Due to this small but essential discontinuity, only process innovations referring to the introduction of a new or significantly improved method of production, are used in the models across surveys.

5.1.8. Construction of EEVC and Its Steps

The EEVC, the primary variable of interest in our analyses, is built in 3 stages, as depicted in Figure 19. The equations used in each step are explained in the related parts.

First Stage

- Imports of each destination market j from the BACI figures are aggregated under HS4 codes, giving a country's total sectoral import.
- Shares of exporters in the imports of a destination market for each HS4 code are calculated, still using the BACI database.
- These shares are multiplied by the product-level elasticities, which are also in HS4 codes.
- The variable named "share-elasticity" is obtained.
- This variable is in HS4 classification

Second Stage

- The sectoral codes in the share_elasticity series are converted into GTAP classification using the UN COMTRADE conversion tables.
- The share_elasticity terms in HS4 codes are aggregated across each exporter-importer sector pair after merging the series with the GTAP classification.
- The share elasticity terms in the GTAP classification, defined uniquely for each importer-exporter sector combination, are merged with their counterparts in the BRI Global Dataset.
- The elasticity of share cost is called share_elasticity_cost and is unique for each exporter (i), exporter (j), and sector (s).

Third Stage

- The share elasticity cost terms are aggregated for each importer and each sector. This shows the total expected change in the import demand of an importer across all export partners in a sector.
- As the construction of the instrument in the study relies on deducting the expected change in the volume of imports to be made from the exporter country in the sample, the share elasticity cost terms defined for each exporter-importer sector are deducted from the total expected change in the import demand of an importer in the related sector.
- This deduction accounts for the change in import demand of each importer, after purifying it from the changes observed in the exports of the sample countries.
- These deducted figures are weighted by the share of each importer in the total sectoral export of a sample country and summed over all importers who import from the exporter country in the sample for each sector.

Fourth Stage
• The instrumental variable, EEVC, constructed in the third stage, is merged with the CIS firm-level data in the fourth stage. Due to the sectoral discrepancy stemming from the construction of the EEVC in the GTAP 10 classification, the sectors are converted to the NACE Rev. 2 classification.

Figure 19. Stages of the EEVC Construction

5.1.8.1. First Stage

In the first stage of construction, we aim to calculate the extent to which the imported volumes would change due to a 1% decline in trade costs, which is equivalent to the trade cost elasticity of import demand. The trade elasticities are obtained from the CEPII database, which involves products with HS4 sector codes. Similarly, the BACI database also provides trade figures in HS4 codes. The transition from trade data to expected changes in import values starts with aggregating the import values across destination markets for each origin and HS-4 code (Eq. 14 and Eq.15). After aggregation, we find each origin's share in the destination market's total import in the relevant HS4 sector (Eq.16)

These shares are then multiplied by the product elasticities, which are also in HS4 codes. The multiplication is named "share_elasticity". The BRI Global data in the next step are classified according to the GTAP classification, which requires the sectoral conversion of share elasticity terms from HS4 to the GTAP classification. The conversion is made using the UN conversion tables, and only sectors with counterparts in the GTAP classification are retained.

After identifying the counterparts of the HS-4 codes in the GTAP list, we aggregate the share elasticity values across destination-origin pairs and within GTAP sectors. This aggregation illustrates the change in import volume between a destination-origin pair in a specific sector (coded in GTAP 10) resulting from a 1% decline in trade costs. This variable, called share_elasticity_gtap, is presented in Eq. 18. After the sectors' conversion, "k" represents the GTAP classification, and "m" is the total number of sectors included in the GTAP classification.

$$Total\ Imports\ of\ a\ Destination\ Market\ j\ in\ Sector\ s = \sum_{s=1}^{n} M_{js} \quad \textbf{(14)}$$

$$Total\ Imports\ of\ Destination\ Market\ j\ From\ Origin\ Country\ i\ in\ Sector\ s = \sum_{\substack{s=1 \\ i}}^{n} M_{ijs} \quad \textbf{(15)}$$

$$Share\ of\ Exports\ from\ Exporter\ i\ in\ Imports\ of\ j\ in\ Sector\ s = \frac{Total\ Imports\ of\ J\ from\ Country\ I\ in\ Sector\ S}{Total\ Imports\ of\ Country\ J\ in\ Sector\ S}$$

(16)

$$Share\_\ Elasticity_{ijs} = Share\ of\ Exports\ from\ Exporter\ i\ in\ Imports\ of\ j\ in\ Sector\ s * Elast_s * (-1)$$

(17)

$$Share\_Elasticity\_GTAP_{kij} = \sum_{k=1}^{m} Share\_Elasticity_{ij} \quad \textbf{(18)}$$

The second stage continues by combining the share elasticity terms from the GTAP dataset with the expected trade cost declines in the BRI Global dataset, which also falls within the GTAP classification.

5.1.8.2. Second Stage

In the second stage, we combine the findings from the first stage, i.e., the share_elasticity_GTAP series, with the figures in the BRI Global Database published by the World Bank (De Soyres, 2019). As stated above, the BRI Global Database includes various percentage predictions (such as lower-bound and upper-bound scenarios) for the expected trade cost declines between country pairs on a sectoral basis. This database is classified in GTAP 10, and since the required conversion has already been made in the first stage, we directly multiply these cost changes by the "share_elasticity_GTAP" value of the related destination-origin pair. The multiplication is called "share_elasticity_cost" and shows the expected change in the amount of trade between the related destination-origin pair in the relevant sector (Eq.19), where i stands for the exporter (the sample countries in our analyses), j stands for the importer and k stands for the sector under GTAP classification.

$$Share\_Elasticity\_Cost_{ijk} = Share\_Elasticity\_GTAP_{jik} * BRI\ Upper\ Cost\ Changes_{ijk} \quad \textbf{(19)}$$

However, the instrumental variable, **EEVC**, has not yet been obtained; it is calculated in the third stage of the analysis.

5.1.8.3. Third Stage

As stated above, the instrumental variable in this thesis, i.e. the **EEVC**, is created from the exporter's perspective. The variable refers to the shocks the importers could experience and reflects on the exporters. To avoid endogeneity issues, possible shocks that could be observed in the transactions between the selected exporter (sample country) and its destination markets are excluded while the total shock experienced by the destination markets is taken into consideration. Following the example above, this implies that for a sample country (i), Bulgaria, and a specific sector (k), the expected changes in the import demand of all destination markets (export partners of Bulgaria) (j) of Bulgaria in that sector should be summed (Eq.20). However, any expected change observed in the trade with Bulgaria should be deducted to make the figure independent of Bulgaria and maintain exogeneity. The variable after deduction (of the expected export volume change from Bulgaria to the destination market j) is called ***demand shock for Bulgaria in sector k observed in the destination market j*** (Eq.21). After deducting the Bulgarian part of the import demand shocks to the destination markets in a sector k, cleared of the Bulgarian effect, are weighted by the share of each destination market (j) in the total exports of Bulgaria(i) in the relevant sector (k) as depicted in Eq.22. Summing over these weighted figures provides the sectoral import demand shock that the Bulgarian exporters face in all destination markets in sector k. Bulgaria observes the demand shocks affecting its export partners, which are beyond Bulgaria's control.

$$Total\ Expected\ Change\ in\ the\ Import\ Demand\ of\ Destination\ j\ in\ sector\ k\ = \sum_i Share\_Elasticity\_Cost_{jik}$$

(20)

$(Total\ Expected\ Change\ in\ the\ Import\ Demand\ of\ Destination\ j\ in\ sector\ k = TECIDD_{JK})$

$$Demand\ Shock\ for\ Exporter\ i\ for\ Dest.j\ in\ Sector\ k = \ TECIDD_{JK} - Share\_Elasticity\_Cost_{\ jik}$$

(21)

$$Total\ Import\ Demand\ Shock\ for\ an\ Exporter\ i\ in\ sector\ k = \quad EEVC_{\ ik} = \sum_j Share\ of\ dest.j\ in\ sector\ s\ in\ total\ exports\ of\ i\ in\ sector\ s * Demand\ Shock\ for\ Exporter\ i\ in\ Dest.j\ in\ Sector\ k$$

(22)

The sum obtained in the final equation is the instrumental variable used in the analysis. Namely, an exporter's total import demand shock equals the expected change in export volume in mirror terms, i.e., EEVC.

5.1.8.4. Fourth Stage

The instrumental variable, EEVC, is constructed in GTAP 10 classification in the third stage. The EEVC figures are merged with the CIS firm-level data in the fourth stage. However, a sectoral discrepancy reemerges, as the CIS data are presented in the NACE-Rev. 2 classification. As in the conversion from the HS codes to the GTAP 10 classification, the GTAP 10 codes are now converted into the NACE Rev. 2 classification using UN conversion tables. The converted sectors from GTAP 10 to NACE Rev. 2 are listed in Table 11 below.

Table 13. Correspondence of Sectors Between GTAP and NACE. REV.2 Classifications

Sector in the BRI Global Dataset	NACE-2 Classification	Sector in the BRI Global Dataset	NACE-2 Classification	Sector in the BRI Global Dataset	NACE-2 Classification
frs	1,2,3,4	cmt	10,11,12	ome	28
fsh	1,2,3,4	sgr	10,11,12	mvh	29
v_f	1,2,3,4	mil	10,11,12	otn	30
wht	1,2,3,4	ofd	10,11,12	omf	31
ocr	1,2,3,4	vol	10,11,12	gdt	35
pfb	1,2,3,4	b_t	10,11,12	wtr	36
osd	1,2,3,4	tex	13,14,15	cns	41,42,43
pdr	1,2,3,4	wap	13,14,15	trd	45,46,47,55,95
c_b	1,2,3,4	lea	13,14,15	otp	49,52,79
wol	1,2,3,4	lum	16	wtp	50
gro	1,2,3,4	ppp	17,18	atp	51
rmk	1,2,3,4	p_c	19		
oap	1,2,3,4	crp	20,21,22		
ctl	1,2,3,4	nmm	23		
coa	5,6,7,8,9	i_s	24		
omn	5,6,7,8,9	nfm	24		
omt	10,11,12	fmp	25		
pcr	10,11,12	ele	26		

Source: Rueda-Cantuche et al. (2017)

5.1.9. Properties of the EEVC Dataset

The EEVC dataset constructed above indicates the expected percent change after the BRI. As seen in Figure 20 below, the highest mean for the EEVC is calculated for the combination sector of the manufacture of rubber products (nace code: 22) and other non-metallic mineral products (nace code: 23). It is followed by the manufacture of chemicals and chemical products, as well as basic pharmaceutical products and pharmaceutical preparations.[115] The means of the EEVC at the country level indicate that Greece would feel the highest average impact. This aligns with expectations, as Greece can benefit from both marine and road transportation. The latter could further be strengthened by the highways and railways constructed in the Western Balkans by Chinese contractors.

The figure also indicates that, although Estonia, Lithuania, and Latvia withdrew from the 16+1 Agreement in 2022, benefits may still be accrued to these countries. Hungary, a strong ally of the BRI project, is not among the top beneficiaries of trade cost declines.

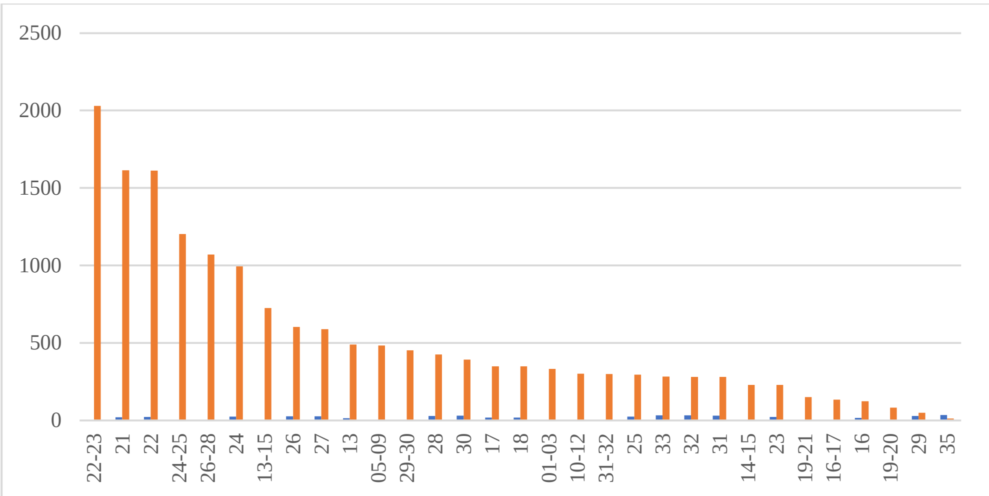

Figure 20. Means of EEVC at the NACE Rev.2 Sectors (*)

Source: Author's Calculations

(*) Since the CIS includes SUF data, it has a narrow and broad sectoral definition, which encompasses two NACE Rev. 2 two-digit sectors. For the continuity of the analyses, they are not dropped from the graph.

[115] It should be noted that the combination sector, 22-23, is not included in the original NACE Rev. 2 classification. It is combined in the SUF data provided by Eurostat.

Germany is also expected to derive substantial benefits, a point that may be closely related to the sectoral distribution outlined above. Having more exports in the sectors mentioned earlier could be a factor that paves the way for greater benefits from the BRI. Spain has a significant advantage in marine trade; however, this does not necessarily mean that Spain will have higher export benefits than Germany. As a result, it can be stated that not only physical access to the trade routes, but also the export structure prior to the BRI, also matters in the scope of the gains that could be expected from the BRI.

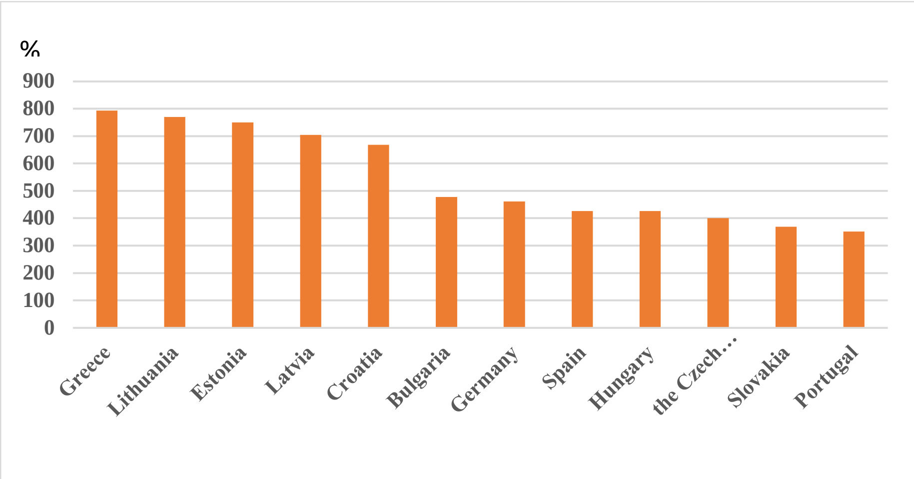

Figure 21. Means of EEVC at the Country Level

Source: Author's Calculations

The EEVC dataset constructed above is calculated in percentage terms. In using the EEVC series in the analyses, it is divided by 100. Therefore, the ultimate EEVC term (brı)used in the analyses stands as a factor of change.

Table 14. Descriptive Statistics of the EEVC Term

	Min	Max	Mean	Standard Deviation	Skewness	Kurtosis
EEVC	0	2388.394	449.772	417.5944	2.132369	7.032163

5.1.10. Data Availability Problems

This study is associated with four problems related to data availability. Highlighting them is significant in understanding how the models are built. These problems can be listed as follows:

1. A significant portion of the data issues stems from using the CIS SUF data, i.e., the data format provided by Eurostat. The SUF data caps the values of many variables and provides data in groups or as growth rates, rather than exact and continuous values. The CDM models primarily utilize the intensity terms of R&D and innovation, along with the predominant use of labour productivity in the final stage of estimation. Intensity terms require continuous values regarding the number of employees and the expenditures on innovative activities. Despite their existence in the original questionnaire forms, the SUF data provides the former in size groups and the latter as ratios of the total turnover. This leads to slightly modifying the CDM framework, and the ratios are used as dependent variables in the first two stages.[116] Size groups are introduced as control variables. The absence of employee numbers also prevents the use of labour productivity in analyses, even though the turnover figures for the latest year are still provided in the SUF data. The productivity term in the 3rd stage of the CDM framework is calculated approximately, using the employment and turnover growth terms, as the logarithm of labour productivity if it were directly calculable.
2. The SUF data does not provide the firms' location information, except for the country in which they are located, despite this information being available in the original data. This lack of information constrains the creation of more BRI-related variables. Indeed, if the firm's location could be recognized even at the NUTS 2 level, the BRI infrastructure investment in the region could be used as another regressor in the models.
3. CIS data is not panel data as explicitly stated by the Eurostat. Therefore, panel data analyses cannot be done. This limitation pushes the analyses to make broader inferences by categorizing firms into groups.
4. The SUF data provided by Eurostat include turnover figures for the latest CIS period and the growth in turnover between the first and third years of the survey. It also provides the share of exports in the firm's total turnover, still relying on the latest year's data. The SUF data also provides the share of exports in total turnover for the latest year. Still, it does not include any

[116] Indeed, their logarithmic form is used as explained below.

information about the **purchase of inputs** incurred by the firm, except those related to innovation activities. Indeed, such information is mostly provided in business register data, and Eurostat does not provide business register data as SUF data. It is, therefore, of utmost importance that some data related to input other than that used for innovative purposes would be an excellent contribution. In this study, only the impact of expected import demand shocks on the destination markets of the sample countries is considered. If there were sufficient information (even) about the largest market from which the firm supplies its inputs, then a more concise effect of the BRI could be calculated. With its current form, the SUF data merely points in the direction of the largest market from which the firm purchases, not the market to which it sells. We do not have business register data that can be merged with the CIS surveys, unlike most studies in the literature. If the business register data were available, the purchases of inputs would also be available.

Despite the problems with data availability, continuity, and coverage matching, this study selects variables that can still provide sound findings for the analyses. Indeed, the use of CDM models, relying solely on CIS data, and the significant findings ultimately obtained are the fundamental contributions of this thesis to the literature. No prior study has solely used the CIS data in CDM-type models. The following sections describe the steps of data cleaning, modifications and creation, which are the final steps in data preparation for the models.

5.1.11. Data Creation, Cleaning and Modification of Variables

5.1.11.1. Creation of the *largest* variable

Since this study aims to measure the impact of BRI-led trade cost declines on the innovative activities of the selected EU countries at the firm level, the variables of interest in the models relate to the firms' export activities and the magnitude of impact stemming from BRI investments. Two variables meet this objective: the EEVC term calculated beforehand and its interaction with the largest (the market from which the firm obtains its largest turnover) variable, which indicates the largest market in total firm turnover, encompassing all three years that the CIS belongs to. The models' *largest* variable is mainly obtained using the *larmar* variable in the surveys (Table 15). Table 12 indicates the conversion valid for the 2014 and 2016 surveys.

Table 15. Conversion from *larmar* to *largest*

larmar	largest
A: local market	1
B: national market	1
C: EU-EFTA	2
D: Non EU-Non EFTA	3

Source: Author's Calculations

However, as mentioned above, the surveys are not coherent regarding the availability of the *larmar* variable. While the 2014 and 2016 surveys include an explicit 'larmar' variable, no such variable exists in the 2018 survey. In the 2018 survey, however, there are variables indicating the explicit shares of national, EU-EFTA and nonEU-nonEFTA markets in total turnover. Turnover shares in this survey are converted into *largest* variable using the conditions defined in Table 16. Any share figure above 50% can link the firm to a specific market. Since the countries in the third category are the largest in number, firms with 50% of their exports in the nonEU-nonEFTA region are labelled under category 3, even though firms in other categories are supposed to have shares **strictly** greater than 50%.

Table 16. Conversion from the Turnover shares in CIS 2018 to *largest* variable

Variables of Turnover Shares in CIS 2018	Condition for creating the ***largest*** variable	largest
Share of National Market: tur_nat	tur_nat>0.5	1
Share of EU-EFTA Market_tur_eu_efta	tur_eu_efta>0.5	2
Share of nonEU-nonEFTA Market_tur_neu_nefta	tur_neu_nefta>=0.5	3

Source: Author's Calculations

The problem, however, still lingers since Spain's data for the 2014 and 2016 surveys all contain missing values for the larmar variable. Therefore, even if Spain has share data for the 2018 survey, and larmar can be obtained, it does not apply to the prior ones. Since Spain's data constitute almost 35% of the total observations for the analysis sample in each period, omitting them would be a significant loss, thereby hampering the robustness of the analyses. Therefore, an imputation is called for. Instead of the largest market information with larmar, variables indicating whether the firm operates in a specific market are used as guidance for imputation. The marloc, marnat, mareu, and maroth are the binary variables that indicate whether firms earn any turnover from local, national, EU-EFTA, and nonEU-nonEFTA markets, respectively. They are independent and do not indicate whether one dominates the other. To fill in the missing values of the largest variable, these variables are re-grouped as in Table 17. Firms that can be surely allocated to a specific market due to their absence in others can be labelled under a particular category of the largest variable.

Table 17. Conversion from the *mar** terms to *largest* variable

marloc	marnat	mareu	maroth	largest
1	0	0	0	1
0	1	0	0	1
1	1	0	0	1
0	0	1	0	2
0	0	0	1	3

Source: Author's Calculations

Following the construction of the *largest* variable, the two main variables of interest of the study are ready to be used in the models. Different model specifications, their position in the theoretical framework, and the alternative samples used to estimate them are explained in the following section.

5.1.11.2. Creation of the *size* variable

The employee information in the CIS SUF data is provided in size groups that differ among countries and sectors. A new *size* term is created to use them coherently in models, and four size groups are allocated to the new *size* variable as in Table 18. As shown in Table 18, if a firm is classified in size group 1, it is labelled as “1” under the new *size* term.

Table 18. Size Groups, Definitions and Conversion

size	Size Group Definitions
1	10 employees and more, no employee information, 10 and more, under 50, 10-49
2	50-249, 50 and more
3	250-499, 500 +

Source: Author's Calculations

After the operations were performed on the merged data of the CIS and EEVC series, the data still require cleaning. As described below, there are inconsistencies within the firm's responses given during the same period. For instance, the firm states that it has not engaged in any R&D activity, but the ratio of R&D expenditure to total turnover is reported as more than zero. These inconsistencies could compromise the effectiveness of the Heckman procedure by undermining its primary rationale. In the formation of the Heckman procedure, where a binary selection variable is used as the dependent variable in the selection, the selection variable should be 1 for the observed variable and 0 for the unobserved variable, which is missing. However, there are inconsistencies in the data that violate this setup.

Moreover, how the Heckman procedure handles such consistencies also depends on the estimation method. In this study, Heckman's two-step estimation is employed primarily because it yields consistent estimates when the dependent variable does not have a normal distribution. The following solutions are suggested to comply with the data setup requirements of the 2-step estimation. It is essential to note that both estimation methods, whether maximum likelihood or two-step, exclude rows with missing selection variables. The rows in which selection variables in this study, rdintrayes and newmkt, are missing are dropped in the estimation of the models. Therefore, it is not introduced as an inconsistency below. Most inconsistencies pertain to the disconnect between the selection and main dependent variables. Below are the descriptions of inconsistencies, solutions provided for each of them.

5.1.11.3. Inconsistencies in the Responses Related to R&D and Innovation Activity

As stated in the theoretical part of the study, CDM-type models are primarily designed to address the selection and simultaneity problems encountered in surveys on innovation. As will be discussed in the methodological part in more detail, firms tend not to report their true innovative performance. They either disguise their innovative effort and present misguided information. It is also observed that firms may not report their innovative efforts unless they exceed a certain threshold. In this respect, an inspection is required in the analysis of firms' responses, which is done using the appropriate econometric techniques, as discussed below. However, those tools rely on certain assumptions, and the merged data (obtained by merging the EEVC series and the original SUF data) reveal inconsistencies against those assumptions. Before using the methods, the inconsistencies observed between the selection variable, rdintrayes or newmkt, and the ratio of R&D expenditures (rdintraratio) and the ratio of innovative sales (turnmar) new to the market in total turnover are listed and clarified as follows. The rationale behind the modifications in data is explained for rdintrayes and rdintraratio, but also applies for the relation between newmkt and turnmar.

- Inconsistency 1

For first block equations: rdintrayes=0, rdintraratio>0

For second block equations: newmkt=0 , turnmar>0

The merged data involves rows in which the firms state that they do not conduct intramural R&D activity (rdintrayes=0) but report ratios for the share of this activity in total turnover. These rows conflict with the rationale of the Heckman two-step estimation. The two-step estimation method uses the rows with zero values for the selection variable in the selection equation and excludes them from the outcome equation. For the clarity of the analysis, all the values of rdintraratio and turnmar corresponding to zero values of rdintrayes and newmkt are replaced with missing values.

- **Inconsistency 2**

For first block equations: rdintrayes=1, rdintraratio=0 OR rdintraratio= Missing

For second block equations: newmkt=1, turnmar=0 OR turnmar=Missing

There are also rows in the merged data that involve positive intramural R&D activity (rdintrayes=1), but report zero or missing ratios. In the Heckman 2-step procedure, it is not a problem that the ratio term is zero. The problem emerges when the ratio variable is missing variable when rdintrayes is 1. By construction of the Heckman 2-step method, these ratios should have non-missing, and preferably positive, values when the selection variable is affirmative. Since such rows would be included in the selection equation but not in the main equation, Heckman two-step procedure is harmed due this value. As shall be described below, the logarithmic form of the ratio terms is used in the models, and the allowance for zeros might be problematic in that step. Yet, to overcome the drop to zero lows after the logarithm, zeros are replaced with 0.0000001 to keep them in the data.

- **Inconsistency 3**

For first block equations: rdintrayes=0, rdintraratio=0

For second block equations: newmkt=0, turnmar=0

Though not as harmful as the above two problems, rows including negative responses for intramural R&D activity and zero values for its share in total turnover also contradict the rationale of the Heckman procedure. By construction of the Heckman procedure, the rows with zero ratios should be missing. Therefore, the zero ratios are manually converted into missing rows.

5.1.12. Variables Used in the Analyses

We use an adjusted version of CDM model to examine the effects of the trade cost declines on the relationship between innovation and productivity. The studies capturing the effects of trade dynamics mainly incorporate firm-level export shares into the CDM structure of the firm. In this study, the impact at the firm level is examined by interacting the dominant market information that the firm sells with the EEVC, i.e. country-sector-specific demand shock expected due to the BRI. The reason behind not directly multiplying the export ratio of the firm with the BRI effect stems from endogeneity concerns. As stated above, qualitative variables, such as rdintrayes, correspond to the entire survey period; whereas quantitative observations, including R&D, innovative sales ratios, and export shares, are calculated and recorded as a percentage of the final year’s total turnover. It is possible that the firm conducted most of its innovative efforts at the beginning of the survey period, paving the way for a change in export shares throughout the final year of the survey period. Even though the time lag is short (3 years), the possibility of an innovative activity having such an effect cannot be ruled out theoretically. Such a possibility also refers to the existence of a reverse causality from the innovative activity (the right-hand-side variable) to the export measure (left-hand-side variable). This leads to the unreliability of the export ratio as an explanatory variable. Therefore, the preference is made in favour of a qualitative variable, namely, the market that the firm is oriented towards and represented by the largest term. By interacting this variable with the logarithm of the EEVC figures, the variable proxying the repercussions of the BRI is obtained and used in the models. The three interaction coefficients obtained in this way are the main coefficients of interest in this thesis in accordance with the research questions. The descriptions of all variables used in the analyses are listed below in Table 19, with particular reference to the block they are used.

Table 19. Set of Variables used in the Models

Description of the Variable	**Variable Name**	**1.Block**	**2.Block**	**3.Block**
Expenditure on R&D Activity in Total Turnover	R&D Expenditure	+	-	-
Existence of Intramural R&D Activity	rdintrayes	+	-	-
Turnover from the Sale of Innovation Output New to the Market	turn	-	+	-
Introduction of Innovation Output New to the Market	newmkt	-	+	-
Productivity Growth	prod_growth	-	-	+
Sample Country's Country Code	origin_code- "cc" in models	+	+	+
Sectoral Code in Nace Rev.2 Classification	sector_code- "sc" in models	+	+	+
Size Group of the Number of Employees	size	+	+	+
The Market Providing the Largest Turnover to the Firm	largest	+	+	+
Expected Export Volume Change -EEVC	BRI	+	+	
Existence of Cooperation in Innovative Activity	co	+	-	
Funding from the Central Government	fungmt	+	-	
Funding from the EU authorities	funeu	+	-	
Funding from Local Authorities	funloc	+	-	
Percentage of the Employees in Different Education Levels	educ	+	-	

Table 19. (continued)

Introduced a new or significantly improved method of production	inpspd	-	+	
Introduction of a new or significantly improved logistic, delivery or distribution system	inpslg	-	+	
Introduction of new methods for producing goods or providing services (including methods for developing goods or services	Innp_pcs_prd	-	+	

Source: CIS (Eurostat) & BRI Global Dataset (World Bank)

As described in the theoretical background, the MMK model used in this thesis relies on the CDM framework, which consists of three blocks that model the innovation input, innovation output, and productivity. Innovation input refers to the expenditure on intramural R&D activity, whereas innovation output refers to the turnover from the sale of innovative production new to the market. In the CDM literature, these terms are used in their intensive forms by dividing them by the number of employees. However, intensity terms cannot be used in this thesis due to the absence of employee numbers in the SUF data. This leads to the use of nominal figures calculated by multiplying the related ratios by the firm's turnover, which is both reported for the last survey year. The formulas for the calculations are depicted in Eq.23-Eq.26. In parallel with the literature, the logarithmic forms of the nominal expenditure and sales turnover figures are used in the analyses.

$$R\&Dexpenditure = Rdintraratio * Turnover \quad (23)$$

$$TurnoverNewtotheMarket = Turnmar * Turnover \quad (24)$$

$$lR\&Dexp = \ln(R\&Dexpenditure) \quad (25)$$

$$lturn = \ln(TurnoverNewtotheMarket) \quad (26)$$

In the second block, the CDM structure and innovation output are modelled. While the second block only models the innovation output, not the related decision in the original CDM; the decision to sell the innovation output new to the market is added as the first equation to the second block of the MMK model. There are three variables in the CIS SUF surveys related to innovation output: dummies and shares of turnover from product innovations new to the market, new to the firm, and turnover from unchanged or marginally modified products. In this study, the turnover from new product innovations to the market is considered the innovation output indicator, as it is the variable that indicates the most variation among the three variables listed above.

In the third block of the MMK framework, productivity growth is modelled despite the dominance of labour productivity in related studies. The formula used to calculate productivity growth is presented in the methodological section.

The descriptive statistics of the variables from each wave of the CIS survey are presented below in Table 20-22. These are the descriptive statistics that pertain to the versions of the series used in the models, except for the BRI variable. The BRI variable's descriptive statistics refer to those series obtained after merging the CIS data with the EEVC series.

Table 20. Descriptive Statistics for the Variables in 2014 CIS

Variable	Obs	Mean	Std. Dev.	Min	Max
lcont	8,755	12.114	2.306827	-0.0018816	22.68063
rdintrayes	22,672	0.3861591	0.4868785	0	1
fungmt	21,882	0.186089	0.3891874	0	1
funloc	21,882	0.0832191	0.2762194	0	1
funeu	21,882	0.1070286	0.3091567	0	1
co	16,316	0.3579309	0.4794063	0	1
size	22,672	1.599241	0.7135403	1	3
largest	16,122	1.298908	0.5665533	1	3
BRI	22,672	4.49142	4.174453	0.0000001	23.88394
lBRI	22,672	1.100711	1.285325	-16.1181	3.173206
empud	20,177	2.382663	1.532661	0	6
newmkt	11,596	0.485771	0.499819	0	1
lturn	5,633	14.04611	2.304438	5.408158	22.9523
inpspd	11,198	0.4832113	0.4997404	0	1
inpslg	11,198	0.174674	0.379705	0	1
inpssu	11,198	0.2889802	0.4533089	0	1
turn_growth	11,131	0.1505166	0.8769241	-1	57.1
emp_growth	11,131	0.0571469	0.3084119	-1	2.083333
prod_growth	11,131	0.0571469	0.3084119	-1	2.083333

Source: CIS Data and Author's Calculations

Table 21. Descriptive Statistics for the Variables in 2016 CIS

Variable	Obs	Mean	Std. Dev.	Min	Max
lcont	8,144	10.79195	2.814803	-0.0007832	19.15557
rdintrayes	24,746	0.3291037	0.4698972	0	1
fungmt	23,462	0.1672918	0.3732441	0	1
funloc	23,462	0.0736084	0.2611381	0	1
funeu	23,462	0.1153781	0.3194844	0	1

Table 21. (continued)

co	17,849	0.3370497	0.4727153	0	1
size	24,746	1.549624	0.6983386	1	3
largest	17,651	1.291712	0.5589842	1	3
BRI	24,746	4.473773	4.183899	0.0000001	23.88394
lBRI	24,746	1.102421	1.261714	-16.1181	3.173206
empud	23,855	2.399036	1.526774	0	6
newmkt	11,994	0.443305	0.496796	0	1
lturn	5,317	14.06474	2.322033	3.862833	24.27001
inpspd	11,548	0.503204	0.5000114	0	1
inpslg	11,548	0.1829754	0.3866631	0	1
inpssu	11,548	0.300052	0.4583001	0	1
turn_growth	11,556	0.1804517	0.7772264	-1	34.9
emp_growth	11,556	0.1610678	0.8826024	-0.9	20
prod_growth	11,556	0.0511038	0.299098	-1	2.272727

Table 22. Descriptive Statistics for the Variables in 2018 CIS

Variable	Obs	Mean	Std. Dev.	Min	Max
lcont	9,459	11.9765	2.204386	1.097867	22.46817
rdintrayes	40,139	0.2346346	0.4237755	0	1
fungmt	36,263	0.0943662	0.2923415	0	1
funloc	36,433	0.0858013	0.2800743	0	1
funeu	36,304	0.0937913	0.2915422	0	1
co	38,522	0.1122735	0.3157068	0	1
size	40,139	1.498742	0.6747565	1	3
largest	34,590	1.266551	0.5236437	1	3
BRI	40,139	4.490199	4.260463	0.0000001	23.88394
lBRI	40,139	1.129283	1.141908	-16.1181	3.173206
empud	23,174	3.078838	1.481032	0	6
newmkt	13,388	0.4424858	0.4966997	0	1
lturn	5,923	13.58983	2.102711	1.88707	23.24699
inno_pcs_prd	13,286	0.5516333	0.4973456	0	1
turn_growth	12,941	0.2489916	1.223982	-1	54.5
emp_growth	12,941	0.1885403	0.9958411	-0.9	20
prod_growth	12,941	0.0814789	0.3388384	-1	2.6

Source: CIS Data and Author’s Calculations

5.2. Description of the Data Used in Models With Spatial Dependence

As stated earlier, one of the most significant contributions of this thesis to the literature is the extension of the traditional CDM (MMK) framework by incorporating spatial effects into the equations within each block of the framework. Since the MMK framework relies on the use of firm-level data, incorporating spatial dependence involves utilizing firm-level weight matrices that indicate the weighted links between firms based on specific definitions of proximity or similarity.

There are different types of weight matrices, as depicted in Table 20, which are used in the studies. In this thesis, distance-based and technical dependency (economic linkage)-based weight matrices are employed to model the nexus of R&D, innovation, and productivity among firms in a spatial context. These two weight matrices are among the mostly used weight matrices in the literature.

Table 23. Types of Weight Matrices Used in the Spatial Analyses

Type	Basis of Connectivity	Weight Structure	Common Use Cases	Notes
Contiguity Matrix	Geographic adjacency	Binary (0/1)	Regional studies, policy spillovers	Queen (shared edge/vertex), Rook (shared edge)
Distance-Based Matrix	Geographic distance	Continuous (e.g., inverse or exponential decay)	Gravity models, spatial autoregression	Can be thresholded or use k-nearest neighbors
K-Nearest Neighbors (KNN)	Nearest neighbors by distance	Binary or weighted (e.g., inverse distance)	Urban/regional firm analysis	Each unit connected to its k nearest units
Economic Flow Matrix	Trade, FDI, or input-output flows	Weighted (e.g., volume or share of trade)	Input-output analysis, technological dependence	Often sectoral/country-based; derived from WIOD or Eurostat tables
Technological Proximity	Patent citations, R&D similarity	Similarity scores (e.g., cosine similarity)	Innovation, knowledge spillovers	Derived from patent data or R&D profiles
Social Network Matrix	Collaboration or ownership links	Binary or weighted by interaction strength	Firm alliances, co-invention networks	Useful in firm-level and innovation studies
Spatial-Economic Matrix	Combined geography + economics	Hybrid (e.g., geographically weighted IO flows)	Regional innovation, spatial spillovers	Incorporates both spatial and economic proximity
Custom/Empirical Matrix	Based on surveys or models	Varies	Policy simulations, CIS data	Often hand-crafted from empirical responses (e.g., CIS, RISIS, etc.)

Source: LeSage and Pace (2009), Elhorst (2014).

5.2.1. Construction of the Geographical Proximity Matrix

Since the CIS SUF data does not provide location information for the firms (even at the NUTS2 level), a geographical weight matrix can only be constructed using the country information for the firms. In this respect, the distances between the capital cities of the sample countries are calculated using their latitude and longitude information obtained from the Geodata provided by Eurostat.[117] The list of the capital cities used in the analyses is depicted in Table 24.

[117] The GEODATA datasets can be accessed through https://ec.europa.eu/eurostat/web/gisco/geodata/administrative-units/countries

Table 24. Capital Cities of the Countries Included in the Analyses

Country	Capital City
Bulgaria	Sofia
Czech Republic	Prague
Germany	Berlin
Estonia	Tallinn
Spain	Madrid
Greece	Athens
Croatia	Zagreb
Hungary	Budapest
Lithuania	Vilnius
Latvia	Riga
Portugal	Lisbon
Slovakia	Bratislava

The geodesic distances, dij, are calculated by the great circle formula using the longitude and latitude information. The distances need to be inverted as presented in the following equation, as higher distances represent firms that are further away, implying lower shares in the weight matrix. The inverse distance- based matrix has diagonals of zero by construction.

$$w_{ij} = \frac{\frac{1}{d_{ij}}}{\left[\sum_j \frac{1}{d_{ij}}\right]} \quad \textbf{(47)}$$

5.2.2. Construction of the Economic Proximity (Linkage) Matrix

The economic proximity captured by technological dependence among sectors is reflected in the analyses of spatial econometric models. In this thesis, a firm-level weight matrix is constructed using Eurostat's FIGARO tables, which cover EU's inter-country input-output tables.[118]The input-output table for 2011 is used in this construction, following the logic behind the construction of the EEVC indicator. Since the 2014 CIS covers the responses from 2012, 2013, and 2014, a year before this coverage is chosen to avoid possible endogenous effects.

The input-output table's columns and rows are named with country-sector combinations. In line with the rationale of input-output tables, each cell wij indicates the contribution made by the country-sector combination in column j to the

[118] Eurostat. ESA Supply, Use and Input-Output Tables. European Commission. Accessible through https://ec.europa.eu/eurostat/web/esa-supply-use-input-tables/database

production of the country-sector combination in row i. The weights are computed as the share of each cell in the total output of row i, consistent with a Hirschman-type structure. For the analyses, a normalized version of the firm-level weight matrix is employed.

$$w_{ij} = \frac{x_{ij}}{\sum_j x_{ij}} \quad , \quad \text{where } x_{ij} = \text{ the input from j in the production of j.} \tag{48}$$

In this thesis, input-output data for 12 countries and 24 sectors in 2011 are downloaded, and a basic weight matrix with 288 rows and columns is obtained. These sectors are listed in Table 25.

Table 25. Analyzed Sectors in the Eurostat Input-Output Tables

Eurostat Input-Output Sectors
Crop and animal production, hunting and related service activities
Forestry and logging
Fishing and aquaculture
Mining and quarrying
Manufacture of food products; beverages and tobacco products
Manufacture of textiles, wearing apparel, leather and related products
Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
Manufacture of paper and paper products
Printing and reproduction of recorded media
Manufacture of coke and refined petroleum products
Manufacture of chemicals and chemical products
Manufacture of basic pharmaceutical products and pharmaceutical preparations
Manufacture of rubber and plastic products
Manufacture of other non-metallic mineral products
Manufacture of basic metals
Manufacture of fabricated metal products, except machinery and equipment
Manufacture of computer, electronic and optical products
Manufacture of electrical equipment
Manufacture of machinery and equipment n.e.c.
Manufacture of motor vehicles, trailers and semi-trailers
Manufacture of other transport equipment
Manufacture of furniture; other manufacturing
Repair and installation of machinery and equipment
Electricity, gas, steam and air conditioning supply

CIS surveys are also built upon the NACE Rev.2 classification. Yet, some of the sectors in Table 49 correspond to the same NACE Rev. 2 two-digit sector, requiring an aggregation in sector classifications. In addition, the dual use of sectoral classification in the SUF data with nace_a and nace_b necessitates further aggregation, as nace_b has a broader coverage than nace_a. Ultimately, 29 sectors are used in the weight matrix, and a basic weight matrix with a dimension of [348, 348] is constructed, as depicted in Table 26.

Table 26. Sectoral Correspondence Between the Input-Output Tables and the CIS SUF Data

Eurostat Input-Output Sectors	**Nace_A**	**Nace_B**
Crop and animal production, hunting and related service activities	01-03	01-03
Forestry and logging	01-03	01-03
Fishing and aquaculture	01-03	01-03
Mining and quarrying	05-09	05-09
Manufacture of food products; beverages and tobacco products	10-12	10-12
Manufacture of textiles, wearing apparel, leather and related products	13	13-15
Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	16	16-17
Manufacture of paper and paper products	17	16-17
Printing and reproduction of recorded media	18	18
Manufacture of coke and refined petroleum products	19-20	19-21
Manufacture of chemicals and chemical products	19-20	19-21
Manufacture of basic pharmaceutical products and pharmaceutical preparations	21	19-21
Manufacture of rubber and plastic products	22	22-23
Manufacture of other non-metallic mineral products	23	22-23
Manufacture of basic metals	24	24-25
Manufacture of fabricated metal products, except machinery and equipment	25	24-25
Manufacture of computer, electronic and optical products	26	26-28
Manufacture of electrical equipment	27	26-28
Manufacture of machinery and equipment n.e.c.	28	26-28
Manufacture of motor vehicles, trailers and semi-trailers	29	29-30
Manufacture of other transport equipment	30	29-30
Manufacture of furniture; other manufacturing	31	31-32
Repair and installation of machinery and equipment	33	33
Electricity, gas, steam and air conditioning supply	35	35

Source: Author's Calculations

The enlargement of the weight matrix covering nace_b is also made for the countries that do not provide data in nace_b in the CIS SUF data. For instance, Bulgaria provides data in the NACE A classification, but it has rows and columns defined in the NACE B format. If these rows and columns were not included, the weight matrix would not be a square matrix, which is essential for the analysis. The enlargement made in this manner does not cause any problems in the construction of the firm-level weight matrix, since those rows in the weight matrix are not transmitted to it. In other words, the weight matrix can include rows and columns for a sector-country pair in the sector definition not used by that country. Those rows and columns are omitted from the firm-level weight matrix as they have no correspondence in the firm data. The firm-level weight matrix is constructed as follows.

5.2.3. Construction of the Firm-Level Weight Matrix

After constructing these weight matrices with their original data, they need to be extended to the firms in the sample. To extend the geographical weight matrix to the sample firms, a mapping is defined from each firm to the weight matrix of the country in which the firm is located. In extension of the economic linkage matrix, a sector-country index is defined for each firm in the sample firm data and each sector-country combination in the economic linkage matrix. In this way, the weight matrices are extended to the firm level and are called firm weight matrices.[119] Both matrices are row-normalized so that weights in each row sum up to 1. In doing so, proportional weights are obtained, preventing the dominance of particular neighbours. Whether the matrices need to possess symmetry is also another point considered in the studies. Symmetry of the weight matrix is not a prerequisite for all types of spatial models, and row standardization breaks the symmetry of the matrices. Both of the matrices in this study are not symmetrical by construction. However, the weight matrix, which depends on the economic linkage, is forced to be symmetric by taking the averages of the weights in mirroring cells of the matrix. The weight matrices are modified before they are used in the models. The reasons behind these modifications and the process by which they are made are explained in the following section.

5.2.3.1. Modifications to the Weight Matrix

As stated above, the weight matrices are transformed before they are used in the models. The primary reason behind these modifications is the sparsity of the firm-level weight matrix, which refers to the observation that most of the elements are

[119] In both the original econometric proximity matrix and the original firm data, a new column, named **sector_country_index**, combining the sector-code (covering 29 sectors) and country code in each row and column is constructed. The formula for the **sector_country_index** is as follows:
sector_country_index= (country_code -1) * 100 + sector_code
This index is used for mapping with firm-level data to the economic proximity matrix. To map with the geographical matrix, only country codes are used.

zero. This sparsity, combined with the large firm size for every period, has resulted in a significant burden in terms of the time required to compute the models, as well as convergence problems. Additionally, Le Sage and Pace (2009) note that the high number of zeros results in local imprecision and inefficiency in capturing localized spillovers. The matrices are modified as follows:

5.2.3.1.1. The Modification of the Weight Matrix Depending on Geographical Distance

A two-step sparsification procedure is applied to the firm-level weight matrix, constructed based on the inverse distances among the capital cities of the countries in the analysis. First, a **top-*k* selection** is implemented, such that only the *k* largest weights in each row of the matrix are kept. Second, a **magnitude-based thresholding** is applied, setting all remaining weights with absolute values below 0.000001 to zero. This process yields a sparse, asymmetric, and row-standardized matrix that highlights strong spatial linkages while maintaining compatibility with sparse matrix algorithms. Following LeSage and Pace (2009), k is selected as 6.[120]

5.2.3.1.2. The Transformation of the Weight Matrix Depending on Technological Dependence

A **magnitude-based thresholding** is also applied on the cells, such that where all elements with absolute values below 0.03, i.e. mean of the original weight matrix's cells, are set zero. This value is chosen by trying values starting with 0.01. The search is stopped at 0.002, as this value allows all spatial models to be estimated, even though the standard errors of some coefficients may still not be estimated. The purpose is to maintain as many cells as possible in the weight matrix. The matrix is finally row-standardized.

The use of spatial econometric techniques necessitates a certain method for estimation. Their compatibility with the sparse matrices and methodological description are listed in Table 27 below.

[120] Le Sage and Pace (2009) frequently uses the 6-nearest neighbors approach.

Table 27. Estimation Methods and Structural Requirements of the Spatial Weight Matrix

Method	Requires Symmetric W	Sparse Matrix Compatible	Description
eigen	-	-	Compatible with full eigenvalue decomposition of the weight matrix. Suitable for small/medium datasets. Works with asymmetric and dense matrices.
Matrix	+	+	Uses sparse matrix Cholesky factorization (via Matrix package). Fast for symmetric sparse matrices.
LU	+	+	Uses LU decomposition from sparse matrix solvers. Very efficient for large symmetric sparse matrices.
Chebyshev	+	+	Uses Chebyshev polynomial approximation for very large matrices. Approximate method — useful for very large-scale data.

Source: Le Sage and Pace (2009)

CHAPTER 6

METHODOLOGY

In this part of the thesis, the methodological approaches used in both types of analyses are presented respectively. In this vein, the models constructed under each block of the MMK framework, excluding spatial dependence, are presented first. Following that, models built to account for spatial dependence are presented, along with their estimation approaches. Since the broad structure of the MMK framework was described in detail in previous sections, the models constructed are presented in this section. In the second part, spatial models are briefly presented before the introduction of the models built and estimation techniques.

6.1. Construction of Models under the MMK Framework without Spatial Dependence

The primary objective of this study is to assess the impact of the anticipated BRI-led trade cost reductions on the innovativeness of selected European firms. While the primary focus is on whether there is a significant relationship between innovativeness and the BRI's expected trade volume impact, obtaining a correlation that changes over time, i.e., from the 2014 CIS survey period to the 2018 CIS, refers to the second research question of the thesis, which investigates whether there are changes in the impact of the BRI across different survey periods. Since each CIS covers the two previous years, the analyses in this study, which span the period from 2014 to 2018, encompass the period from 2012 to 2018, including the commencement of the BRI in 2013. Therefore, the setup mainly relies on estimating the **same** models for each survey period and comparing their findings. The variables of interest in the study are the EEVC and the *largest* market information from which the firm obtains its highest turnover. While the latter is added to the models as a categorical variable, the former is used in logarithmic form to diminish the skewness and facilitate the interpretation of the results. Moreover, these two terms are interactively incorporated into the model, as the impact of transportation infrastructure is highly related to the distance of the trade partner, the mode of transportation, and the product sector. In this study, we differentiate firms according to their most significant market, i.e. their market orientation, considering that the more distant their partner, the greater the impact of the BRI on the firm's innovative performance. Therefore, the interaction of BRI and the *largest* term is added to the models in all blocks. The significance and the strength of the differences in coefficients (across surveys) are the primary focus of the analysis while checking for the significance and plausibility of the conventional coefficients in the CDM models.[121] The EEVC (BRI) term, on the other hand, can be considered similar to a country-sector fixed effect due to its construction.

By building a setup that relies on cross-sectional analyses separately for the 2014, 2016 and 2018 CIS periods, the time dimension lost due to the non-longitudinal structure of the data is partially compensated. As stated above, CIS data is not longitudinal.

Due to the data format, one of the most required variables, the number of employees, is provided in size groups, making it impossible to calculate a firm's labour productivity and the intensity terms (per employee) for R&D and innovation, which are the most commonly used dependent variables in CDM studies. As stated in the data section, the dependent variables related to R&D and innovation are the expenditures on these activities, which are calculated by multiplying the ratio of the related expenditure (or share of turnover from sales) to total turnover by the total turnover, as follows.[122]

[121] As shall be presented below, some coefficients are found to be against the theoretical background of the model such as negative coefficient of the predicted R&D ratio term found in the second block. Yet still for the continuity in the analysis, the use of the interaction term is not abandoned as the study's primary aim is to catch the differences with respect to the largest market.

[122] Turnover is defined as the market sales of goods and services. The figures include all taxes except the value added tax. For credit institutions, the turnover is the sum of interests receivable and similar income.

$$R\&D\ Expenditure(Turnover\ from\ innovative\ sales) = rdintraratio * (turnmar)turnover \quad \textbf{(27)}$$

On the other hand, the Eurostat SUF data provides turnover and employment growth rates between the first and last year of the survey period. As labour productivity cannot be calculated, productivity growth is used in the third block of the MMK model. The formula for productivity growth is presented in Eq. 28. Instead of using the difference between turnover growth and employment growth, this specification is employed to mitigate the excessive values of turnover growth that can be observed for observations with zero employment growth.

$$Productivity\ Growth = \left(\frac{Turnover\ Growth - Employment\ Growth}{Employment\ Growth + 1}\right) \quad \textbf{(28)}$$

As a result, a significantly augmented version of the original CDM model is obtained. The differences mainly refer to ratio terms instead of intensity terms, and productivity growth is also considered, in addition to the use of the MKK model. The models and the variables used in estimations are described in more detail in the next section.

Lastly, the findings from these models should be considered as causal inferences, as panel data estimation techniques cannot be used and CIS data have not been merged with any other firm data, which paves the way for the omitted variable problem. For the sake of readability, the narrative has been structured to include directional statements. Yet, under such data constraints, stressing causality would be overbearing. The representation of the existence of a relationship between the dependent and explanatory variables suffices within the scope of this thesis.

The CDM model comprises three stages to explain the R&D-innovation-productivity framework. In this study, we build on the conventional CDM model and utilise the MMK model, as the decision to innovate should not be disregarded when analysing the impact of innovation input on innovation output. Under the MMK model, the number of equations in the framework increases to 5 by default. Therefore, the minimum number of equations per CIS survey is five, resulting in a total of 15 equations.The models are constructed for each survey period; however, country coverages may differ due to data availability issues. For instance, for the 2018 CIS analyses, both Spain and the Czech Republic are excluded since the *empud* variable is absent for these countries in the 2018 CIS. The final models for each block in the MMK model are explained below:

6.1.1. First Block: Modelling Innovation Input, i.e the R&D Decision and the Ratio of Intramural R&D Expenditure

$$rdintrayes_i = \begin{Bmatrix} 1 \; if \; rd_i^* = C + \beta_1 cc + \beta_2 sc + \beta_3 size + \beta_4 co + \beta_5 fungmt + \beta_6 funeu + \beta_7 funloc + \beta_8 i.largest * c.lBRI + \beta_9 i.empud + u_i > 0 \\ 0 \; if \; rd_i^* = C + \beta_1 cc + \beta_2 sc + \beta_3 size + \beta_4 co + \beta_5 fungmt + \beta_6 funeu + \beta_7 funloc + \beta_8 i.largest + \beta_8 i.largestc.lBRI + \beta_9 i.empud + u_i \leq 0 \end{Bmatrix} \tag{29}$$

$$lR\&Dexp_i = \begin{Bmatrix} ird_i^* = C + \beta_1 ccode + \beta_2 scode + \beta_3 size + \beta_4 coop + \beta_5 fungmt + \beta_6 funeu + \beta_7 funloc + \beta_8 i.largest * c.lBRI + v_i \; if \; rdintrayes_i = 1 \\ ird_i^* = 0 \; if \; rdintrayes_i = 0 \end{Bmatrix} \tag{30}$$

In the first model in the block, the decision to engage in intramural R&D is modelled using Eq. 29. The dependent variable, rdintrayes, indicates whether the firm has undertaken intramural R&D activity. In line with the selection problem observed in innovation data, firms may have intramural R&D activity that was not reported in the survey. Therefore, a latent variable, ird_i^* ,is calculated such that the firm is labelled to conduct R&D activity if rd* is greater than zero and labelled to have no R&D activity if the latent variable is equal to zero. Eq.30 models the logarithm of the R&D expenditure, $lR\&Dexp_i$,on intramural R&D activity and $ird_i^*$is the latent variable for the share of the R&D expenditure. If the latent variable of the first equation leads to the affirmative decision with *rdintrayes* taking the value of 1, then $lR\&Dexp_i = ird_i^* =$. Therefore, the first equation is modelled for all firms, as the use of the Heckman selection two-step procedure (described below) also considers the behaviour of firms not engaging in R&D intramural activity in the first step. The second equation, however, is estimated for firms that engage in R&D activity. That is, if the latent value is found to be less than or equal to zero, those firms are not included in the second model. Another distinction between the first and the second models is that the *empud* variable is used only in the first one.

The error terms of the two models, and are assumed to have joint normal distribution with zero mean and unit variance as follows:

$$\begin{pmatrix} u_i \\ v_i \end{pmatrix} \sim \mathrm{N}\left(\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}\right), \begin{bmatrix} 1 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & 1 \end{bmatrix}\right)$$

Following the literature, the explanatory variables in both equations are the size group of the firm, the existence of cooperation in innovative activity, different types of funding provided for the innovative activity and the *largest* variable indicating the orientation market of the firm, i.e. the market that the firm obtains the highest turnover, and the interaction term of the *largest* variable and the impact of the BRI-led trade cost declines. In addition to these variables, the variable on tertiary education of the firms is added to the first, i.e. selection, equation. For both equations, country and fixed effects are added to the models.

6.1.2. Second Block: Modelling Innovation Output, i.e Turnover from the Sales of Innovative Output New to the Market

In the second block of the analysis, the predicted values of the dependent variables in the first block are used as latent variables in the equations.

Due to the use of different variables for assessing the existence of process innovation in the production process in the 2014, 2016, and 2018 CIS surveys, the explanatory variables in the second block differ as follows.[123] As suggested by the MMK model, the decision to introduce the innovation output to the market (newmkt=1), is also modelled before modelling the turnover from the innovative sales. In the second block equations, the latent variables of the probability of the firm engaging in R&D activity and the R&D expenditures are used in the first and second equations, respectively. Similar to the models in the first block, the second equation in this block also depends on the latent (predicted) value from the first equation in this block. Namely, the level of turnover from innovative sales is equal to its observed

[123] However, the interpretation of the coefficients is the same. Both of them refer to the existence of process innovation that improves the production processes.

value if the firm is found to introduce its innovative output to new markets, i.e. mkt^* is found to be greater than zero making *newmkt* equal to one. Otherwise, it is zero.

6.1.2.1. Models for the 2014 and 2016 CIS Surveys

(31)

$$newmkt_i = \begin{cases} 1 \; if \; mkt_i^* = C + \beta_1 \, ccode + \beta_2 \, scode + \beta_3 \, size + \beta_4 \, coop + \beta_5 \, inpspd + \beta_6 \, inpslg + \beta_7 \, inpssu + \beta_7 \; rd_i^* + \beta_8 \, i.largest * c.BRI + z_i > \\ 0 \; if \; mkt_i^* = C + \beta_1 \, ccode + \beta_2 \, scode + \beta_3 \, size + \beta_4 \, coop + \beta_5 \, inpspd + \beta_6 \, inpslg + \beta_7 \, inpssu + \beta_7 \; rd_i^* + \beta_8 \, i.largest * c.lBRI + z_i \leq \end{cases}$$

(32)

$$lturn_i = \begin{cases} lturnlat_i = C + \beta_1 \, ccode + \beta_2 \, scode + \beta_3 \, size + \beta_4 \, coop + \beta_5 \, inpspd + \beta_6 \, inpslg + \beta_7 \, inpssu + \beta_7 \; ird_i^* + \beta_8 \, i.largest * c.leffect2 + \\ lturnlat_i = 0 \; if \; newmkt_i = 0 \end{cases}$$

6.1.2.2. Models for the 2018 CIS Survey

(33)

$$newmkt_i = \begin{Bmatrix} 1 \; if \; mkt_i^* = C + \beta_1 \, ccode + \beta_2 \, scode + \beta_3 \, size + \beta_4 \, inno_{prd_{gd}} + \beta_5 \; rd_i^* + \beta_6 \, i.largest * c.lBRI + m_i > 0 \\ 0 \; if \; mkt_i^* = C + \beta_1 \, ccode + \beta_2 \, scode + \beta_3 \, size + \beta_4 \, inno_{prd_{gd}} + \beta_5 \; rd_i^* + \beta_6 \, i.largest * c.lBRI + m_i \leq 0 \end{Bmatrix}$$

(34)

$$lturn_i = \begin{Bmatrix} lturnlat_i = C + \beta_1 \, ccode + \beta_2 \, scode + \beta_3 \, size + \beta_4 \, inno_{prd_{gd}} + \beta_5 \; rd_i^* + \beta_6 \, i.largest * c.lBRI + n_i \; if \; newmkt_i = 1 \\ lturnlat_i = 0 \; if \; newmkt_i = 0 \end{Bmatrix}$$

6.1.3. Third Block: Modelling Productivity Growth

The third block of the model is not estimated using labour productivity because the number of employees is not available in the CIS SUF data. Still using the predicted (latent) values of the shares of turnover from innovative sales new to the market, which are used to explain the productivity growth calculated in Eq.35. The predicted values are estimated as the latent value of a variable in logarithmic form (lturn). In contrast, the raw value of the productivity growth is used in the models. The model is estimated using Ordinary Least Squares (OLS) with robust standard errors that account for both heteroskedasticity and autocorrelation. In estimating this regression, the firm's expenditure on physical capital and machinery is also used as an explanatory variable. Additionally, observations beyond the 99th percentile of the prod_growth series are removed as outliers. Eq.35 also includes the firm’s expenditure on physical capital and machinery in logarithmic form. Similar to the expenditure on R&D activities, the expenditure on physical capital and machinery is calculated by multiplying the reported ratio of this expenditure by the firm's turnover. It should once again be emphasised that, due to the lack of data on the number of employees, this thesis cannot employ labour productivity in the third block of the analyses.

On the other hand, the thesis aims to make inferences about the nexus between R&D, innovation, and productivity, which is a core part of the innovation ecosystem. Due to the use of productivity growth, rather than productivity itself (with any definition), in the last block of the analyses, this thesis refrains from making strong inferences about EU productivity. Instead, the focus is kept on the first two blocks of the framework, which provides significant insight into the EU policymaking. Similar to the attitude in the first two blocks, the interaction term of the BRI is still added to the regression to investigate the existence of any direct effect from the BRI implications on productivity.

$$prod\_growth = C + \beta_1 lturn_i + \beta_2 i.largest_i + \beta_3 i.largest_i * c.lBRI + \beta_4 ccode + \beta_5 sc + \beta_6 lmac_i + v_i \tag{35}$$

6.1.4. Estimation Method

This thesis employs the Heckman procedure to estimate latent variables that may not be directly observed due to selection and sample selection biases. Although most studies in the CDM literature employ generalised Tobit models for estimation, this study prefers to use the Heckman selection model due to the requirement for incorporating the impact of BRI-led trade costs on the selection process. Tobit models do not allow for an explicit presentation of the selection and main equation. Yet, with the Heckman procedure, the selection equation can be differentiated.

Like the Tobit models, the Heckman procedure acknowledges that some observations of the dependent variable are not reported. Yet the main reason for selection bias in the Heckman procedure is not censoring, as it is in Tobit models.

Firms might deliberately hide their innovative activities. By estimating the probability of their observance (i.e., being selected), the missing, or unobserved, values of the dependent variable can be calculated (Heckman, 1979). The Heckman procedure can be estimated in two ways: with maximum likelihood estimation or with the Heckman two-step procedure. In this thesis, Heckman two-step procedure is preferred due to 2 reasons (Nawata, 1994):

1. Two-step estimation is less sensitive to the non-normality of the dependent variable; however, the non-normal errors obtained after estimation still matter and may cause bias. Therefore, the distribution of the errors should still be checked. The bias that could be created is checked for using bootstrapping. On the other hand, Heckman's 2-step procedure has some drawbacks such as the lower efficiency obtained for the coefficients (Heckman, 1979). Additionally, standard errors may be inconsistent and require correction through bootstrapping.
2. Two-step estimation is easier to estimate for large samples. Considering that the sample size is greater than 5000 in each model, convergency problems in the MLE estimation are avoided by the Heckman 2-step procedure.

The Heckman 2-step estimation involves two stages of estimation. In the first stage, a probit model is estimated using the selection variable as the dependent variable. Out of this estimation, the Inverse Mills Ratio (IMR) is calculated from this model as follows:

$$\Lambda(z) = \frac{\phi(z)}{\Phi(z)} \qquad \textbf{(36)}$$

where

$z=Z\gamma$ is the linear predictor from the probit model (i.e., the selection equation),
$\phi(z)$ is the standard normal probability density function (PDF),
$\Phi(z)$ is the standard normal cumulative distribution function (CDF).

This IMR, obtained from the probit model design, designates the expected value of the error term in the outcome equation, given the condition of being selected. In other words, the probability of being selected is estimated to be greater than 0 in the probit estimation. In the selected sample, the error term does not have a mean of zero, and as the procedure inserts IMR into the main model, this bias is corrected. The main equation is estimated with OLS by inserting the IMR as an additional variable.

The two-step estimation (in Stata) provides the IMR and its significance in the main model. If IMR is statistically significant, then this indicates that the inclusion is necessary, i.e. selection bias exists. If IMR is not significant, then selection bias is not a significant problem and does not mandate the use of the Heckman procedure. For continuity of the analysis, however, all estimations are performed using the Heckman two-step procedure, considering that the use of this procedure under insignificant selection bias causes minimal harm.

Since the MMK framework relies on the use of the predicted values of R&D expenditure, R&D propensity and the predicted innovation output in the succeeding blocks' equations as an instrumental variable, the instrumental variable estimation also needs to be discussed.

6.2. Models under the MMK Framework without Spatial Dependence

Analyses integrating the spatial dimension can be conducted by focusing on either spatial dependence or spatial heterogeneity (Anselin, 1998). Spatial dependence refers to the functional relationship between economic observations in different spatial points. The spatial heterogeneity, on the other hand, is related to the stability across space. While dependence mostly focuses on distance, heterogeneity focuses on the exact location of the economic unit. The descriptions and specifications of each type of model are described in Elhorst (2014) and LeSage and Pace (2009).

In their seminal paper, LeSage & Pace (2009) state that failure to consider the spatial dimension in analyses would put a dent and sometimes corrupt our ability to comprehend economic developments. This limitation stems from the omitted information, disguised in the error terms of a regression, that is associated with the spatial dimension. This omission would lead to biased estimators and cast a shadow on the reliability of point estimates. The heteroskedasticity that could arise from neglecting the spatial dependence is a prominent example of such undesired outcomes. The neglect of omitted variables also decreases the power of heteroscedasticity tests, further exacerbating the problems with a decreased likelihood of detecting the root problem (Anselin, 1990; Anselin and Ray, 1991).

Spatial econometric methods are extensions of the linear regression model that is possible through three components. The linear regression can be described as follows:

$$y = X\beta + u$$

where y is the dependent variable represented with a matrix of dimension [t,1] where t is the number of observations. X represents the set of explanatory variables with dimension [t,k] where k is the number of explanatory variables. u is the matrix of error terms with dimension [t,1] with i.i.d properties i.e. $\Omega_u = \sigma_u^2 I_n$ where Ωu is the variance-covariance matrix.

Prior to conducting any spatial analysis, it is essential to check for spatial dependence using spatial autocorrelation tests. One of the most prominent tests is the Moran's I test, which is applied after fitting a non-spatial linear regression model such as OLS.

$$I = \frac{N \sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} d_i d_j}{S \sum_{i=1}^{N} d_i^2}$$

In the equation above, N represents number of observations, wij is the element of ith row and jth column in the spatial weight matrix W. Deviations from the mean are measured by $di = yi - \bar{y}$. The Moran statistic, Moran's I, exhibits values ranging between -1 and 1. If neighboring spatial units exhibit the same sign after deviating from the mean, there is positive spatial correlaiton, i.e Moran's I has positive values.

It has negative values when neighboring spatial units exhibit the opposite sign after deviating from the mean, indicating negative spatial dependence.

Before presenting the model used in the estimations, a brief overview of spatial econometric models is provided below, outlining their theoretical foundations and key differences.

6.2.1. Spatial Lag Dependence: Spatial Autoregressive Model (SAR)

The spatial lag dependence model introduces spatial dependence into the dependent variable by adding its spatial lag, i.e., its multiplication with the weight matrix W, with dimension [nxn], to the right-hand side of the regression. In the model scalar ρ is set between -1 and 1 to prevent the model's explosion. This restriction is crucial, as otherwise, the spatially lagged effect of the dependent variable would exceed that of the dependent variable itself. The SAR model and its decomposition is presented as follows. It is seen that the inverse of the W's deduction from the identity matrix is used to obtain the reduced form. The restriction of ρ between limits also ensures the invertibility of the first component in Eq.38. The formation of the model and the likelihood function used to estimate the model are presented between Eq.38- Eq.39.

$$y = \rho W y + X\beta + u \quad \textbf{(37)}$$

$$y = (I_n - \rho W)^{-1}(X\beta + u) \quad \textbf{(38)}$$

$$y = (I_n - \rho W)^{-1} X\beta + (I_n - \rho W)^{-1} u \quad \textbf{(39)}$$

$$\ln(L) = -n/2 * \ln(2\pi\sigma^2) + \ln|I - \rho W| - (1/2\sigma^2) * e'e \quad \textbf{(40)}$$

where: $e = y - \rho Wy - X\beta$.

6.2.2. Spatial Dependence on the Error Term: Spatial Error Model (SEM Model)

The SEM model inserts spatial dependence into the error terms, implying that a random shock to the errors affects both the focal unit and its neighbours. The related equations and the log likelihood function used to estimate the model are presented in Eqs. 41-44.

$$y = X\beta + u \quad \textbf{(41)}$$

$$u = \lambda Wu + \varepsilon = (I_n - \lambda W)^{-1}\varepsilon \quad \textbf{(42)}$$

$$E(\varepsilon) = 0 \quad , \quad V(\varepsilon) = \sigma_\varepsilon^2 I_n \quad \textbf{(43)}$$

$$\ln(L) = -n/2 * \ln(2\pi\sigma^2) + \ln|I - \lambda W| - (1/2\sigma^2) * e'e \quad \textbf{(44)}$$

where: $e = (I - \lambda W)(y - X\beta)$

Similar to the restriction on ρ, there is also a restriction on lambda, $-1<\lambda<1$, to prevent the explosion of the model. The full decomposition of the SEM model is as follows:

$$y = X\beta + (I_n - \lambda W)^{-1}\,\varepsilon = \lambda Wy + X\beta - \lambda WX\beta + \varepsilon \quad \textbf{(45)}$$

λ is the scalar and for the non-explosiveness $-1<\lambda<1$ condition is ensured. Kurtaran (2025) states that the most important difference between the SAR and SEM model is related to the consistency of β estimates. Omitting the spatial dependency of the dependent variable, i.e., ignoring the use of a SAR model, leads to inconsistency and bias problems. However, ignoring the spatial autocorrelation of errors only results in inefficiency as the coefficients of the regressors are concerned.

6.2.3. Mixed Spatial Dependence Models: GNSM, SDM, SDEM, and SARAR

The models presented focus on the inclusion of spatial dependence only with the dependent variable or the error term of the regressions. The following models presented involve exposing the spatial lag to different combinations of these model components as depicted in Table 28. In this thesis, the most generalized form of the spatial model, the GNSM model, is used. The model and the loglikelihood function used to estimate the model can be described as follows:

$$y = \rho Wy + X\beta + \theta WX + u$$

(46)

$$u = \lambda W u + \varepsilon$$

$$\ln(L) = -n/2 * \ln(2\pi\sigma^2) + \ln|I - \rho W| + \ln|I - \lambda W| - (1/2\sigma^2) * e'e$$

$$\text{where: } e = (I - \lambda W)[y - \rho W y - X\beta - WX\theta]$$

Table 28. Types of Mixed Spatial Models

Spatial Durbin Error	$y = X\beta + \theta WX + u \quad u = \lambda W u + \varepsilon$
Spatial Durbin Model (SDM)	$y = \rho W y + X\beta + u \quad u = \lambda W u + \varepsilon$
SARAR model	$y = \rho W y + X\beta + \theta WX + u$

By using the GNSM model, spatial lags are included in all components of the regression. Since this thesis is the first study to incorporate spatial dependence into the conventional CDM framework across all blocks, the preference is made in favour of exposing all components to spatial dependence. In parallel with the first approach, the emphasis is on using the same model across all survey periods to maintain continuity in the analyses and coherence in the thesis.

In this second part of the thesis, the Heckman two-step procedure introduced in the first approach is extended by incorporating spatial dependence into the model. The Heckman two-step procedure involves two steps: the first is a probit estimation, and the second is an OLS regression that includes the inverse Mills ratio, calculated from the probit estimation.

When extending the Heckman procedure to account for spatial dependence, the question arises regarding the step at which the spatial lag should be introduced. In this thesis, the spatial dependence is integrated only into the second part, i.e. the outcome equation of the Heckman procedure. Such a preference is made due to the computational burden encountered in estimating spatial models with discrete variables (Le Sage and Pace, 2009). The sparsity of the weight matrices, particularly the weight matrix constructed using economic linkages, leads to convergence problems in estimation.

The second step of the Heckman procedure, which originally uses OLS, is extended by integrating spatial dependence through the use of one of the spatial estimation models. In doing so, the inverse Mills ratio is used as an explanatory variable in the spatial estimation, in order to proxy the implications of the first step of the Heckman selection procedure.

This thesis is the first study to integrate spatial dependence into **each block** of the CDM (MMK) framework. Additionally, the primary objective of the thesis is to assess the impact of Chinese BRI-led changes in trade volume on the European innovation ecosystem using three waves of the CIS. Since the CIS data is not longitudinal, the time dimension is inserted into the analyses by using three consecutive CIS periods. The three different survey periods exhibit significant variations in their questionnaire structure (particularly between the 2016 and 2018 surveys), leading to obligatory changes in the set of explanatory variables. This in fact poses a threat to the consistency and coherence of the analyses. This is the reasion behind the initial preference for maintaining the same models across survey periods. In the first approach, this is mostly achieved, except for the use of different models in the second block equations. However, in the analyses with spatial dependence, the set of spatially lagged explanatory variables shows variation due to multicollienarity problems.

Despite such a mandated change in the set of spatially lagged explanatory variables, the generalized nesting spatial model that considers spatial dependence for dependent, (selected) independent variables and error terms is used in all models across three survey periods. The most generalised spatial model is used to avoid neglecting any spatiality that may be hidden in one of these parts. As the pioneering study that integrates spatial dependence into the CDM model, it is considered that using the most general form provides a solid foundation for further studies.[124]

$$y = \rho Wy + X\beta + \theta WX + u \qquad \textbf{(49)}$$

$$u = \lambda Wu + \varepsilon$$

$$\text{where } \varepsilon \sim \text{N}(0, \sigma^2\mathbf{I})$$

[124] However, it is evident that alternative types of spatial models also need to be considered when finding the best model for each equation within a specific survey period. Therefore, alternative spatial models, estimated using different model structures, are presented in Appendix A.

As shown in Eq. 49, the spatial lags of the explanatory variables could also be included into the regressions. This preference requires selecting the explanatory variables which would have spatial lags. In line with the main objective of this thesis, the spatial lags of the interaction terms, i.e., the interaction between the BRI effect and the largest market orientation variable, are included in the estimations in every block. In doing so, the level effect of the BRI (EEVC), the *largest* term (indicating the market in which the firm obtains its highest turnover), and the interaction of these terms, along with their spatial lags, are added to the model.[125] In each block, regressions relying on the geographical distance matrix exclude the country-fixed effects due to multicollinearity.

[125] However, in some models either of these variables might need to be dropped due to multicollinearity problems.

CHAPTER 7

EMPIRICAL RESULTS

In this section, the findings from models constructed under the MMK framework, both in the traditional manner and with spatial dependence, are presented respectively. All estimations are performed using bootstrapping, and particular effort is made to ensure model consistency across different survey periods. That is, the same dependent and explanatory variables are used across different survey periods as long as the estimation is allowed for. In models estimated with spatial econometric methods, some explanatory variables are excluded due to multicollinearity. In Appendix A, additional models are presented that cover alternative spatial models.

7.1. Results from Models in Traditional MMK Framework

7.1.1. Results from the First Block Regressions

The findings in Table 29 indicate significant lambda for all survey periods, supporting the use of the Heckman selection procedure. Similarly, as size group of a firm increases, both the tendency to engage in R&D activity and the expenditure on R&D activities increases; which are consistent with the findings of Lööf et al. (2001), Mairesse et al. (2005), Griffith et al. (2006), and Doyar (2023). It should be highligthed that in this thesis, the nominal level of the R&D expenditure is used as the dependent variable, unlike most studies in the literature. Studies such as Cohen and Klepper (1996) distinguish the impact of firm size on R&D propensity and intensity, stating that size may affect only the former. This proposition is also supported by Crépon et al. (1998), the seminal work on the CDM framework. Since this thesis does (can) not use the intensity terms, size coefficients remain significant, with a notably higher impact observed for the largest firms. The propensity of firms to engage in R&D activity also increases as they cooperate with other firms and get funding from external sources. However, such positive effects are not observed in the outcome equation, i.e. on the expenditure on R&D activities, except for the impact of funding from EU programs. These findings align with those of Hashi and Stojcic (2013) and Mairesse et al. (2005).

Table 29. Results from the First Block Regressions

	2014	**2016**	**2018**	**2014**	**2016**	**2018**	**2014**	**2016**	**2018**
	Selection Equation	**Selection Equation**	**Selection Equation**	**Selection Equation**	**Selection Equation**	**Selection Equation**	**Share Equation**	**Share Equation**	**Share Equation**
	rdintrayes	rdintrayes	rdintrayes	rdintrayes	rdintrayes	rdintrayes	l(R&Dexp)	l(R&Dexp)	l(R&Dexp)
	β	*β*	*β*	*β*=dy/dx	*β*=dy/dx	*β*=dy/dx	*β*=dy/dx	*β*=dy/dx	*β*=dy/dx
size									
Less than 50	***Base***	***Base***	***Base***	***Base***	***Base***	***Base***	***Base***	***Base***	***Base***
50-249	0.312*** (0.035)	0.183*** (0.033)	0.375*** (0.0303)	0.087*** (0.010)	0.055*** (0.010)	0.053*** (0.005)	0.869*** (0.064)	0.895*** (0.063)	0.822*** (0.0881)
250 and more	0.660*** (0.054)	0.379*** (0.049)	0.715*** (0.0513)	0.188*** (0.016)	0.115*** (0.015)	0.117*** (0.010)	2.555*** (0.102)	2.356*** (0.090)	2.074*** (0.132)
coop	0.670*** (0.035)	0.575*** (0.032)	1.700*** (0.0459)	0.182*** (0.009)	0.170*** (0.009)	0.228*** (0.005)	-0.065 (0.091)	-0.079 (0.081)	0.107 (0.223)
fungmt	0.640*** (0.038)	0.572*** (0.037)	0.341*** (0.0453)	0.174*** (0.010)	0.169*** (0.011)	0.046*** (0.006)	0.110 (0.090)	0.174** (0.077)	0.135 (0.0914)
funloc	0.398*** (0.061)	0.401*** (0.062)	0.0994 (0.0624)	0.108*** (0.016)	0.118*** (0.018)	0.013* (0.008)	0.086 (0.083)	-0.125 (0.093)	0.0438 (0.114)
funeu	0.215*** (0.047)	0.082** (0.040)	0.515*** (0.0402)	0.058*** (0.013)	0.024** (0.012)	0.069*** (0.005)	0.327*** (0.078)	0.326*** (0.072)	0.129 (0.101)
empud									
1	0.143** (0.066)	0.201*** (0.064)	0.410*** (0.0710)	0.037** (0.017)	0.055*** (0.018)	0.036*** (0.006)			
2	0.344*** (0.063)	0.374*** (0.064)	0.690*** (0.0744)	0.092*** (0.016)	0.106*** (0.017)	0.071*** (0.007)			
3	0.539*** (0.059)	0.564*** (0.059)	0.876*** (0.0723)	0.148*** (0.015)	0.165*** (0.016)	0.100*** (0.007)			
4	0.740*** (0.068)	0.798*** (0.065)	1.007*** (0.0786)	0.208*** (0.018)	0.239*** (0.019)	0.124*** (0.009)			
5	0.899*** (0.092)	0.894*** (0.088)	0.941*** (0.0936)	0.255*** (0.026)	0.270*** (0.026)	0.112*** (0.012)			
6	0.715*** (0.111)	1.218*** (0.111)	1.218*** (0.108)	0.200*** (0.030)	0.372*** (0.033)	0.168*** (0.019)			
lBRI	-0.096** (0.038)	0.0346* (0.018)	-0.0470 (0.0370)	-0.027** (0.011)	0.015** (0.006)	-0.011** (0.005)	0.128* (0.071)	0.107*** (0.039)	0.114* (0.0613)
largest									
Local/National	***Base***	***Base***	***Base***	***Base***	***Base***	***Base***	***Base***	***Base***	***Base***
EU-EFTA	-0.010 (0.071)	-0.030 (0.059)	0.112* (0.0646)	0.002 (0.012)	0.010 (0.011)	-0.004 (0.005)	0.507*** (0.129)	0.341*** (0.118)	0.212 (0.139)
NonEU-NonEFTA	0.423*** (0.125)	0.282** (0.117)	0.189 (0.131)	0.090*** (0.020)	0.090*** (0.021)	0.027** (0.010)	0.636*** (0.193)	0.830*** (0.231)	0.148 (0.302)
largest*lBRI									
EU-EFTA	0.015 (0.045)	0.056 (0.035)	-0.12*** (0.0409)	-0.02 (0.01)	0.03** (0.011)	-0.02*** (0.006)	-0.182** (0.076)	-0.074 (0.070)	0.100 (0.0868)
NonEU-NonEFTA	-0.086 (0.078)	0.015 (0.073)	-0.004 (0.081)	-0.05** (0.02)	0.01 (0.02)	0 (0.01)	-0.095 (0.110)	-0.234* (0.131)	0.217 (0.172)
constant	-2.40*** (0.14)	-1.658*** (0.132)	-2.897*** (0.140)				10.81*** (0.33)	10.860*** (0.298)	10.490*** (0.601)
Sector Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Country Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
/mills									
lambda	-0.98*** (0.18)	-1.26*** (0.16)	-0.55*** (0.20)	-0.98*** (0.18)	-1.26*** (0.16)	-0.55*** (0.20)	-0.98*** (0.18)	-1.26*** (0.16)	-0.55*** (0.20)
Number of Observations	9289	11350	20608	9289	11350	20608	9289	11350	20608

The standard errors are obtained with 1000 bootstrap. *, ** and ***indicate significance at 10%, 5% ve 1% levels.

The coefficients for the *largest* term (indicating the largest market from which the firm obtains its turnover) indicate that firms whose most significant market is in the nonEU-nonEFTA region exhibit a higher probability of engaging in R&D activities, compared to firms oriented towards the national market or the EU-EFTA region. As expenditures on R&D activities are considered, however, it is seen that firms oriented towards markets outside the national market incur significantly different levels of expenditure compared to those focusing on national markets. This discrepancy is evident primarily in the findings for the 2014 and 2016 CIS periods, which align with the findings of Bauman and Kritikos (2016) and Hall et al. (2013), who stress the importance of international markets and competitors in pushing firms to increase their R&D investment.

In this vein, the coefficient of 0.64 found for the 2014 CIS indicates that a firm's concentration on markets outside the EU-EFTA (nonEU-nonEFTA) is associated with an approximately 89.6% higher value for the R&D expenditure.[126] The findings for the *largest* variable can also be interpreted in analogy with the use of competitors in Hall et al. (2009), where they note that the existence of European or international competitors (that firms encounter in their markets of orientation) pushes firms to engage in more R&D activity**.** The findings on the impact of tertiary education on R&D propensity are statistically significant, and as the percentage of employees with tertiary education increases, firms' propensity to engage in R&D activity also increases. Since the *empud* variable is used to detect the selectivity bias, i.e. as the only variable differing from the outcome equation, its coefficients are only presented for the selection equation. The results indicate that the marginal effect of the BRI on the R&D expenditures of firms that focus heavily on local/national markets is positive across all survey periods. According to the findings, a 1% increase in export volume, driven by the BRI, leads to a 0.12% increase in the R&D expenditures of firms oriented towards local/national markets in the 2014 CIS. However, a 1% increase in export volume led by the BRI would be associated with a 0.6% decline in R&D expenditures for firms oriented towards the EU-EFTA regions and an 13% decline for those oriented towards the nonEU-nonEFTA regions, respectively.[127]

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[126] This value is calculated by the formula: % change=$(e^{0.69}-1)\times 100 \approx (1.993-1)\times 100=99.3\%$

[127] These adverse effects of the BRI can be attributed to the use of the *largest* model, which may have already captured much of the impact that could stem from the existence of competition in international markets.

It is interesting to observe that the main effect of the BRI on R&D tendency is negative, while its impact on R&D expenditure is positive. Since the impact of the BRI is incorporated into the model in interaction with the largest term (indicating the firm's market orientation), the main effect of the BRI indicates the impact on firms oriented towards local/national markets.

The negative coefficient in the selection equation indicates that the overall inclination to engage in R&D decreases for firms oriented in local/national markets, whereas the positive coefficient in the output equation indicates that those who remain active in R&D activity deploy more resources to it.

This finding suggests that elimination may occur among firms focused on local/national markets. Bloom et al. (2016) states that increased import competition from China can curb the R&D incentives of less productive firms. As global trade flows into the EU and changes the dynamics of competition, the R&D tendency of nationally oriented firms might decrease, as these firms would be exposed to the evolving dynamics but would not reap the benefits. So, BRI curbs the weak ones' R&D efforts, while the remaining ones could behave more aggressively. In other words, the extensive margin of R&D might decrease, whereas the intensive margin increases.

As stated before, the CIS data in this thesis is not longitudinal and three consecutive periods are used to capture a "glimpse" of the time dimension. In this vein, the 2014 CIS corresponds to the initial years of the BRI, whereas the 2016 and 2018 periods indicate the years of progress. It is expected that the impact of the BRI will have effects that evolve in a predictable pattern, either increasing or decreasing. The findings from the first block do not exhibit such a pattern, either in the R&D propensity equation or the R&D expenditure equation. However, the findings provide affirmative evidence of a significant BRI effect that varies according to the market orientation of firms. On the other hand, the discussion of coefficients other than the BRI presents results that are primarily in line with those found in the literature.

7.1.2. Results from the Second Block Models

This section presents the results from the regressions in the second block of the MMK framework in Table 28. In the first part of this block, the decision to produce innovation output is initially modelled. In the second part, the turnover from sales of innovation output new to the market is modelled, inserting the predicted value of R&D expenditure as an explanatory variable. The first part of the Heckman procedure also includes the predicted probability of the R&D engagement obtained from the first block. Despite the insignificance noted for the larger firms for introducing innovation output, the findings for the main equation indicate that larger firms experience significantly higher turnover compared to medium- and small-sized firms.

As the contribution of auxiliary types of innovation is analysed, the highest impact is noted for the introduction of a new or significantly improved method of production (*inpspd*). In contrast, improvements in logistics systems (in logistics) also exhibit a close contribution. The contribution of new logistics systems is noteworthy, as firms selling innovative products to new markets may also benefit from their improved logistics systems.

The BRI is found to have a negative impact on the tendency of firms oriented in the EU-EFTA markets to introduce innovative output new to the market, albeit only in 2014 CIS. The turnover of firms introducing new innovations to the market is negatively associated with firms oriented in the EU-EFTA markets, again only in 2014 CIS. In fact, the BRI is found to have significant impact only in 2014 CIS. Since this period corresponds to the initial years of the BRI, firms' setback (or hesitancy) in introducing new products to the market could be associated with a "wait and see" approach.

For the outcome equation, it is important to note that the coefficient of the predicted value of R&D expenditure derived from the first stage is statistically significant and positive. This finding validates our regressions for the first block as well. A 1%

increase in R&D spending could be associated with 0.10% increase in turnover from the sales of “new to the market” innovation output.

Table 30. Results from the Second Block Regressions

	2014	2016	2018	2014	2016	2018	2014	2016	2018
	Selection Equation	**Selection Equation**	**Selection Equation**	**Selection Equation**	**Selection Equation**	**Selection Equation**	**Share Equation**	**Share Equation**	**Share Equation**
	newmkt	newmkt	newmkt	newmkt	newmkt	newmkt	l(turn)	l(turn)	l(turn)
	β	*β*	*β*	*β*=dy/dx	*β*=dy/dx	*β*=dy/dx	*β*=dy/dx	*β*=dy/dx	β=dy/dx
size									
Less than 50	***Base***	***Base***	***Base***	***Base***	***Base***	***Base***	***Base***	***Base***	Base
50-249	-0.0772* (0.0406)	-0.0878** ((0.0424))	-0.065* (0.039)	-0.0255* (0.0138)	-0.029** (0.013)	-0.0230 (0.0141)	1.3290*** (0.0810)	1.4337*** (0.0776)	1.429*** (0.092)
250 and more	-0.0522 (0.0621)	-0.0055 ((0.0582))	0.004 (0.063)	-0.0173 (0.0212)	-0.002 (0.018)	0.0016 (0.0222)	3.0983*** (0.1327)	3.0067*** (0.1084)	2.934*** (0.139)
inpspd	0.3546*** (0.0405)	0.2337*** (0.0399)		0.1177*** (0.0129)	0.071*** (0.012)		0.3378*** (0.1124)	0.4342*** (0.0944)	
inpslg	0.1405** (0.0567)	0.2245*** (0.0508)		0.0466*** (0.0175)	0.079*** (0.015)		0.4226*** (0.0812)	0.1951* (0.0997)	
inpssu	0.1220*** (0.0453)			0.0405*** (0.0153)	0.035*** (0.013)		0.1628** (0.0772)	0.0891 (0.0744)	
Predicted R&D Investment							0.1070*** (0.0297)	0.1025*** (0.0374)	0.006 (0.042)
Predicted Probability of R&D Engagement	1.3638*** (0.0958)	1.4610*** (0.1025)	0.657*** (0.074)	0.4525*** (0.0306)	0.487*** (0.032)	0.234*** (0.0256)			
inno_pcs_prd			0.352*** (0.035)			0.125*** (0.0123)			-0.079 (0.287)
largest									
local/national	***Base***	***Base***	***Base***	***Base***	***Base***	***Base***	***Base***	***Base***	***Base***
EU-EFTA	0.1175 (0.0857)	-0.0612 (0.0717)	-0.010 (0.077)	-0.0066 (0.0159)	-0.018 (0.014)	-0.0192 (0.0154)	0.4640*** (0.1351)	0.5035*** (0.1271)	0.344** (0.158)
NonEU-NonEFTA	0.1439 (0.1451)	0.0078 (0.1336)	-0.161 (0.163)	0.0280 (0.0249)	0.003 (0.023)	-0.0080 (0.0294)	0.4862* (0.2644)	0.4860** (0.2233)	0.289 (0.398)
lBRI	-0.0128 (0.0529)	-0.0245 (0.0262)	-0.030 (0.055)	-0.0144 (0.0169)	-0.013 (0.009)	-0.0121 (0.0181)	0.0325 (0.0990)	0.0728 (0.0920)	-0.201 (0.145)
largest*lBRI									
EU-EFTA	-0.1156** (0.0542)	-0.0285 (0.0447)	-0.035 (0.046)	-0.04* (0.02)	-0.03 (0.01)	-0.02 (0.02)	-0.1710** (0.0863)	-0.0205 (0.0769)	0.054 (0.105)
NonEU-NonEFTA	-0.0504 (0.0902)	-0.0084 (0.0832)	0.108 (0.101)	-0.02 (0.03)	0 (0.02)	0.02 (0.04)	0.0219 (0.1550)	0.0409 (0.1398)	0.228 (0.245)
constant	-0.3367 (0.2217)	-0.16 (0.24)	- 0.561*** (0.188)				9.9625*** (0.6214)	10.2070*** (0.6731)	
Sector Dummies	***yes***	***yes***	***yes***	***yes***	***yes***	***yes***	***yes***	***yes***	yes
Country Dummies	***yes***	***yes***	***yes***	***yes***	***yes***	***yes***	***yes***	***yes***	yes
/mills									
lambda	0.94** (0.42)	0.16 (0.52)	-1.448 (1.22)	0.94** (0.42)	0.16 (0.52)	-1.448 (1.22)	0.94** (0.42)	0.16 (0.52)	-1.448 (1.22)
Number of Observations	6085	7022		6085	7022		6085	7022	
Wald chi (2)	2196.56***	3276.75***		2196.56***	3276.75***		2196.56***	3276.75***	
rho	0.57	0.1	0.107	0.57	0.1	0.107	0.57	0.1	0.107
sigma	1.65	1.48	1.49	1.65	1.48	1.49	1.65	1.48	1.49

The standard errors are obtained with 1000 bootstrap. *, ** and ***indicate significance at 10%, 5% ve 1% levels.

Despite the positive and significant coefficient, it is worth noting that its value is relatively small compared to other findings in the literature. For instance, Janz et al. (2003) find values around 0.50 in their study, focussing on the intensity terms of R&D and innovation for Germany and Sweeden. Hashi and Stojčić (2013) also find values similar to those of Janz et al. (2003) in their study, which focuses on Central and Eastern European countries. It could be suggested that the dominance of the sample by these countries could also lead to lower coefficients. Yet, the findings of Hashi and Stojčić (2013) defy making such strong inferences. Still, the findings of Mairesse et al. (2012) for China exhibit coefficients closer to those of this study. As a result, no specific inference can be made regarding the country coverage; however, the findings are not unreasonable.

In the selection equation, the probability of R&D engagement (derived from the first block equations for all firms) increases the likelihood of introducing innovation output new to the market, which aligns with the findings of Doyar (2023), as stated above.

7.1.3. Results from the Third Block Models

Unlike the findings in the first two blocks of the MMK framework, the results for the third block are not promising at all, even though the F-statistics indicate that the null hypothesis that all variables are equal to zero is rejected for all survey periods. Although the coefficient of the predicted level of innovative sales is mostly significant across models, it is extremely small, preventing the model from making accurate inferences. These results can be attributed to the fact that, unlike the bulk of the related literature, this thesis employs productivity growth, rather than labour productivity itself, in the analyses. Therefore, the findings on productivity growth are presented merely to complete the MMK framework's structure.

Table 31. Results from the Third Block Regressions

	2014	**2016**	**2018**
	Productivity Growth	**Productivity Growth**	**Productivity Growth**
Predicted Level of Innovative Sales	**-0.0028 (0.0035)**	**-0.0006 (0.0024)**	**0.0073** (0.0036)**
Logarithm of Expenditure on Physical Capital and Machinery	-	-	0.0003 (0.0006)
size			
Less than 50	***Base***	***Base***	***Base***
50-249	***-0.0219 (0.0152)***	***-0.0308*** (0.0100)***	***-0.0398*** (0.0113)***
250 and more	-0.0522** (0.0242)	-0.0642*** (0.0155)	-0.0948*** (0.0195)
largest			

Table 31. (continued)

local/national	***Base***	***Base***	***Base***
EU-EFTA	-0.00112147	0.0327* (0.0178)	-0.0170 (0.0212)
NonEU-NonEFTA	-0.0507 ((0.0483))	-0.0162 (0.0321)	-0.0180 (0.0456)
log(BRI)	0.0164 (0.0157)	0.0018 (0.0059)	-0.0047 ((0.0140))
largest*log(BRI)			
local/national	***Base***	***Base***	***Base***
EU-EFTA	0.0132 ((0.0159))	0.0042 (0.0109)	0.0014 (0.0130)
NonEU-NonEFTA	***0.0192*** ***((0.0307))***	***0.0222*** ***(0.0194)***	***-0.0074*** ***(0.0278)***
constant	0.0469 (0.1042)	0.0298 (0.0623)	0.2359*** (0.0495)
Sector Dummies	yes	yes	yes
Country Dummies	yes	yes	yes
Number of Observations	2862	4222	5919
F statistic	1.57***	1.9***	4.54***

7.1.4. Diagnostic Results

Following the estimations, diagnostic tests are performed to evaluate the underlying assumptions of the model, including error normality, the absence of heteroskedasticity, and the correctness of the functional form.

Table 32. Diagnostic Results

Model		Multicollinearity	Heteroscedasticity	Normality of Errors	Functional Form
First Block-Selection	2014	2.82	520.83***	3567***	0.015 (0.018)
	2016	2.93	994.96***	1760***	0.0113 (0.02)
	2018	1.95	965.18***	3181***	-0.04 (0.05)
First Block-Outcome	2014	3.62	160.73***	482.45***	67.92***
	2016	2	204.34***	244.06***	18.11***
	2018	2.56	126.68***	201.1***	7.51***
Second Block-Selection	2014	2.21	487.53***	132.27***	-0.35***
	2016	2.13	457.66***	219.71***	7.35***
	2018	2.08	137.79***	661.748***	-0.23*** (0.05)
Second Block-Outcome	2014	2.13	112.88***	33.79***	10.08***
	2016	2.04	108.67***	12.33***	7.36***
	2018	2.67	38.93	926.83***	1.69
Third Block	2014	2.56	163.65***	51.57***	0.56
	2016	2.27	603.6***	16.76***	1.18
	2018	2.47	424.9***	8.86***	1.53

Using the tests proposed by Fox (1991), it is found that the diagnostic tests results indicate that the models do not from multicollinearity problems. As stated by Fox (1991), the variance inflation factors above 10 signal a multicollinearity problem that inflates standard errors and renders coefficient estimates unstable and less reliable (Fox, 1991).

All models suffer from heteroscedasticity problem. The heteroscedasticity tests are done by using the **Breusch–Pagan (1980) Lagrange Multiplier (LM) test**. The adopted version of the test for non-linear models is used (and constructed manually) to test for heteroscedasticity in selection equations. The results indicate that all models suffer from heteroscedasticity. The bootstrapping used in the estimations alleviates problems such as the biasedness of the coefficients and unreliability of confidence intervals, stemming from heteroscedasticity.

Errors are not normally distributed in any model specification. Similar to heteroscedasticity, confidence intervals are not reliable when errors of the models are not normally distributed. In addition to the bootstrapping used in the estimations, the large sample size also helps alleviate concerns around normality, thanks to the central limit theorem. Due to their strength in handling large sample sizes, the Jarque-Bera test (1987) is used to test for the normality of the errors. From the perspective of the thesis, the test for the functional form is the most critical one, as the analyses are conducted under severe data limitations. The results in Table 30, in the last column, indicate misspecification in the models, except for the selection equations in the first block and the productivity growth equation in the third block. These results are not surprising given the severe data limitations under which the analyses were conducted. The most significant of these is the absence of data on the number of employees.

7.1.5. Discussion of the Findings from the Traditional MMK Framework

The impact of the BRI is added to the traditional MMK framework by interacting the logarithm of the EEVC term with the market orientation of the firms. The findings from the first block of equations are found to be more significant and stronger than those in the second block.

The findings in the first block provide insight into the impact of the BRI on the decision to engage in R&D and incur R&D expenditure. It is seen that the BRI decreases the tendency to engage in R&D for firms with all types of market orientation. Yet, when the R&D investment (expenditure) is considered, the positive effects are found only for firms focusing on national markets. Firms focusing on markets outside national borders are found to decrease their R&D expenditure.

These findings are crucial, as they suggest the potential elimination of nationally oriented firms in the face of global shocks. When weak firms are eliminated, the remaining firms can push forward with their R&D efforts.

The negative findings for firms' R&D expenditure focusing outside national borders are also striking, as their market orientation improves their R&D performance when the BRI effect is absent. The BRI poses an external policy shock to EU firms as the Chinese government initiates it. From the perspective of these firms focusing on the EU-EFTA region, the BRI creates competitive pressures both inside and outside the EU-EFTA region. The responses of these firms are not positive, instead they retreat. Bloom et al. (2016) document the same behaviour for UK firms in response to the influx of Chinese imports. Similarly, Aghion et al. (2005) identify an inverted U relationship between heightened competition and innovation. "Some" competition might trigger the inclination to engage in R&D activity, but "more" of it could lead firms to give up the innovative activity completely. Autor et al. (2020) also state that, amidst the pressures of Chinese imports, technologically advanced U.S. firms increase their innovative activity, but those lacking sufficient absorptive capacity tend to give up. Therefore, the BRI can penalise firms that are regionally focused or not sufficiently globalised. In other words, it can systematically displace firms and crowd out their market share both within the EU and outside it. These findings echo the emphasis on strengthening the EU single market in the Draghi Report (2024). Draghi (2024, p. 11) highlights the fragmentation within the EU single market and warns that, in the face of global projects, this fragmentation creates further weaknesses. To counterbalance the state-controlled BRI, a single market emerges as a crucial tool that needs to be strengthened.

The negative effects of the BRI on the decision to introduce innovative output and the level of turnover from such sales by EU-EFTA firms can also be discussed in light of the arguments stated above. Similar forces would be at play.

7.2. Results from MMK Models with Spatial Dependence

As stated above, this thesis places particular emphasis on maintaining the model structure across different survey periods. This emphasis refers to the use of the same set of explanatory variables and model structure. However, the discrepancy between the 2014-2016 and 2018 CIS questionnaire formats necessitates a change in the set of explanatory variables that was initially mandated in the second block of the MMK framework. Additionally, explanatory variables may be subject to variation due to issues arising in estimation, such as multicollinearity. Multicollinearity has emerged as a significant problem in the analysis of spatial models, and forgoing the spatial lags of certain variables has been inevitable. Yet, the equations have still been modelled using the same spatial model that injects spatial lags into the dependent variable, BRI-related explanatory variables and error terms. Before presenting the model results, the dependent variables must be tested to determine whether they exhibit spatial dependence.

Moran’s I statistics of the dependent variables are presented below in Table 31. The Moran test statistics (Moran, 1950) indicate whether there is spatial autocorrelation in the dependent variables of the first two blocks, the logarithm of R&D expenditures and turnover from the sale of innovation output new to the market, respectively. In most survey periods under both weight matrices, spatial dependence is detected. For those periods in which no spatial dependence is noted, the analyses are still conducted, as this thesis is the first study to integrate spatial dependence into the traditional MMK framework. For the coherence of the analyses, the spatial econometrics techniques are applied to all of them.

Table 33. Moran's I Test Statistics of the Dependent Variables

		Moran Test Statistics of the Dependent Variables	
		Geographical	Economic Linkage
2014	Log(R&Dexpenditure)	0.004	0.2***
2014	Log(TurnoverfromSales)	-0.01	0.01***
2016	Log(R&Dexpenditure)	0.01***	0.02***
2016	Log(TurnoverfromSales)	0.009*	0.12***
2018	Log(R&Dexpenditure)	-0.02	0.09***
2018	Log(TurnoverfromSales)	-0.02	0.01***

*,**,*** indicate statistical significance at 10%, 5% and 1% respectively.
The rejection of the test statistics indicates the existence of spatial dependence.

7.2.1. Results from the First Block Equations with Spatial Dependence

In this section, the findings from the models that integrate spatial dependence to the first block of the MMK framework are presented under geographical and economic proximity, respectively.

7.2.1.1. Results from the First Block Equations Under Geographical Proximity

The results from estimating the R&D expenditure equation in the first block of the MMK framework, which includes spatial dependence based on geographical proximity, are presented in Table 33. The LR test statistics indicate that the use of the spatial model improves over the non-spatial specification, i.e the Heckman specification, for the 2014 and 2016 CIS.

Similar to the analyses without spatial dependence, the level impact of the BRI is found to be positive, although it is only observed for the 2014 CIS. Also, the orientation of firms in EU-EFTA and nonEU-nonEFTA markets are associated with higher R&D expenditures. Size group and funding variables are also found to be positive, in line with the findings without spatial dependence. The impact of the BRI is still investigated across different market orientations. The level impact of the BRI is significant, indicating that if the firm is oriented in local/national markets, then the BRI impact accrues positively to that firm.

Table 34. Results from the First Block Equations with Geographical Proximity

	2014	2016	2018
rho	-0.359*** (0.137)	-0.080 ((-))	0.016 (0.356)
Constant	12.146*** (0.935)	2.622 (3.077)	10.860*** (3.686)
co	0.173* (0.089)	-0.102 (0.078)	-0.107 (0.144)
fungmt	0.477*** (0.083)	0.178** (0.071)	0.089 (0.081)
funeu	0.239*** (0.071)	0.359*** (0.063)	0.060 (0.080)
funloc	0.427*** (0.085)	-0.133 (0.091)	0.053 (0.112)
imr	-0.701*** (0.175)	-1.272*** (0.149)	-0.746*** (0.125)
factor(largest)2	0.295** (0.122)	0.355*** (0.088)	0.175 (0.122)
factor(largest)3	0.828*** (0.165)	0.836*** (0.177)	0.087 (0.256)
lBRI	0.225*** (0.066)	0.101*** (0.037)	0.114 (0.073)
lBRI:factor(largest)2	-0.128 (0.093)	-0.088* (0.050)	0.117 (0.077)
lBRI:factor(largest)3	-0.153** (0.073)	-0.236** (0.106)	0.238 (0.152)
factor(size)2	0.853*** (0.068)	0.859*** (0.060)	0.768*** (0.079)
factor(size)3	2.601*** (0.100)	2.328*** (0.078)	1.981*** (0.108)
lag.lBRI	1.706*** (0.605)	-3.957 ((-))	-0.013 (0.122)
lag.factor(largest)2	8.541*** (1.999)	11.127*** (0.180)	-3.429*** (1.300)
lag.factor(largest)3	27.507 (19.685)	66.801 (-)	-1.494** (0.643)
lag.lBRI:factor(largest)2	-7.797*** (1.701)	-1.789*** (0.182)	1.689** (0.659)
lag.lBRI:factor(largest)3	-14.253 (11.183)	-38.233 (-)	
lambda	0.054 (-)	0.982*** (0.005)	0.113 (0.352)
r.squared	0.491	0.633	0.375
AIC	14264.457	15795.986	10464.594
LR Test Statitic	276.48***	3019.9***	7.48
BIC	14582.622	16118.946	10754.731
logLik	-7081.228	-7846.993	-5183.297
nobs	3784	4157	2755

The standard errors are obtained using 1000 bootstrap samples.*, ** and ***indicate significance at 10%, 5% ve 1% levels.(-) indicates that the standard error of the coefficient can not be estimated.

Yet, if the firm is oriented towards the EU-EFTA and nonEU-nonEFTA markets, then the effect of the BRI is diminished. The direction of the findings from non-spatial models remains largely unchanged. As the spatially lagged variables are considered, it is observed that the closer a firm is geographically to firms whose turnover is mostly from the national market, the more positively the focal firm is affected by the implications of the BRI. Although this finding is only noted in the 2014 CIS, it is crucial since the interaction of the BRI term with other market orientations yields different results.

According to the 2014 and 2016 CIS results, if a firm is surrounded by firms oriented towards the EU-EFTA markets, then the focal firm's R&D expenditure is positively affected by this fact, signifying the importance of knowledge spillovers. When the impact of the BRI is taken into account, however, it becomes apparent that the R&D performance of firms diminishes. This fact can be attributed to the competitive effects that prevail among firms located close to each other. As the BRI's influence is felt in a region, the forces that perpetuate the R&D expenditures of firms start to function negatively in terms of the firm's R&D performance. It could be suggested that the enhanced trade inflow to the EU area (most notably in lower prices made possible by trade cost declines due to the BRI) could push EU-EFTA-oriented firms to broaden their market share, diverting their focus and resources Shortly, under intensified intra-EU competition, the priority list of the firms could significantly change.

7.2.1.2. Results from the First Block Equations with Economic Proximity

The results from estimating the R&D expenditure equation in the first block of the MMK framework, which includes spatial dependence based on economic proximity, are presented in Table 34. The log-likelihood test statistics indicate that the use of the spatial model improves over the non-spatial specification, as well as the Heckman specification, for the 2014 and 2016 CIS surveys.

The level impact of the BRI is found to be positive only in 2014 CIS, and in smaller magnitudes than the analysis above that relies on geographical proximity. The orientation of firms in EU-EFTA and nonEU-nonEFTA markets are associated with higher R&D expenditures. Size group and funding variables are also found to be positively correlated, in line with the findings that exclude spatial dependence and geographical proximity.

Table 35. Results from the First Block Equations using the Economic Proximity

	2014	2016	2018
rho	0.020** (0.010)	0.024 (0.021)	-0.472** (0.218)
(Intercept)	10.474*** (0.222)	10.284*** (0.141)	15.797*** (2.492)
co	-0.043 (0.029)	-0.089** (0.037)	0.065 (0.072)
fungmt	0.106** (0.053)	0.159*** (0.058)	0.144** (0.068)
funeu	0.409*** (0.075)	0.314*** (0.063)	0.133* (0.073)
funloc	0.087 (0.073)	-0.121 (0.093)	0.014 (-)
imr	-0.890*** (0.013)	-1.301*** (0.090)	-0.586*** (0.070)
lBRI	0.176* (0.093)	0.053* (0.027)	-0.016 (-)
factor(largest)2	0.644*** (0.134)	0.273*** (0.096)	0.213** (0.109)
factor(largest)3	0.410* (0.230)	0.721*** (0.179)	0.119 (0.224)
factor(size)2	0.832*** (0.067)	0.891*** (0.061)	0.830*** (0.077)
factor(size)3	2.653*** (0.089)	2.341*** (0.079)	2.082*** (0.102)
lBRI:factor(largest)2	-0.196*** (0.073)	-0.053 (0.055)	0.109* (0.060)
lBRI:factor(largest)3	0.062 (0.133)	-0.177* (0.106)	0.230 (0.152)
lag.lBRI	0.014 (0.021)	0.021 (-)	0.174 (0.134)
lag.factor(largest)2	0.099 (0.189)	1.395*** (0.246)	-0.339 (-)
lag.factor(largest)3	1.117* (0.672)	2.906*** (1.028)	1.053 (1.690)
lag.lBRI:factor(largest)2	-0.261* (0.151)	-0.065 (0.075)	-0.209*** (0.051)
lag.lBRI:factor(largest)3	-0.935*** (0.332)	-1.333*** (0.497)	0.447 (0.669)
lambda	-0.042 (0.141)	0.060 (-)	0.556*** (0.132)
r.squared	0.563	0.638	0.386
AIC	10805.256	15736.036	10459.100
BIC	11158.480	16115.989	10796.607
LR Test Statistic	13.947***	29.149**	11.886
logLik	-5343.628	-7808.018	-5172.550
nobs	2942	4157	2755

The standard errors are obtained using 1000 bootstrap samples.*, ** and ***indicate significance at 10%, 5% ve 1% levels.(-) indicates that the standard error of the coefficient can not be estimated.

Unlike the model above, which relies on geographical proximity, the contrasting effect of the BRI is observed when the focal firm has close linkages with firms oriented towards markets outside the EU. In Table 33, if the focal firm is located near firms oriented in the EU-EFTA market, the positive effect of "such" neighbours observed without the BRI effect becomes negative when the BRI effect is introduced into the model. When economic proximity is considered, as in Table 35, this contrasting effect is observed when the firm has strong backwards linkages with firms oriented towards markets outside the EU-EFTA region.

Such behaviour is consistent with studies suggesting that globalisation and shifting trade patterns can suppress domestic innovation incentives when firms become increasingly reliant on imported technologies or external production networks (Rodrik, 2018; Autor et al., 2020). When the BRI is introduced, EU-based input suppliers oriented toward non-EU markets may reallocate resources, strategic attention, or innovation efforts to markets outside the EU. This change in focus can harm relational stability and increase uncertainty in input provision, leading to a reduction in the incentive to engage in R&D, particularly the type targeting long-term benefits. Another explanation could be related to the lock-in, whose scope is enlarged as the reliance of the EU firms increases on their suppliers who are oriented towards markets outside the EU-EFTA and transmit lower input costs to the EU area. In other words, as those suppliers supply inputs at lower costs due to enhanced global supply chains.

7.2.2. Results from the Second Block Equations with Spatial Dependence

7.2.2.1. Results from the Second Block Equations with Geographical Proximity

The results from estimating the turnover from innovative sales in the second block of the MMK framework, which includes spatial dependence based on geographical proximity, are presented in Table 35.

The log-likelihood test statistics indicate that the use of the spatial model improves over the non-spatial specification, as well as the Heckman specification, for all survey periods. As the size of the firm's group increases and the firm engages in auxiliary types of innovation, the turnover from innovative sales also increases. The predicted value of R&D expenditure is found to be positively significant, in line with expectations.

The findings from Table 35 indicate that when the BRI impact is not considered, being geographically surrounded by EU firms oriented toward nonEU-nonEFTA markets is associated with a decrease in innovative sales, as observed in the 2014 and 2018 CIS results. This finding may hint at low local knowledge diffusion among firms in the same neighbourhood. This effect is reversed when the BRI effect is taken into account. When the BRI effect is accounted for, being geographically surrounded by globally oriented firms (i.e., firms oriented in the nonEU-nonEFTA markets) is observed to have a positive effect on their turnover from innovative sales. As the BRI enhances global connectivity and brings forward new priorities, firms oriented in nonEU-nonEFTA markets become better integrated into expanding trade and innovation networks beyond Europe. Their presence in the local economy may then provide access to new markets and complementary capabilities, leading to an increase in innovative sales performance among proximate firms.

Being geographically surrounded by EU firms oriented toward EU-EFTA markets, however, is associated with an increase in innovative sales across all survey periods. This effect is reversed when the BRI effect is taken into account in the 2018 CIS. This suggests that being surrounded by firms that are economically oriented toward the EU-EFTA region leads to the sharing of similar institutional and technological frameworks, standards, and market knowledge. These local synergies enhance a firm's ability to translate innovation activities into revenue. However, this positive effect reverses after the BRI. It could be suggested that as the BRI evolves, the regional cohesion of firms oriented in EU-EFTA markets weakens, as broader global shifts disrupt local innovation dynamics by diverting such firms' attention towards better investment opportunities and entry into new markets, most likely at lower costs, facilitated by the BRI infrastructure investment.

Another significant finding from Table 35 is the presence of a significant lambda for the 2014 and 2016 CIS periods. This finding suggests that unobserved factors affecting innovation output are spatially correlated across country-sector units. In other words, localised shocks or latent factors influencing innovation in one region or sector tend to spread to neighbouring areas. Such spatial clustering may either amplify or dampen the impact of structural shifts required in the post-BRI era.

7.2.2.2. Results from the Second Block Equations with Economic Proximity

The results from estimating the turnover from innovative sales in the second block of the MMK framework, which includes spatial dependence based on economic proximity, are presented in Table 36. The log-likelihood test statistics indicate that the use of the spatial model improves over the non-spatial specification for all survey periods. As the size of the firm's group increases and the firm uses auxiliary types of innovation, the turnover from innovative sales also increases. The predicted value of R&D expenditure is found to be significantly positive, consistent with previous findings.

The findings from Table 35 indicate that when the BRI impact is not considered, having strong economic links with firms oriented toward nonEU-nonEFTA markets is associated with both negative and positive effects, as indicated by the 2014, 2016, and 2018 CIS results, respectively.[128] However, when the BRI effect is included, the effects noted for each survey are reversed. Similarly, if the focal firm has economic links with firms oriented towards the EU-EFTA region, the inclusion of the BRI still reverses the repercussions from such firms. Regardless of the initial impact of the market orientation of firms which provide inputs to the focal firm, it is seen that the BRI can reverse this. The sign changes are valid for all periods, and it is not guaranteed whether the BRI effect will enhance or hinder innovation.

Table 36. Results from the Second Block Equations with Geographical Proximity

Variable	**2014**	**2016**	**2018**
rho	-0.177 (0.125)	-0.664*** (0.053)	0.000 (0.000)
(Intercept)	11.396*** (1.362)	21.164*** (0.789)	11.799*** (0.143)
inno_pcs_prd			0.277*** (0.068)
inpspd	0.390*** (0.075)	0.094* (0.052)	

[128] The negative impact of economic links with firms oriented in nonEU-nonEFTA markets (found for the 2018 CIS) can be attributed to the low compatibility in input standards.

Table 36. (continued)

inpslg	0.430*** (0.078)	0.343*** (0.073)	
inpssu	0.170** (0.072)	0.022 (-)	
imr2	1.216*** (0.182)	-0.588 (-)	0.099 (0.108)
lBRI	0.047 (0.067)	0.088* (0.049)	-0.236*** (0.082)
factor(largest)2	0.483*** (0.122)	0.541*** (0.083)	0.328*** (0.091)
factor(largest)3	0.520*** (0.116)	0.512 (-)	0.138 (0.234)
factor(size)2	1.309*** (0.071)	1.466*** (0.057)	1.366*** (0.070)
factor(size)3	3.071*** (0.106)	3.040*** (0.084)	2.897*** (0.104)
y1	0.123*** (0.013)	0.056 (-)	0.057*** (0.010)
lBRI:factor(largest)2	-0.188** (0.076)	-0.014 (0.037)	0.019 (0.038)
lBRI:factor(largest)3	0.013 (0.028)	0.034 (-)	0.323** (0.151)
lag.lBRI	1.014*** (0.286)	-1.075 (-)	0.419* (0.224)
lag.factor(largest)2	3.622** (1.630)	4.490*** (0.395)	17.767*** (2.670)
lag.factor(largest)3	-23.235* (12.147)	133.604*** (13.817)	-9.576* (5.213)
lag.lBRI:factor(largest)2	2.275 (-)	-1.404 (-)	-12.750*** (2.124)
lag.lBRI:factor(largest)3	19.383* (10.746)	-73.899*** (7.427)	6.458* (3.908)
lambda	0.580*** (0.044)	0.519*** (0.041)	0.000 (0.000)
AIC	10444.491	11601.199	10098.015
BIC	10747.966	11910.287	10381.600
LR Test Statistic	268.53***	281.86***	86.53***
logLik	-5171.245	-5749.600	-5001.008
nobs	2837	3167	2719

Table 37. Results from the Second Block Equations with Economic Proximity

Variable	2014	2016	2018
rho	-0.067 (0.198)	-0.199 (-)	0.000 (0.000)
(Intercept)	11.749*** (2.495)	13.973*** (0.797)	11.799*** (0.143)
inno_pcs_prd			0.277*** (0.068)
inpspd	0.080 (0.093)	-0.105 (0.086)	
inpslg	0.312*** (0.099)	0.302*** (0.081)	
inpssu	0.118 (0.093)	0.021 (-)	
imr2	-0.354* (0.211)	-1.140 (-)	0.099 (0.108)
lBRI	-0.048 (0.086)	-0.014 (0.052)	-0.236*** (0.082)
factor(largest)2	0.436*** (0.154)	0.414*** (0.136)	0.328*** (0.091)
factor(largest)3	0.522 (-)	0.599 (-)	0.138 (0.234)
y1	0.10*** (0.020)	0.07*** (0.01)	0.057*** (0.010)
factor(size)2	1.495*** (0.089)	1.521*** (0.076)	1.366*** (0.070)
factor(size)3	3.413*** (0.115)	3.229*** (0.100)	2.897*** (0.104)
lBRI:factor(largest)2	-0.121 (0.089)	0.111 (0.082)	0.019 (0.038)
lBRI:factor(largest)3	0.036 (-)	0.069 (-)	0.323** (0.151)
lag.lBRI	0.340 (0.215)	0.487*** (0.184)	0.419* (0.224)
lag.factor(largest)2	-0.627 (0.524)	0.912*** (0.174)	17.767*** (2.670)
lag.factor(largest)3	2.147** (1.018)	4.226*** (1.580)	-9.576* (5.213)
lag.lBRI:factor(largest)2	-0.107 (-)	-0.709* (0.406)	-12.750*** (2.124)
lag.lBRI:factor(largest)3	-0.682 (0.660)	-2.262*** (0.803)	6.458* (3.908)
lambda	-0.308 (0.362)	-0.640*** (0.147)	0.000 (0.000)
r.squared	0.527	0.526	0.478
AIC	6411.432	7527.962	10098.015
BIC	6733.703	7860.216	10381.600
logLik	-3146.716	-3704.981	-5001.008
nobs	1741	2062	2719

The standard errors are obtained using 1000 bootstrap samples.*, ** and ***indicate significance at 10%, 5% ve 1%
levels. (-) indicates that the standard error of the coefficient cannot be estimated.

7.2.3. Results from the Third Block Equations

The performance of the third block equations depicted in Table 38 are mostly in line with the findings for the third block under the first approach. Although the LR statistics indicate improvement over the estimations under the first approach, most of the coefficients are found to be nearly zero. These results can be attributed to the fact that, unlike the bulk of the related literature, this thesis employs productivity growth, rather than labour productivity itself, in the analyses. Therefore, the findings on productivity growth are presented merely to complete the MMK framework's structure.

Table 38. Results from the Third Block Equations

	Economic Proximity			**Geographic Proximity**		
	2014	**2016**	**2018**	**2014**	**2016**	**2018**
	Productivity Growth	**Productivity Growth**	**Productivity Growth**	**Productivity Growth**	**Productivity Growth**	**Productivity Growth**
	prod_growth	prod_growth	prod_growth	prod_growth	prod_growth	prod_growth
Predicted Level of Innovative Sales	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Logarithm of Expenditure on Physical Capital and Machinery	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
largest						
local/national	***Base***	***Base***	***Base***	***Base***	***Base***	***Base***
EU-EFTA	-0.08 (0.10)	0.03 (0.06)	-0.05 (0.04)	-0.06 (0.09)	0.06 (0.06)	-0.03 (0.04)
NonEU-NonEFTA	0.05 (0.17)	0.00 (0.10)	-0.006	0.06 (0.16)	0.06 (0.10)	-0.08 (0.06)
largest*leffect2						
local/national	0.06** (0.02)	-0.01 (0.01)	-0.03 (0.02)	0.05*** (0.02)	0.00 (0.01)	-0.03 (0.02)
EU-EFTA	0.07** (0.03)	-0.02 (0.01)	-0.01 (0.03)	0.06** (0.02)	-0.01 (0.01)	-0.02 (0.03)
NonEU-NonEFTA	0.04 (0.03)	-0.01 (0.02)	0.02 (0.04)	0.04 (0.03)	-0.01 (0.02)	0.00 (0.04)
lBRI	0.01 (0.02)	0.03* (0.02)	0.04 (0.02)	0.05** (0.02)	0.03 (0.02)	0.02 (0.02)
Spatially Lagged Variables						
largest						
lBRI	0.01 (0.03)	0.08* (0.02)	0.03 (0.04)	0.20** (0.03)	-0.01 (0.02)	0.001 (0.01)
local/national	***Base***	***Base***	***Base***	***Base***	***Base***	***Base***
EU-EFTA	0.45 (0.49)	-0.01 (0.22)	-0.05 (0.04)			
NonEU-NonEFTA	0.08 (1.34)	1.36** (0.61)	-0.006			
largest*lBRI						
EU-EFTA	-0.07 (0.07)	0.06 (0.03)	-0.01 (0.03)	0.28* (0.15)	-0.02 (0.03)	-0.13** (0.05)
NonEU-NonEFTA	0.07 (0.21)	-0.14 (0.09)	0.02 (0.04)	0.14* (0.07)	0.01 (0.02)	0.01 (0.18)
Country Dummies	***Yes***	***Yes***	***Yes***	***Yes***	***Yes***	***Yes***
Sector Dummies	***Yes***	**Yes**	***Yes***	***Yes***	**Yes**	***Yes***
Number of Observations	1043	1661	1908	1043	1661	1908
LR test value	21594**	40.893***	31.07***	12.807*	15.872**	34.376***
rho	-0.19	0.37***	-0.25	-0.02	-0.03	-0.17
lambda	-0.76	-2.19***	-0.85	-0.14	-0.07	-0.39**

7.2.4. Diagnostic Results

The Moran test statistics indicate that, particularly when the economic linkage matrix is used, there is spatial autocorrelation in the dependent variables, supporting the use of spatial models. The errors of the spatial models are also tested to determine whether any spatial dependence remains in the errors. The Moran test statistics indicate that, in almost all models constructed using the geographical weight matrix, there is no significant autocorrelation remaining in the error terms. This indicates that the spatial model specifications adequately account for spatial effects; i.e., the spatial models, particularly those constructed with a geographical matrix, are correctly specified.

Table 39. Moran Test Statistics of the Error Terms of the Models

		Moran Test Statistics of the Dependent Variables	
		Geographical	Economic Linkage
2014	Log(R&Dexpenditure)	0.004	0.2***
2014	Log(TurnoverfromSales)	-0.01	0.01***
2016	Log(R&Dexpenditure)	0.01***	0.02***
2016	Log(TurnoverfromSales)	0.009*	0.12***
2018	Log(R&Dexpenditure)	-0.02	0.09***
2018	Log(TurnoverfromSales)	-0.02	0.01***

*, ** and ***indicate significance at 10%, 5% ve 1% levels.

7.2.5. Discussion of the Findings from the Extension of the Traditional MMK Framework with Spatial Dependence

Integrating spatial dependence into the MMK framework reveals how the Belt and Road Initiative (BRI) alters innovation behavior across EU-EFTA firms through both geographical and economic proximity. Spatial models consistently outperform non-spatial ones, highlighting the importance of local and networked interdependencies in shaping firm-level innovation outcomes.

Under geographical proximity, firms focused on national markets benefit from the BRI in terms of increased R&D expenditure—particularly in the 2014 period—while those oriented toward EU-EFTA or global markets experience diminished or adverse effects. Proximity to nationally oriented neighbours supports innovation through localised spillovers. However, when internationally oriented peers surround firms in geographical and economic proximity, the introduction of the BRI reverses positive effects.

In the second block, which analyses turnover from innovative sales, spatial effects again prove to be significant. The initial impact of proximate firms (in both geographic and economic manner) is reversed as the BRI is introduced to the model. In the first block regressions, the sign of the coefficient changes are mostly from positive to negative, whereas in the second block, changes in signs are observed in both directions. What is important here is to note the disruptive capacity of the BRI.

It could be suggested that, prior to BRI, firms benefit from innovation ecosystems that are made coherent under the guidance of EU policymakers. Common regulatory standards and the provision of funding through programs such as Horizon Europe decrease uncertainty and make priorities more straightforward. As the BRI progresses, alternative global markets may capture the attention of proximate firms, and the effort invested in improving local knowledge spillovers may be diverted elsewhere. In other words, spatial extensions reveal that the BRI reshapes not only firm incentives but also the nature of innovation spillovers within the EU. These findings underscore the need for policy frameworks that strengthen not only regional ecosystems but also defend the cohesion of the European innovation ecosystem, particularly as global pressures continue to evolve.

CHAPTER 8

CONCLUSION

This thesis has examined the complex and evolving relationship between China's Belt and Road Initiative (BRI) and the innovation behavior of European firms. Through three interrelated research questions, the thesis aims to understand whether the BRI has had a significant impact on the innovative activities and decisions of European firms, whether this impact is spatially evident, and how it varies based on firms' market orientations and over time. Using firm-level data from the Community Innovation Survey (CIS), the thesis pioneers in introducing the spatially extended version of the well-known CDM/MMK framework to investigate how innovation inputs (such as R&D decisions and expenditures), innovation outputs (sales from innovative products), and firm productivity are affected under the influence of the Chinese BRI.

The broader context for this research is the European Union's long-standing commitment to fostering innovation as a driver of competitiveness, economic growth, and cohesion. The EU has established one of the world's most integrated innovation systems, supported by extensive funding mechanisms, such as Horizon Europe, and structured through policy frameworks like the Smart Specialisation Strategy (S3). These policies aim to leverage regional strengths and promote inclusive development through innovation. At the core of the EU model is the belief that a unified internal market, harmonized standards, and coordinated institutions can reduce uncertainty and enhance the efficiency of knowledge production and diffusion across borders. However, in recent years, this optimistic framework has been challenged by growing external pressures, particularly those stemming from shifting geopolitical and trade dynamics.

One of the most prominent of these developments is the BRI—a state-led initiative launched by China in 2013 to expand its global economic reach through strategic investments in infrastructure, logistics, and connectivity. While initially framed as a development effort, the BRI also functions as a geopolitical instrument that reconfigures trade routes, supply chains, and spheres of influence. For Europe, the BRI introduces not only direct competition from Chinese firms but also the emergence of alternative infrastructure and trade networks that bypass traditional EU-centered routes. These transformations carry significant implications for European firms operating within a tightly coordinated, yet increasingly exposed, innovation ecosystem.

The contribution of this thesis is threefold. On a theoretical level, it is the first empirical study to examine how a large-scale, state-led global strategy, such as the BRI, affects firm-level innovation in the European context. While previous literature has explored the BRI's implications for trade and infrastructure, this work fills a critical gap by assessing how these macro-level shifts translate into micro-level firm behaviors, particularly through the lens of innovation. Methodologically, this research enhances the CDM/MMK framework by integrating spatial dependence directly into all blocks of the system, using spatial weight matrices derived from both geographical proximity and economic linkages. This approach enables the modelling of interdependencies across firms and sectors, capturing not only the direct effects of policy shocks but also the indirect effects transmitted through regional spillovers. Empirically, the thesis draws on a novel dataset that combines CIS microdata with sector-level trade cost reductions derived from the World Bank's BRI Global Dataset, following the instrumental variable methodology of Aghion et al. (2018). This unique integration enables the identification of the BRI's effects across different market orientations.

The findings are both compelling and concerning. In the first block of the MMK framework, which examines R&D engagement and spending, the BRI is associated with a broad decline in the likelihood of firms engaging in R&D across all market orientations. While firms oriented toward domestic markets tend to increase their R&D expenditure under the BRI, those oriented toward EU-EFTA or global markets (nonEU-nonEFTA) exhibit declines. These trends suggest that the BRI may be serving as a selection mechanism, eliminating weaker, nationally oriented firms. This pattern is consistent with previous literature that identifies inverted-U relationships between competition and innovation, where only the most capable firms persist and adapt, while others reduce their innovative efforts or exit innovation activities altogether.

Incorporating spatial dependence into the MMK model further reinforces these conclusions. Spatially lagged terms reveal that the negative impacts of the BRI extend beyond individual firms to affect proximate firms—both geographically and economically connected. Proximity to internationally oriented firms, which was once a source of positive spillovers and innovation synergy, becomes a liability under the BRI-induced global realignment. In several cases, the sign of the spatial coefficient reverses with the introduction of the BRI variable, indicating a significant shift in how neighbouring firm behaviour affects focal firm outcomes. Importantly, these spatial effects are not symmetric; firms embedded in fragmented or misaligned ecosystems are more likely to experience disrupted knowledge flows, eroded trust, and weakened strategic cohesion.

In the second block of the model, which focuses on turnover from innovative sales, the disruptive effects of the BRI become even more apparent. The analysis finds clear sign reversals in the coefficients associated with proximity and market orientation, depending on whether the BRI is accounted for. While in pre-BRI models, proximity to EU- or globally oriented firms is positively correlated with innovation output, this relationship weakens or reverses post-BRI. Conversely, firms previously disadvantaged by their proximity to globally oriented partners begin to show improvement, likely reflecting adaptation or realignment in response to external pressure. These findings underscore the need to understand spillovers as **context-dependent** and sensitive to shifts in the external trade and policy environment.

In addressing the research questions posed at the outset, the analyses yield affirmative answers across the board. First, the BRI has a significant influence on the innovation behaviour of European firms, affecting both R&D decisions and outputs. Second, this influence clearly possesses a spatial dimension, extending through both geographical and economic proximity channels. Third, the effect of the BRI varies depending on the market orientation of the firms involved—both focal and proximate. This market-based differentiation proves more stable and consistent than variations across different survey years, suggesting that the BRI's impact is shaped more by structural firm characteristics than by temporal factors. Thus, it is not possible to make a generalized statement that the BRI's effect grows or weakens over time; rather, its influence is mediated through firm-level exposure.

The implications of these findings for EU policy are substantial. First, they challenge the assumption that economic integration and regional clustering automatically support innovation. While clustering and inter-firm linkages often generate positive externalities under stable conditions, such advantages can be undermined when external shocks disrupt the strategic alignment of firms. The presence of proximate firms is not inherently beneficial; their orientation, resilience, and capacity to transmit useful knowledge are critical in determining whether proximity yields innovation.

Second, these findings suggest the urgent need to redesign the EU innovation policy to account for geopolitical realities. The Smart Specialisation Strategy (S3), while successful in linking innovation policy to regional capabilities and promoting entrepreneurial discovery, lacks a global strategic dimension. S3 assumes that imrovement of local strengths is sufficient to drive innovation. Yet, the evidence presented here indicates that firms are not only regionally embedded but also highly exposed to global networks. Those operating in or alongside EU-EFTA or nonEU-nonEFTA markets are especially vulnerable to displacement or exclusion, and their risks should be made visible through the S3 lens. In addition to the regional focus, the strategy's sector-based focus might overlook the firm-level heterogeneity in innovation capacity and adaptive capability.

To remain effective in the face of growing global volatility, the EU's innovation policies must evolve into a broader framework accompanied by geopolitical foresight, firm-level diagnostics, and a close eye kept on the EU's trade and industrial strategy. Innovation policy should be informed not only by local comparative advantage but also by an awareness of external competitive threats. Funding instruments like Horizon Europe, the European Innovation Council (EIC), and ERA Hubs must support firms not only in producing innovation but in understanding and adapting to global disruption.

Finally, the findings reinforce warnings raised in recent strategic assessments, including the Draghi Report (2024), which stresses the need to address fragmentation within the EU single market. Without greater coherence and strategic coordination, the EU risks becoming more vulnerable to external shocks and less capable of defending its position in the global innovation hierarchy. The BRI, as shown in this thesis, does not merely reshape infrastructure and trade flows—it reconfigures the very foundations of innovation by altering who collaborates, competes, and survives.

In conclusion, this thesis underscores the pressing need for an innovative policy agenda that is both resilient and outward-looking. The survival and success of the EU's innovation ecosystem will depend not only on internal excellence and regional planning but also on the capacity to anticipate, absorb, and respond to global change. The BRI exemplifies the kind of exogenous shock that will increasingly shape the environment in which European firms innovate. Recognizing and adapting to these realities is no longer optional—it is essential for sustaining Europe's competitive edge in the decades to come.

There are points that could be developed in further studies. First, the time period of the study could be extended covering the pre-BRI periods through 2008, 2010 and 2012 CIS data in order to apply a quasi-experimental approach that clearly differentiaies between the pre and post BRI periods. In doing so, a clearer picture can be attained regarding the BRI. Second, the original CIS data could be used, which would allow the use of number of employees. In doing so, decent labour productivity figures could be calculated, and the weakest block of the MMK framework, which this thesis could substantially improve. The original data also includes the NUTS 2 information of firms. By using that data, geographical proximity could be inserted more realistically. Third, the channels through which the BRI affects them can be further analysed by combining the CIS data with business register data. Such a combination could provide insight into input purchases or reveal relationships with Chinese firms. Third, the spatial weight matrix, which relies on economic linkages, could be made dynamic by using more recent input-output tables.

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APPENDICES

A. CORRELATION MATRICES OF THE VARIABLES

TABLE A.1 Correlation Matrix of the Variables in the Selection Equation of the First Block for the 2014 CIS

	largest	sector	size	country_code	lcont	empud	log(BRI)	co	fungmt	funeu	funloc
largest	1	0.279	0.266	0.352	0.838	0.155	0.441	0.147	0.199	0.192	0.053
sector	0.279	1	0.185	0.294	0.841	0.191	0.916	0.18	0.199	0.136	0.142
size	0.266	0.185	1	0.248	0.905	0.142	0.321	0.273	0.199	0.156	0.071
country_code	0.352	0.294	0.248	1	0.907	0.142	1	0.188	0.226	0.321	0.153
lcont	0.838	0.841	0.905	0.907	1	0.865	0.848	0.88	0.915	0.898	0.928
empud	0.155	0.191	0.142	0.142	0.865	1	0.238	0.181	0.181	0.136	0.134
log(BRI)	0.441	0.916	0.321	1	0.848	0.238	1	0.274	0.318	0.382	0.233
co	0.147	0.18	0.273	0.188	0.88	0.181	0.274	1	0.282	0.154	0.177
fungmt	0.199	0.199	0.199	0.226	0.915	0.181	0.318	0.282	1	0.288	0.216
funeu	0.192	0.136	0.156	0.321	0.898	0.136	0.382	0.154	0.288	1	0.114
funloc	0.053	0.142	0.071	0.153	0.928	0.134	0.233	0.177	0.216	0.114	1

TABLE A.2 Correlation Matrix of the Variables in the Outcome Equation of Second Block Using 2014 CIS

	largest	sector	size	country_code	rdintrayes	empud	log(BRI)	co	fungmt	funeu	funloc
largest	1	0.279	0.266	0.352	0.257	0.155	0.441	0.147	0.199	0.192	0.053
sector	0.279	1	0.185	0.294	0.338	0.191	0.916	0.18	0.199	0.136	0.142
size	0.266	0.185	1	0.248	0.304	0.142	0.321	0.273	0.199	0.156	0.071
country_ code	0.352	0.294	0.248	1	0.308	0.142	1	0.188	0.226	0.321	0.153
rdintrayes	0.257	0.338	0.304	0.308	1	0.308	0.435	0.326	0.38	0.176	0.239
empud	0.155	0.191	0.142	0.142	0.308	1	0.238	0.181	0.181	0.136	0.134
log(BRI)	0.441	0.916	0.321	1	0.435	0.238	1	0.274	0.318	0.382	0.233
co	0.147	0.18	0.273	0.188	0.326	0.181	0.274	1	0.282	0.154	0.177
fungmt	0.199	0.199	0.199	0.226	0.38	0.181	0.318	0.282	1	0.288	0.216
funeu	0.192	0.136	0.156	0.321	0.176	0.136	0.382	0.154	0.288	1	0.114
funloc	0.053	0.142	0.071	0.153	0.239	0.134	0.233	0.177	0.216	0.114	1

TABLE A.3 Correlation Matrix of the Variables in the Selection Equation of the First Block for the 2016 CIS

	largest	**sektor**	**buyukluk**	**origin_code**	**lcont**	**empud**	**log(BRI)**	**co**	**fungmt**	**funeu**	**funloc**
largest	1	0.282	0.198	0.259	0.888	0.146	0.393	0.153	0.119	0.134	0.05
sektor	0.282	1	0.202	0.301	0.856	0.197	0.918	0.221	0.199	0.12	0.136
buyukluk	0.198	0.202	1	0.232	0.93	0.17	0.333	0.278	0.156	0.112	0.058
origin_ code	0.259	0.301	0.232	1	0.896	0.173	1	0.25	0.146	0.254	0.244
lcont	0.888	0.856	0.93	0.896	1	0.905	0.847	0.912	0.932	0.912	0.957
empud	0.146	0.197	0.17	0.173	0.905	1	0.27	0.235	0.171	0.11	0.104
log(BRI)	0.393	0.918	0.333	1	0.847	0.27	1	0.339	0.286	0.344	0.299
co	0.153	0.221	0.278	0.25	0.912	0.235	0.339	1	0.285	0.175	0.171
fungmt	0.119	0.199	0.156	0.146	0.932	0.171	0.286	0.285	1	0.298	0.193
funeu	0.134	0.12	0.112	0.254	0.912	0.11	0.344	0.175	0.298	1	0.117
funloc	0.05	0.136	0.058	0.244	0.957	0.104	0.299	0.171	0.193	0.117	1

TABLE A.4 Correlation Matrix of the Variables in the Outcome Equation of Second Block Using 2016 CIS

	largest	**sektor**	**size**	**origin_code**	**lturn**	**Lbri**	**inpspd**	**inpslg**	**inpssu**
largest	1	0.282	0.198	0.259	0.993	0.393	0.099	0.067	0.08
sektor	0.282	1	0.202	0.301	0.993	0.918	0.132	0.11	0.104
size	0.198	0.202	1	0.232	0.995	0.333	0.137	0.147	0.133
origin_ code	0.259	0.301	0.232	1	0.996	1	0.288	0.22	0.227
lturn	0.993	0.993	0.995	0.996	1	0.992	0.992	0.993	0.993
Lbri	0.393	0.918	0.333	1	0.992	1	0.335	0.262	0.277
inpspd	0.099	0.132	0.137	0.288	0.992	0.335	1	0.311	0.337
inpslg	0.067	0.11	0.147	0.22	0.993	0.262	0.311	1	0.421
inpssu	0.08	0.104	0.133	0.227	0.993	0.277	0.337	0.421	1

TABLE A.5 Correlation Matrix of the Variables in the Selection Equation of the First Block for the 2018 CIS

	largest	sektor	buyukluk	origin_code	lcont	empud	log(BRI)	co	fungmt	funeu	funloc
largest	1	0.25	0.185	0.206	0.685	0.14	0.341	0.122	0.07	0.057	0.051
sektor	0.25	1	0.196	0.285	0.672	0.198	0.919	0.219	0.121	0.099	0.139
buyukluk	0.185	0.196	1	0.236	0.748	0.205	0.326	0.25	0.138	0.048	0.01
origin_ code	0.206	0.285	0.236	1	0.868	0.17	1	0.204	0.203	0.259	0.307
lcont	0.685	0.672	0.748	0.868	1	0.752	0.784	0.692	0.669	0.781	0.575
empud	0.14	0.198	0.205	0.17	0.752	1	0.28	0.249	0.094	0.089	0.039
log(BRI)	0.341	0.919	0.326	1	0.784	0.28	1	0.315	0.253	0.317	0.339
co	0.122	0.219	0.25	0.204	0.692	0.249	0.315	1	0.263	0.088	0.19
fungmt	0.07	0.121	0.138	0.203	0.669	0.094	0.253	0.263	1	0.081	0.212
funeu	0.057	0.099	0.048	0.259	0.781	0.089	0.317	0.088	0.081	1	0.039
funloc	0.051	0.139	0.01	0.307	0.575	0.039	0.339	0.19	0.212	0.039	1

TABLE A.6 Correlation Matrix of the Variables in the Outcome Equation of the Second Block for the 2018 CIS

	largest	sektor	buyukluk	origin_code	lturn	letki2	inno_pcs_prd
largest	1	0.25	0.185	0.206	0.71	0.341	0.078
sektor	0.25	1	0.196	0.285	0.679	0.919	0.133
buyukluk	0.185	0.196	1	0.236	0.696	0.326	0.105
origin_code	0.206	0.285	0.236	1	0.754	1	0.267
lturn	0.71	0.679	0.696	0.754	1	0.729	0.678
letki2	0.341	0.919	0.326	1	0.729	1	0.308
inno_pcs_prd	0.078	0.133	0.105	0.267	0.678	0.308	1

B. DEFINITIONS OF CONCEPTS & ALTERNATIVES

Innovation: An innovation refers to the enterprises putting a new or significantly improved product (good or service), process, new marketing method, or new organizational method into practice in business activities, workplace organization or in out-of-firm relations. There could be many sub-categories of innovation such as product or process innovation. What is crucial in labelling certain products, processes, marketing, or organizational methods as innovation is that they are new or have been significantly developed for the firm. In other words, firms do not need to come up with brand-new activities; adapting them from external sources for the first time within the firm is also evaluated as innovation.

Product Innovation: Introduction of goods and /or services that are brand new or those that have been significantly improved in terms of capabilities, user-friendliness, components or sub-systems. Modifications with only aesthetic concerns and the sale of new goods and services purchased from other firms with no modifications are not considered innovations.

Process innovation refers to the enterprise's implementation of a new or significantly improved production process, distribution method, or supply chain activity. Like product innovation, the direct application of processes originating from other firms is not regarded as process innovation. Since CIS 2018, in line with the OSLO Manual's 4^{th} Edition, process innovation has been replaced with business process innovation, which encompasses marketing and organisational innovations described below. Therefore, they are not available under specific categories in CIS 2018.

Organizational innovation: If an enterprise puts at least one new organizational method in its business practices, workplace organization or out-of-firm relations, it is considered organizational innovation.

Marketing innovation: If the enterprise puts at least one new marketing concept or strategy into practice by deviating significantly from its already practised marketing methods and using them for the first time in the firm. That is, there might be marketing strategies that have been stored in the corporate memory of the firm, and their application for the first time falls into the category of marketing innovation. Changes in routines of the methods due to seasonal reasons or regular schedules are not considered innovations. There must be considerable modifications to product design, packaging, placement, promotion, or pricing.

R&D Activity: These activities encompass creative and systematic work aimed at devising new applications of existing knowledge and developing a comprehensive stock of knowledge that also includes knowledge of humanity, culture, and society.

Innovation-active: An enterprise is labelled as "innovation active" if it has continued or abandoned innovation activities in the survey period. Putting innovations into practice or acquiring commercial profits are not prerequisites for enterprises to be innovative and active. **Non-innovative** enterprises exhibit neither version of innovation activity during the reference period.

Table A.7 Description of the NACE Rev.2 Sectors Included in the Analyses

Nace Rev.2 Two Digit Code	**Description of the Sector**
01	Crop and animal production, hunting and related service activities
02	Forestry and logging
03	Fishing and aquaculture
04	Mining of coal and lignite
05	Extraction of crude petroleum and natural gas
06	Mining of metal ores
07	Other mining and quarrying
08	Mining support service activities
10	Manufacture of food products
11	Manufacture of beverages
12	Manufacture of tobacco products
13	Manufacture of textiles
14	Manufacture of wearing apparel
15	Manufacture of leather and related products
16	Manufacture of wood and of products of wood and cork, except furniture
17	Manufacture of paper and paper products
18	Printing and reproduction of recorded media
19	Manufacture of coke and refined petroleum products
20	Manufacture of chemicals and chemical products
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
22	Manufacture of rubber and plastic products
23	Manufacture of other non-metallic mineral products
24	Manufacture of basic metals
25	Manufacture of fabricated metal products, except machinery and equipment
26	Manufacture of computer, electronic and optical products
27	Manufacture of electrical equipment
28	Manufacture of machinery and equipment n.e.c.

Table A.7. (continued)

29	Manufacture of motor vehicles, trailers and semi-trailers
30	Manufacture of other transport equipment
31	Manufacture of furniture
32	Other manufacturing
33	Repair and installation of machinery and equipment
35	Electricity, gas, steam and air conditioning supply

Different Definitions of Funding Variables in the 2018 CIS

In the analyses for the 2018 CIS, the funding terms also differ from the previous two surveys. The sources of funding are extended to cover the financial support derived from the issuance of equities and debt financing. Despite the proliferation, most variables cannot be used in the analyses because the number of observations is minimal for most of them. The definitions of the funding variables and the number of available observations in the 2018 CIS are listed in Table A.2. Considering both the continuity of the models and the number of observations in the models, *fund_gov_ctl*, *fund_eu_hp2020* and the *fund_aut_loc_reg* are used in the first block model in compliance with fungmt, funeu and funloc, respectively.

Table A.8. Definitions of Funding Variables in the 2018 CIS

fund_equit_succ	Successfully obtained equity finance
fund_equit_nsucc	Unsuccessful trials to obtain equity finance
fund_nequit	Did not try to obtain equity finance
fund_equit_succ_rndinnmarket	Successfully obtained equity finance, and used it partly or fully for R&D or other innovation activity
fund_debt_succ	Successfully obtained debt finance
fund_debt_nsucc	Unsuccessful trials to obtain debt finance
fund_ndebt	Did not try to obtain debt finance
fund_debt_succ_rndinn	Successfully obtained debt finance, and used it partly or fully for R&D or other innovation activity
fund_aut_loc_reg	Financial support received from local or regional authorities
fund_aut_loc_reg_rndinn	Financial support from local or regional authorities used partly or fully for R&D or other innovation activity
fund_gov_ctl	Financial support received from national governments
fund_gov_ctl_rndinn	Financial support from national government used partly or fully for R&D or other innovation activity
fund_eu_hp2020	Financial support received from EU 2020 Horizon Programme
fund_eu_hp2020_rndinn	Financial support from EU 2020 Horizon Programme used partly or fully for R&D or other innovation activity
fund_eu_oth	Financial support received from other EU institutions
fund_eu_oth_rndinn	Financial support from EU institutions used partly or fully for R&D or other innovation activity

Source: Community Innovation Survey

C. ALTERNATIVE SPATIAL MODELS

Table A.9 Spatial Models for First Block Regressions in 2014 CIS Estimated Under Geographical Proximity

Variable	SARAR-Durbin	SEM	SAR	SAR-Durbin	SEM-Durbin
rho	-0.359*** (0.137)		-0.499*** (0.061)	-0.352*** (0.105)	
(Intercept)	12.146*** (0.935)	6.302*** (0.488)	16.501*** (0.637)	11.834*** (0.933)	6.302*** (0.488)
co	0.173* (0.089)	0.195** (0.084)	0.084 (0.076)	0.174** (0.084)	0.195** (0.084)
fungmt	0.477*** (0.083)	0.480*** (0.080)	0.508*** (0.073)	0.478*** (0.079)	0.480*** (0.080)
funeu	0.239*** (0.071)	0.250*** (0.070)	0.190*** (0.068)	0.240*** (0.069)	0.250*** (0.070)
funloc	0.427*** (0.085)	0.438*** (0.084)	0.583*** (0.084)	0.428*** (0.084)	0.438*** (0.084)
imr	-0.701*** (0.175)	-0.669*** (0.162)	-0.911*** (0.123)	-0.700*** (0.160)	-0.669*** (0.162)
factor(largest)2	0.295** (0.122)	0.282** (0.112)	0.016 (-)	0.295*** (0.109)	0.282** (0.112)
factor(largest)3	0.828*** (0.165)	0.820*** (0.155)	0.679*** (0.152)	0.828*** (0.158)	0.820*** (0.155)
lBRI	0.225*** (0.066)	0.240*** (0.062)	0.326*** (0.061)	0.225*** (0.061)	0.240*** (0.062)
lBRI:factor(largest)2	-0.128 (0.093)	-0.131 (0.087)	-0.117 (0.087)	-0.129 (0.089)	-0.131 (0.087)
lBRI:factor(largest)3	-0.153** (0.073)	-0.151** (0.067)	-0.107*** (0.040)	-0.153** (0.065)	-0.151** (0.067)
factor(size)2	0.853*** (0.068)	0.866*** (0.066)	0.722*** (0.064)	0.854*** (0.066)	0.866*** (0.066)
factor(size)3	2.601*** (0.100)	2.620*** (0.093)	2.428*** (0.085)	2.602*** (0.093)	2.620*** (0.093)
lag.lBRI	1.706*** (0.605)	3.203*** (0.350)		1.893*** (0.378)	3.203*** (0.350)
lag.factor(largest)2	8.541*** (1.999)	15.422*** (1.439)		9.213*** (1.280)	15.422*** (1.439)
lag.factor(largest)3	27.507 (19.685)	14.036 (9.775)		25.414** (12.085)	14.036 (9.775)
lag.lBRI:factor(largest)2	-7.797*** (1.701)	-13.485*** (1.226)		-8.361*** (1.157)	-13.485*** (1.226)
lag.lBRI:factor(largest)3	-14.253 (11.183)	-7.334 (5.432)		-13.109* (6.941)	-7.334 (5.432)
lambda	0.054 (-)	-0.418 (-)			-0.418 (-)
r.squared	0.491	0.490	0.462	0.491	0.490
adj.r.squared					
AIC	14264.457	14268.100	14464.812	14262.499	14268.100
BIC	14582.622	14580.027	14745.546	14574.426	14580.027
logLik	-7081.228	-7084.050	-7187.406	-7081.249	-7084.050
nobs	3784.000	3784.000	3784.000	3784.000	3784.000

Table A.10 Spatial Models for First Block Regressions in 2016 CIS Under Geographical Proximity

Variable	SARAR-Durbin	SEM	SAR	SAR-Durbin	SEM-Durbin
rho	-0.080 (-)		0.180*** (0.019)	-0.976*** (0.012)	
(Intercept)	2.622 (3.077)	11.680*** (0.747)	12.721*** (0.263)	25.666*** (0.330)	11.680*** (0.747)
co	-0.102 (0.078)	-0.102 (0.076)	-1.171*** (0.097)	-0.944*** (0.089)	-0.102 (0.076)
fungmt	0.178** (0.071)	0.147** (0.074)	-1.329*** (0.093)	-0.877*** (0.086)	0.147** (0.074)
funeu	0.359*** (0.063)	0.337*** (0.063)	0.335*** (0.087)	0.114 (0.078)	0.337*** (0.063)
funloc	-0.133 (0.091)	-0.141 (0.093)	-1.050*** (0.127)	-0.510*** (0.112)	-0.141 (0.093)
imr	-1.272*** (0.149)	-1.309*** (0.154)	-3.208*** (0.175)	-3.374*** (0.176)	-1.309*** (0.154)
lBRI	0.101*** (0.037)	0.094*** (0.035)	0.170*** (0.049)	0.211*** (0.042)	0.094*** (0.035)
factor(largest)2	0.355*** (0.088)	0.344*** (0.101)	0.284** (0.134)	0.104 (0.106)	0.344*** (0.101)
factor(largest)3	0.836*** (0.177)	0.838*** (0.173)	-0.441*** (0.135)	-0.067 (0.191)	0.838*** (0.173)
factor(size)2	0.859*** (0.060)	0.889*** (0.062)	0.709*** (0.085)	0.497*** (0.074)	0.889*** (0.062)
factor(size)3	2.328*** (0.078)	2.354*** (0.079)	1.849*** (0.107)	1.629*** (0.094)	2.354*** (0.079)
lBRI:factor(largest)2	-0.088* (0.050)	-0.121** (0.060)	-0.076 (0.081)	-0.007 (0.039)	-0.121** (0.060)
lBRI:factor(largest)3	-0.236** (0.106)	-0.241** (0.103)	-0.008 (0.018)	-0.096 (0.108)	-0.241** (0.103)
lag.lBRI	-3.957 (-)	-1.670*** (0.551)		0.441*** (0.117)	-1.670*** (0.551)
lag.factor(largest)2	11.127*** (0.180)	1.167 (6.310)		-15.970*** (0.617)	1.167 (6.310)
lag.factor(largest)3	66.801 (-)	-92.369*** (11.377)		-73.287*** (1.581)	-92.369*** (11.377)
lag.lBRI:factor(largest)2	-1.789*** (0.182)	1.236 (3.190)		4.976*** (0.331)	1.236 (3.190)
lag.lBRI:factor(largest)3	-38.233 (-)	56.688*** (5.137)		45.124*** (1.044)	56.688*** (5.137)
lambda	0.982*** (0.005)	-0.945*** (0.011)			-0.945*** (0.011)
r.squared	0.633	0.632	0.252	0.454	0.632
adj.r.squared					
AIC	15795.986	15797.227	18712.214	17450.145	15797.227
BIC	16118.946	16113.854	18997.178	17766.773	16113.854
logLik	-7846.993	-7848.613	-9311.107	-8675.073	-7848.613
nobs	4157.000	4157.000	4157.000	4157.000	4157.000

Table A.11 Spatial Models for First Block Regressions in 2018 CIS Estimated Under Geographical Proximity

Variable	SARAR-Durbin	SEM	SAR	SAR-Durbin	SEM-Durbin
rho	0.016 (-)		-0.008 (0.015)	0.042 (-)	
(Intercept)	10.848 (-)	11.000*** (0.406)	10.932*** (0.216)	10.495 (-)	11.000*** (0.406)
co	-0.106 (-)	-0.106 (0.142)	-0.130 (0.123)	-0.112 (0.124)	-0.106 (0.142)
fungmt	0.090 (-)	0.090 (0.081)	0.099 (0.082)	0.089 (0.082)	0.090 (0.081)
funeu	0.062 (0.059)	0.062 (0.080)	0.072 (0.073)	0.061 (0.082)	0.062 (0.080)
funloc	0.055 (-)	0.055 (0.112)	0.062 (0.097)	0.056 (0.104)	0.055 (0.112)
imr	-0.744 (-)	-0.744*** (0.123)	-0.768*** (0.104)	-0.749*** (0.107)	-0.744*** (0.123)
lBRI	0.117 (-)	0.117 (0.073)	0.141** (0.063)	0.117*** (0.038)	0.117 (0.073)
factor(largest)2	0.202** (0.101)	0.202* (0.121)	0.140 (0.104)	0.201* (0.117)	0.202* (0.121)
factor(largest)3	0.437*** (0.113)	0.437*** (0.124)	0.044 (-)	0.434*** (0.124)	0.437*** (0.124)
factor(size)2	0.772*** (0.069)	0.772*** (0.079)	0.765*** (0.076)	0.771*** (0.076)	0.772*** (0.079)
factor(size)3	1.987*** (0.078)	1.987*** (0.108)	1.949*** (0.101)	1.987*** (0.102)	1.987*** (0.108)
lag.lBRI	-0.006 (0.006)	-0.003 (0.112)		-0.004 (0.024)	-0.003 (0.112)
lag.factor(largest)2	-3.546 (-)	-3.506*** (1.194)		-3.483*** (0.951)	-3.506*** (1.194)
lag.factor(largest)3	-1.550 (-)	-1.416*** (0.504)		-0.870 (-)	-1.416*** (0.504)
lag.largest_2_lBRI	1.743*** (0.439)	1.761*** (0.634)		1.794*** (0.636)	1.761*** (0.634)
lambda	0.115 (-)	0.116 (-)			0.116 (-)
lBRI:factor(largest)2	0.096 (-)	0.096 (0.076)	0.130* (0.070)	0.095 (0.074)	0.096 (0.076)
lBRI:factor(largest)3			0.261 (-)		
r.squared	0.374	0.374	0.373	0.374	0.374
adj.r.squared					
AIC	10465.039	10463.040	10461.996	10463.128	10463.040
BIC	10749.255	10741.335	10722.528	10741.423	10741.335
logLik	-5184.520	-5184.520	-5186.998	-5184.564	-5184.520
nobs	2755.000	2755.000	2755.000	2755.000	2755.000

Table A.12 Spatial Models for First Block Regressions in 2014 CIS Estimated Under Economic Proximity

Variable	SARAR-Durbin	SEM	SAR	SAR-Durbin	SEM-Durbin
rho	0.020** (0.010)		-0.014** (0.007)	0.001 (0.003)	
(Intercept)	10.474*** (0.222)	11.364*** (0.319)	11.867*** (0.127)	11.691*** (0.204)	11.364*** (0.319)
co	-0.043 (0.029)	-0.076 (0.089)	-0.073 (0.074)	-0.091 (0.080)	-0.076 (0.089)
fungmt	0.106** (0.053)	0.338*** (0.083)	0.479*** (0.079)	0.420*** (0.080)	0.338*** (0.083)
funeu	0.409*** (0.075)	0.198** (0.079)	0.183** (0.078)	0.187** (0.078)	0.198** (0.079)
funloc	0.087 (0.073)	0.412*** (0.090)	0.474*** (0.091)	0.428*** (0.090)	0.412*** (0.090)
imr	-0.890*** (0.013)	-1.227*** (0.152)	-1.289*** (0.126)	-1.306*** (0.132)	-1.227*** (0.152)
lBRI	0.176* (0.093)	0.697*** (0.150)	0.288*** (0.080)	0.476*** (0.104)	0.697*** (0.150)
factor(largest)2	0.644*** (0.134)	0.017 (0.141)	0.125 (0.130)	0.124 (0.140)	0.017 (0.141)
factor(largest)3	0.410* (0.230)	0.402* (0.219)	0.656*** (0.216)	0.398*** (0.141)	0.402* (0.219)
factor(size)2	0.832*** (0.067)	0.683*** (0.073)	0.622*** (0.073)	0.624*** (0.073)	0.683*** (0.073)
factor(size)3	2.653*** (0.089)	2.508*** (0.100)	2.424*** (0.098)	2.414*** (0.098)	2.508*** (0.100)
lBRI:factor(largest)2	-0.196*** (0.073)	-0.075 (0.080)	-0.155** (0.075)	-0.151* (0.079)	-0.075 (0.080)
lBRI:factor(largest)3	0.062 (0.133)	0.008 (0.125)	-0.124 (0.122)	0.024 (0.061)	0.008 (0.125)
lag.lBRI	0.014 (0.021)	-0.397*** (0.120)		-0.217*** (0.083)	-0.397*** (0.120)
lag.factor(largest)2	0.099 (0.189)	0.336 (0.474)		-1.045*** (0.325)	0.336 (0.474)
lag.factor(largest)3	1.117* (0.672)	-0.339 (0.993)		3.545*** (0.667)	-0.339 (0.993)
lag.lBRI:factor(largest)2	-0.261* (0.151)	0.286 (0.310)		0.385* (0.215)	0.286 (0.310)
lag.lBRI:factor(largest)3	-0.935*** (0.332)	0.500 (0.540)		-1.058*** (0.382)	0.500 (0.540)
lambda	-0.042 (0.141)	0.544*** (0.070)			0.544*** (0.070)
r.squared	0.563	0.507	0.477	0.486	0.507
AIC	10805.256	11227.877	11306.261	11270.669	11227.877
BIC	11158.480	11527.219	11575.669	11570.011	11527.219
logLik	-5343.628	-5563.939	-5608.130	-5585.335	-5563.939
nobs	2942.000	2942.000	2942.000	2942.000	2942.000

Table A.13 Spatial Models for First Block Regressions in 2016 CIS Estimated Under Economic Proximity

Variable	SARAR-Durbin	SEM	SAR	SAR-Durbin	SEM-Durbin
rho	0.024 (0.021)		0.840*** (0.021)	0.694*** (0.028)	
(Intercept)	10.284*** (0.141)	13.900*** (0.524)	1.794*** (0.303)	3.485 (-)	13.900*** (0.524)
co	-0.089** (0.037)	-0.522*** (0.088)	-0.187** (0.080)	-0.192*** (0.045)	-0.522*** (0.088)
fungmt	0.159*** (0.058)	-0.639*** (0.084)	-0.379*** (0.080)	-0.387*** (0.070)	-0.639*** (0.084)
funeu	0.314*** (0.063)	0.491*** (0.075)	0.431*** (0.076)	0.583*** (0.075)	0.491*** (0.075)
funloc	-0.121 (0.093)	-0.855*** (0.108)	-0.525*** (0.109)	-0.764*** (0.102)	-0.855*** (0.108)
imr	-1.301*** (0.090)	-2.004*** (0.174)	-0.887*** (0.133)	-0.948*** (0.069)	-2.004*** (0.174)
lBRI	0.053* (0.027)	-0.322*** (0.123)	0.148*** (0.041)	-0.005 (-)	-0.322*** (0.123)
factor(largest)2	0.273*** (0.096)	0.620*** (0.124)	0.332*** (0.115)	0.665 (-)	0.620*** (0.124)
factor(largest)3	0.721*** (0.179)	0.620*** (0.210)	0.326** (0.159)	0.847*** (0.195)	0.620*** (0.210)
factor(size)2	0.891*** (0.061)	0.883*** (0.073)	0.934*** (0.075)	0.925*** (0.065)	0.883*** (0.073)
factor(size)3	2.341*** (0.079)	2.276*** (0.094)	2.196*** (0.095)	2.324*** (0.070)	2.276*** (0.094)
lag.lBRI	0.021 (-)	0.723*** (0.185)		0.243 (-)	0.723*** (0.185)
lag.factor(largest)2	1.395*** (0.246)	-1.152 (0.862)		-1.131*** (0.391)	-1.152 (0.862)
lag.factor(largest)3	2.906*** (1.028)	-3.225 (2.738)		-10.562*** (1.319)	-3.225 (2.738)
lambda	0.060 (-)	0.905*** (0.018)			0.905*** (0.018)
lBRI:factor(largest)2	-0.053 (0.055)	-0.043 (0.075)	0.059 (0.066)	0.027 (-)	-0.043 (0.075)
lBRI:factor(largest)3	-0.177* (0.106)	-0.173 (0.126)	-0.037 (0.079)	-0.183* (0.097)	-0.173 (0.126)
lag.lBRI:factor(largest)2	-0.065 (0.075)	-2.955*** (0.461)		-1.016*** (0.256)	-2.955*** (0.461)
lag.lBRI:factor(largest)3	-1.333*** (0.497)	5.232*** (1.499)		3.809*** (0.621)	5.232*** (1.499)
r.squared	0.638	0.494	0.424	0.448	0.494
AIC	15736.036	17279.238	17794.346	17572.743	17279.238
BIC	16115.989	17595.865	18079.311	17889.370	17595.865
logLik	-7808.018	-8589.619	-8852.173	-8736.371	-8589.619
nobs	4157	4157	4157	4157	4157

Table A.14 Spatial Models for First Block Regressions in 2018 CIS Estimated Under Economic Proximity

Variable	SARAR	SEM	SAR	SAR-Durbin	SEM-Durbin
rho	-0.472** (0.218)		-0.037 (0.049)	-0.011 (-)	
(Intercept)	15.797*** (2.492)	10.452*** (0.462)	10.909*** (0.468)	10.632*** (0.369)	10.511*** (0.499)
co	0.065 (0.072)	0.089 (0.173)	0.109 (0.088)	0.115 (0.151)	0.092 (0.173)
fungmt	0.144** (0.068)	0.136 (0.085)	0.139* (0.071)	0.145* (0.078)	0.143* (0.085)
funeu	0.133* (0.073)	0.133 (0.088)	0.130** (0.057)	0.135 (0.085)	0.136 (0.088)
funloc	0.014 (-)	0.033 (0.112)	0.044 (0.107)	0.046 (0.075)	0.032 (0.112)
imr	-0.586*** (0.070)	-0.565*** (0.154)	-0.552*** (0.056)	-0.546*** (0.138)	-0.562*** (0.154)
lBRI	-0.016 (-)	0.112 (0.080)	0.114* (0.066)	0.036 (-)	0.001 (0.144)
factor(largest)2	0.213** (0.109)	0.215* (0.124)	0.204* (0.119)	0.215* (0.128)	0.223* (0.127)
factor(largest)3	0.119 (0.224)	0.151 (0.257)	0.149 (0.219)	0.127 (0.222)	0.136 (0.260)
factor(size)2	0.830*** (0.077)	0.824*** (0.082)	0.825*** (0.075)	0.822*** (0.081)	0.821*** (0.082)
factor(size)3	2.082*** (0.102)	2.072*** (0.114)	2.076*** (0.094)	2.075*** (0.112)	2.071*** (0.114)
lag.lBRI	0.174 (0.134)			0.135 (-)	0.191 (0.213)
lag.factor(largest)2	-0.339 (-)			-0.550 (-)	-0.597 (0.695)
lag.factor(largest)3	1.053 (1.690)			0.902 (-)	0.463 (2.484)
lambda	0.556*** (0.132)	0.200 (0.129)			0.228* (0.117)
lBRI:factor(largest)2	-0.209*** (0.051)	0.098 (0.077)		0.102 (0.079)	0.097 (0.080)
lBRI:factor(largest)3	0.447 (0.669)	0.213 (0.152)		0.228* (0.134)	0.223 (0.154)
lag.lBRI:factor(largest)2	0.109* (0.060)		0.104 (0.073)	0.086 (-)	0.108 (0.441)
lag.lBRI:factor(largest)3	0.230 (0.152)		0.215 (0.133)	-0.412 (-)	-0.232 (1.740)
r.squared	0.386	0.382	0.376	0.377	0.383
AIC	10459.100	10456.795	10458.814	10466.222	10463.397
BIC	10796.607	10758.775	10760.794	10797.807	10794.983
logLik	-5172.550	-5177.398	-5178.407	-5177.111	-5175.699
nobs	2755	2755	2755	2755	2755

Table A.15 Spatial Models for Second Block Regressions in 2014 CIS Estimated Under Economic Proximity

Variable	SARAR-Durbin	SEM	SAR	SAR-Durbin	SEM-Durbin
rho	-0.067 (0.198)		-0.172* (0.102)	-0.172* (0.102)	
(Intercept)	11.749*** (2.495)	11.184*** (0.566)	13.157*** (1.423)	13.157*** (1.423)	10.820*** (0.613)
inpspd	0.080 (0.093)	0.091 (0.099)	0.086 (0.096)	0.086 (0.096)	0.078 (0.099)
inpslg	0.312*** (0.099)	0.319*** (0.097)	0.321*** (0.097)	0.321*** (0.097)	0.307*** (0.097)
inpssu	0.118 (0.093)	0.112 (0.091)	0.113 (0.089)	0.113 (0.089)	0.121 (0.091)
imr2	-0.354* (0.211)	-0.307 (0.248)	-0.341 (0.262)	-0.341 (0.262)	-0.358 (0.248)
lBRI	-0.048 (0.086)	0.100 (0.099)	-0.042 (-)	-0.042 (-)	-0.061 (0.136)
factor(largest)2	0.436*** (0.154)	0.436*** (0.148)	0.446*** (0.166)	0.446*** (0.166)	0.432*** (0.158)
factor(largest)3	0.522 (-)	0.640*** (0.221)	0.524** (0.223)	0.524** (0.223)	0.521** (0.238)
factor(size)2	1.495*** (0.089)	1.481*** (0.088)	1.505*** (0.089)	1.505*** (0.089)	1.490*** (0.088)
factor(size)3	3.413*** (0.115)	3.396*** (0.114)	3.415*** (0.116)	3.415*** (0.116)	3.405*** (0.114)
lag.lBRI	0.340 (0.215)		0.310* (0.176)	0.310* (0.176)	0.372* (0.224)
lag.factor(largest)2	-0.627 (0.524)		-0.456 (0.673)	-0.456 (0.673)	-0.693 (0.706)
lag.factor(largest)3	2.147** (1.018)		2.619** (1.330)	2.619** (1.330)	1.888* (1.081)
lambda	-0.308 (0.362)	-0.320 (0.205)			-0.406* (0.233)
lBRI:factor(largest)2	-0.121 (0.089)	-0.124 (0.088)	-0.121 (0.103)	-0.121 (0.103)	-0.120 (0.095)
lBRI:factor(largest)3	0.036 (-)	-0.026 (0.130)	0.037 (0.130)	0.037 (0.130)	0.037 (0.143)
lag.lBRI:factor(largest)2	-0.107 (-)		-0.196 (0.491)	-0.196 (0.491)	-0.064 (0.499)
lag.lBRI:factor(largest)3	-0.682 (0.660)		-0.651 (0.698)	-0.651 (0.698)	-0.717 (0.592)
r.squared	0.527	0.526	0.532	0.532	0.527
AIC	6411.432	6408.257	6410.837	6410.837	6409.743
BIC	6733.703	6697.754	6727.646	6727.646	6726.551
logLik	-3146.716	-3151.128	-3147.419	-3147.419	-3146.871
nobs	1741	1741	1741	1741	1741

Table A.16 Spatial Models for Second Block Regressions in 2016 CIS Estimated Under Economic Proximity

Variable	SARAR-Durbin	SEM	SAR	SAR-Durbin	SEM-Durbin
rho	-0.199 (-)		-0.416*** (0.110)	-0.416*** (0.110)	
(Intercept)	13.973*** (0.797)	11.388*** (0.539)	16.630*** (1.419)	16.630*** (1.419)	11.388*** (0.539)
inpspd	-0.105 (0.086)	-0.100 (0.085)	-0.115 (0.083)	-0.115 (0.083)	-0.100 (0.085)
inpslg	0.302*** (0.081)	0.299*** (0.088)	0.305*** (0.088)	0.305*** (0.088)	0.299*** (0.088)
inpssu	0.021 (-)	0.014 (0.080)	0.020 (-)	0.020 (-)	0.014 (0.080)
imr2	-1.140 (-)	-1.138*** (0.233)	-1.142*** (0.109)	-1.142*** (0.109)	-1.138*** (0.233)
lBRI	-0.014 (0.052)	-0.024 (0.091)	-0.029 (-)	-0.029 (-)	-0.024 (0.091)
factor(largest)2	0.414*** (0.136)	0.418*** (0.138)	0.435*** (0.144)	0.435*** (0.144)	0.418*** (0.138)
factor(largest)3	0.599 (-)	0.614*** (0.224)	0.584** (0.240)	0.584** (0.240)	0.614*** (0.224)
factor(size)2	1.521*** (0.076)	1.515*** (0.079)	1.529*** (0.080)	1.529*** (0.080)	1.515*** (0.079)
factor(size)3	3.229*** (0.100)	3.215*** (0.100)	3.222*** (0.095)	3.222*** (0.095)	3.215*** (0.100)
lBRI:factor(largest)2	0.111 (0.082)	0.105 (0.084)	0.106 (0.086)	0.106 (0.086)	0.105 (0.084)
lBRI:factor(largest)3	0.069 (-)	0.062 (0.136)	0.074 (0.148)	0.074 (0.148)	0.062 (0.136)
lag.lBRI	0.487*** (0.184)	0.526*** (0.182)	0.454*** (0.172)	0.454*** (0.172)	0.526*** (0.182)
lag.factor(largest)2	0.912*** (0.174)	0.588 (0.535)	1.216** (0.608)	1.216** (0.608)	0.588 (0.535)
lag.factor(largest)3	4.226*** (1.580)	3.237** (1.364)	6.177*** (1.892)	6.177*** (1.892)	3.237** (1.364)
lag.lBRI:factor(largest)2	-0.709* (0.406)	-0.696* (0.413)	-0.714 (0.547)	-0.714 (0.547)	-0.696* (0.413)
lag.lBRI:factor(largest)3	-2.262*** (0.803)	-2.004*** (0.762)	-2.726*** (1.053)	-2.726*** (1.053)	-2.004*** (0.762)
lambda	-0.640*** (0.147)	-0.916*** (0.247)			-0.916*** (0.247)
r.squared	0.526	0.526	0.532	0.532	0.526
AIC	7527.962	7528.393	7531.016	7531.016	7528.393
BIC	7860.216	7855.016	7857.639	7857.639	7855.016
logLik	-3704.981	-3706.197	-3707.508	-3707.508	-3706.197
nobs	2062	2062	2062	2062	2062

Table A.17 Spatial Models for Second Block Regressions in 2018 CIS Estimated Under Economic Proximity

Variable	SARAR-Durbin	SEM	SAR	SAR-Durbin	SEM-Durbin
rho	0.021 (0.046)		-0.231 (-)	-0.365*** (0.131)	
(Intercept)	11.418*** (2.223)	12.136*** (4.485)	10.808*** (0.923)	11.265*** (1.968)	11.308** (4.586)
inno_pcs_prd	2.551*** (0.826)	2.352*** (0.911)	2.485*** (0.466)	2.525*** (0.793)	2.387*** (0.909)
imr2	-10.553*** (2.057)	-11.120*** (2.502)	-10.753*** (1.132)	-10.723*** (2.172)	-10.996*** (2.500)
lBRI	-0.913* (0.471)	-0.474 (0.662)	-0.514* (0.295)	-2.368 (2.540)	-3.154*** (1.062)
factor(largest)2	-1.163 (0.936)	-1.193 (1.161)	-1.282 (0.870)	-1.587 (1.321)	-1.891 (1.210)
factor(largest)3	-4.553** (2.154)	-5.288** (2.284)	-5.420*** (1.734)	-4.899** (2.313)	-5.221** (2.401)
factor(size)2	-0.551 (0.585)	-0.529 (0.686)	-0.618 (0.630)	-0.652 (0.680)	-0.659 (0.684)
factor(size)3	0.506 (0.741)	0.731 (0.902)	0.625** (0.316)	0.442 (0.890)	0.449 (0.898)
lag.factor(largest)2	0.577 (1.251)			5.912 (6.452)	6.241 (4.268)
lag.factor(largest)3	-18.410 (13.338)			-24.061 (18.177)	-9.763 (15.988)
lambda	-0.828*** (0.218)	-0.707*** (0.201)			-1.000 (-)
lBRI:factor(largest)2	0.692 (0.614)	0.852 (0.739)	0.906* (0.513)	1.029 (0.826)	1.254 (0.777)
lBRI:factor(largest)3	2.386* (1.316)	3.052** (1.402)	3.048*** (0.289)	2.680* (1.411)	2.890** (1.465)
lag.lBRI				2.636 (3.456)	4.283*** (1.628)
lag.lBRI:factor(largest)2	3.158* (1.790)			0.818 (5.436)	-1.898 (3.016)
lag.lBRI:factor(largest)3	22.379** (9.296)			23.814 (14.611)	12.758 (10.863)
r.squared	0.153	0.15	0.159	0.16	0.151
AIC	16692.804	16694.128	16704.231	16700.924	16686.789
BIC	16991.654	16964.784	16974.887	16999.774	16985.639
logLik	-8293.402	-8299.064	-8304.115	-8297.462	-8290.395
nobs	2077	2077	2077	2077	2077

Table A.18 Spatial Models for Second Block Regressions in 2014 CIS Estimated Under Geographic Proximity

Variable	SARAR-Durbin	SEM	SAR	SAR-Durbin	SEM-Durbin
rho	-0.177 (0.125)		-0.157*** (0.031)	0.458 (-)	
(Intercept)	11.396*** (1.362)	8.773*** (1.221)	13.945*** (0.448)	0.085 (-)	8.773*** (1.221)
inpspd	0.390*** (0.075)	0.269*** (0.074)	0.225*** (0.072)	0.246*** (0.071)	0.269*** (0.074)
inpslg	0.430*** (0.078)	0.388*** (0.079)	0.324*** (0.082)	0.374*** (0.078)	0.388*** (0.079)
inpssu	0.170** (0.072)	0.182** (0.073)	0.107 (0.073)	0.162** (0.070)	0.182** (0.073)
imr2	1.216*** (0.182)	0.475*** (0.165)	0.436*** (0.134)	0.377** (0.154)	0.475*** (0.165)
lBRI	0.047 (0.067)	0.076 (0.082)	0.105 (0.081)	0.115 (0.071)	0.076 (0.082)
factor(largest)2	0.483*** (0.122)	0.438*** (0.122)	0.030 (0.085)	0.422*** (0.117)	0.438*** (0.122)
factor(largest)3	0.520*** (0.116)	0.741*** (0.200)	0.571*** (0.113)	0.746*** (0.107)	0.741*** (0.200)
factor(size)2	1.309*** (0.071)	1.498*** (0.069)	1.533*** (0.072)	1.499*** (0.069)	1.498*** (0.069)
factor(size)3	3.071*** (0.106)	3.561*** (0.094)	3.703*** (0.097)	3.561*** (0.093)	3.561*** (0.094)
y1	0.123*** (0.013)				
lBRI:factor(largest)2	-0.188** (0.076)	-0.146* (0.077)		-0.144** (0.073)	-0.146* (0.077)
lBRI:factor(largest)3	0.013 (0.028)	-0.003 (0.122)		-0.002 (-)	-0.003 (0.122)
lag.lBRI	1.014*** (0.286)	1.786*** (0.622)		1.025*** (0.379)	1.786*** (0.622)
lag.factor(largest)2	3.622** (1.630)	7.709*** (2.608)		11.376*** (1.296)	7.709*** (2.608)
lag.factor(largest)3	-23.235* (12.147)	-3.432 (31.207)		-42.774*** (13.465)	-3.432 (31.207)
lag.lBRI:factor(largest)2	2.275 (-)	0.543 (4.541)		10.733*** (2.489)	0.543 (4.541)
lag.lBRI:factor(largest)3	19.383* (10.746)	3.013 (28.783)		41.714*** (12.500)	3.013 (28.783)
lambda	0.580*** (0.044)	0.542*** (0.067)			0.542*** (0.067)
r.squared	0.520	0.506	0.460	0.505	0.506
AIC	10444.491	10522.547	10754.202	10527.826	10522.547
BIC	10747.966	10814.121	11004.123	10819.401	10814.121
logLik	-5171.245	-5212.273	-5335.101	-5214.913	-5212.273
nobs	2837	2837	2837	2837	2837

Table A.19 Spatial Models for Second Block Regressions in 2016 CIS Estimated Under Geographic Proximity

Variable	SARAR-Durbin	SEM	SAR	SAR-Durbin	SEM-Durbin
rho	-0.664*** (0.053)		-0.158*** (0.032)	-0.333*** (0.041)	
(Intercept)	21.164*** (0.789)	12.444*** (0.423)	14.435*** (0.448)	18.729*** (0.611)	13.605*** (0.467)
inpspd	0.094* (0.052)	0.058 (0.064)	0.188*** (0.067)	-0.053 (0.073)	0.007 (0.067)
inpslg	0.343*** (0.073)	0.326*** (0.072)	0.302*** (0.075)	0.224*** (0.071)	0.274*** (0.073)
inpssu	0.022 (-)	-0.071 (0.064)	0.102 (0.066)	-0.053 (0.058)	-0.040 (0.065)
imr2	-0.588 (-)	-0.493*** (0.101)	-0.105 (0.117)	-1.529*** (0.160)	-1.260*** (0.184)
letki2	0.088* (0.049)	-0.109** (0.049)	0.180*** (0.048)	0.101** (0.049)	0.096* (0.051)
factor(largest)2	0.541*** (0.083)	0.478*** (0.111)	0.386*** (0.070)	0.598*** (0.068)	0.601*** (0.111)
factor(largest)3	0.512 (-)	0.450** (0.208)	0.555*** (0.105)	0.538 (0.378)	0.584*** (0.203)
factor(buyukluk)2	1.466*** (0.057)	1.594*** (0.064)	1.500*** (0.067)	1.515*** (0.063)	1.535*** (0.064)
factor(buyukluk)3	3.040*** (0.084)	3.419*** (0.079)	3.214*** (0.082)	3.096*** (0.080)	3.146*** (0.084)
y1	0.056 (-)				
letki2:factor(largest)2	-0.014 (0.037)	0.022 (0.069)		-0.001** (0.000)	-0.003 (0.068)
letki2:factor(largest)3	0.034 (-)	-0.080 (0.126)		0.026 (0.257)	0.023 (0.123)
lag.letki2	-1.075 (-)			-2.173*** (0.154)	-1.860*** (0.277)
lag.factor(largest)2	4.490*** (0.395)			0.689 (0.605)	-0.920 (0.594)
lag.factor(largest)3	133.604*** (13.817)			179.976*** (15.345)	133.630*** (30.404)
lag.letki2:factor(largest)2	-1.404 (-)			1.619*** (0.403)	2.344*** (0.447)
lag.letki2:factor(largest)3	-73.899*** (7.427)			-99.667*** (8.470)	-74.069*** (16.822)
lambda	0.519*** (0.041)	-0.696*** (0.049)			-0.506*** (0.081)
r.squared	0.535	0.500	0.474	0.530	0.533
AIC	11601.199	11819.947	11969.965	11626.249	11609.611
BIC	11910.287	12086.611	12224.508	11923.215	11906.577
logLik	-5749.600	-5865.974	-5942.983	-5764.124	-5755.805
nobs	3167	3167	3167	3167	3167

Table A.20 Spatial Models for Second Block Regressions in 2018 CIS Estimated Under Geographic Proximity

Variable	SARAR-Durbin	SEM	SAR	SAR-Durbin	SEM-Durbin
rho	0.000 (0.000)		-0.048 (0.102)	-0.886*** (0.076)	
(Intercept)	11.799*** (0.143)	11.799*** (0.440)	12.877*** (1.326)	23.121*** (0.966)	11.799*** (0.440)
inno_pcs_prd	0.277*** (0.068)	0.277*** (0.082)	0.233*** (0.080)	0.232*** (0.060)	0.277*** (0.082)
imr2	0.099 (0.108)	0.099 (0.212)	-0.147 (0.193)	-0.033 (-)	0.099 (0.212)
lBRI	-0.236*** (0.082)	-0.236*** (0.084)	-0.185* (0.103)	-0.204** (0.081)	-0.236*** (0.084)
factor(largest)2	0.328*** (0.091)	0.328** (0.128)	0.361*** (0.108)	0.341*** (0.019)	0.328** (0.128)
factor(largest)3	0.138 (0.234)	0.138 (0.282)	0.155 (0.318)	0.138 (0.331)	0.138 (0.282)
y1	0.057*** (0.010)	0.057*** (0.011)	0.066*** (0.011)	0.057*** (0.010)	0.057*** (0.011)
factor(size)2	1.366*** (0.070)	1.366*** (0.071)	1.351*** (0.071)	1.363*** (0.070)	1.366*** (0.071)
factor(size)3	2.897*** (0.104)	2.897*** (0.104)	2.905*** (0.107)	2.917*** (0.104)	2.897*** (0.104)
lBRI:factor(largest)2	0.019 (0.038)	0.019 (0.082)	-0.008 (0.056)	0.015 (-)	0.019 (0.082)
lBRI:factor(largest)3	0.323** (0.151)	0.323* (0.168)	0.283 (0.189)	0.316* (0.191)	0.323* (0.168)
lag.lBRI	0.419* (0.224)	0.419* (0.218)		-0.132 (0.159)	0.419* (0.218)
lag.factor(largest)2	17.767*** (2.670)	17.767*** (2.745)		6.442*** (1.466)	17.767*** (2.745)
lag.factor(largest)3	-9.576* (5.213)	-9.576* (5.160)		6.563*** (0.922)	-9.576* (5.160)
lag.lBRI:factor(largest)2	-12.750*** (2.124)	-12.750*** (2.102)			-12.750*** (2.102)
lag.lBRI:factor(largest)3	6.458* (3.908)	6.458* (3.849)			6.458* (3.849)
lambda	0.000 (0.000)	0.000 (-)			0.000 (-)
r.squared	0.478	0.478	0.461	0.475	0.478
AIC	10098.015	10096.015	10172.135	10116.906	10096.015
BIC	10381.600	10373.692	10420.272	10382.767	10373.692
logLik	**-5001.008**	**-5001.008**	**-5044.067**	**-5013.453**	**-5001.008**
nobs	2719	2719	2719	2719	2719

D. CURRICULUM VITAE

Emine Meltem Baştan
Ekonomist, PhD

İş Deneyimi

Memur
Türkiye Cumhuriyet Merkez Bankası (TCMB), Ankara Şubesi
2009 Nisan– 2009 Kasım
Uzman Yardımcısı
Türkiye Cumhuriyet Merkez Bankası (TCMB), İdare Merkezi, Ankara
2009 – 2019
Uzman
Türkiye Cumhuriyet Merkez Bankası (TCMB), İdare Merkezi, İstanbul
2019 – Halen

Eğitim

Orta Doğu Teknik Üniversitesi (ODTÜ), Ankara
- Lisans, İktisat, 2007
- Yüksek Lisans, İktisat, 2007

Cardiff Üniversitesi, Birleşik Krallık
- Yüksek Lisans, Finans, 2015

Bilgisayar Becerileri
Stata, R, Eviews

Yabancı Diller

İngilizce (C1), TOEFL: 104
Almanca (B1)

E. TURKISH SUMMARY / TÜRKÇE ÖZET

Çin'in Kuşak ve Yol Girişiminin Avrupa İnovasyon Ekosistemi Üzerindeki Etkisi

Avrupa Birliği (AB), Ufuk Avrupa gibi önemli politika araçları sayesinde sınır ötesi araştırma ve geliştirme (Ar-Ge) iş birliklerini teşvik etmek, bilgi transferini artırmak ve farklı firma ve sektörlerde yeniliği ölçeklendirmek amacıyla önemli miktarda fon tahsis etmiştir. Aynı zamanda, Uyum Politikası ve Akıllı Uzmanlaşma Stratejileri (S3), her bölgenin özgün karşılaştırmalı üstünlüklerinden yararlanmak için yenilik desteklerini bölgeye özgü hale getirmede etkili olmuştur. Özellikle S3, bölge temelli yeniliği teşvik etmede AB'nin imza çerçevesi haline gelmiş; bölgelerin doğal güçlü yönlerine odaklanarak uzmanlaşmalarını ve uzun vadeli inovasyon planlaması için güçlü yönetişim yapıları geliştirmelerini teşvik etmiştir (Foray, 2015, 2018).

Bu eşgüdümlü çabalar sayesinde AB'deki işletmeler, büyük ve birleşik bir iç pazardan faydalanmaktadır. Ortak standartlar, tutarlı kurallar ve kurumlar arası iyi iş birliği bu pazarı desteklemektedir. Bu unsurlar, işletmeler için maliyetleri düşürmekte ve belirsizliği azaltarak onların yeni fikirler geliştirmesini, sınır ötesi ortaklıklarla çalışmasını ve bölgesel/küresel tedarik zincirlerine entegre olmasını kolaylaştırmaktadır. Çoğu zaman bu işletmeler, üniversiteler, araştırma merkezleri, sanayi grupları ve kamu kurumları etrafında inşa edilen güçlü yenilik topluluklarının parçasıdır. Bu topluluklar yalnızca tesis ve nitelikli personel erişimi değil, aynı zamanda işletmelerin birbirinden öğrenmesini ve bilgi paylaşımından faydalanmasını sağlayarak hem küçük gelişmeler hem de büyük atılımlar için kritik olanaklar sunar (Asheim, Grillitsch, & Trippl, 2016; Balland, Boschma, Crespo, & Rigby, 2019). AB'nin yenilik başarısı, istikrarlı kurumlar, iyi yönetilen ekonomiler ve araştırma/altyapıya yönelik uzun vadeli yatırımlarla daha da güçlenmiştir. Avrupa inovasyon modeli aynı zamanda uyarlanabilirliğe ve açıklığa da önem vererek, korumacılığa ya da sadece ulusal sanayileri desteklemeye dayanmadan, iş birliği ve esneklik yoluyla rekabetçiliğini sürdürmektedir.

Ancak bu güçlü yönlere rağmen, Avrupa’daki işletmelerin faaliyet gösterdiği dünya giderek daha istikrarsız hale gelmiştir. Son on yılda dışsal güçler, küresel inovasyon, ticaret ve yatırım ortamını dönüştürmeye başlamıştır. Bu değişimler, istikrarlı ve öngörülebilir ortamlara dayalı işletmeler için yeni belirsizlikler ve riskler getirmektedir.

Bu gelişmeler arasında en önemlilerinden biri, Çin'in 2013'te başlattığı büyük ölçekli, devlet destekli küresel stratejisi olan Kuşak ve Yol Girişimi’dir (KYB). KYB, Asya, Afrika, Orta Doğu ve Avrupa’da dev ulaştırma, lojistik, dijital ve enerji altyapı yatırımlarıyla ekonomik bağlantılar kurmayı ve genişletmeyi hedeflemektedir. Her ne kadar kalkınma projesi olarak sunulsa da, KYB Çin’in küresel pazarlara daha derinlemesine entegre olmasının, ticaret yollarını kendi lehine kaydırmasının ve ekonomik araçlarla etkisini artırmasının stratejik bir yoludur. Devlet fonları, siyasi anlaşmalar, kamu destekli şirketler ve diplomatik ortaklıklar yoluyla desteklenen bu girişim, malların, paranın ve bilginin küresel akışını yeniden şekillendirmektedir.

KYB beraberinde birçok sorunu ve eleştiriyi de beraberinde getirmektedir. İlk olarak, Çin önemli bir kapasite fazlası sorunu ile karşı karşıyadır; bu da yeni talep kaynakları arayışını zorunlu kılmaktadır. Son yıllarda Çin hükümetinin iç tüketimi artırmaya yönelik belirgin tercihlerine rağmen, ülkenin ihracat odaklı üretim modeli, kaçınılmaz olarak yeni pazarlara açılma ihtiyacını doğurmaktadır. Çin, ucuz işgücüne dayalı karşılaştırmalı üstünlüğünün Batılı geleneksel pazarlardaki getirilerini büyük ölçüde tüketmiş durumdadır (Yu, 2024). Bu sınırlama ve dijital çağın artan baskıları nedeniyle Çin, bu pazarlara yönelik ihracatının niteliğini artırmayı da hedeflemektedir. Bu sırada, düşük kaliteli üretimini düşük gelirli ülkelere kaydırarak Batı pazarlarındaki dalgalanmalardan etkilenmeyen güvenli bir ihracat üssü oluşturmak istemektedir. Bu nedenle, gelişmekte olan ya da düşük gelirli ülkelerin desteklenmesi ve yeni, daha kapsamlı anlaşmalarla güçlendirilmesi gerekmektedir. Bu hedeflere ulaşma konusunda çeşitli zorluklar bulunsa da, Çin’in dünya ihracatındaki lider konumu ve güçlü yukarı-aşağı yönlü bağlantılara sahip tedarik zincirleri içinde merkezi bir yerinin olması, Çin hükümetine büyük ölçekli girişimlerde bulunma gücü kazandırmıştır.

İkinci olarak, Çin'in dış politikası 1980'lerin başında reformlar ve dışa açılma politikasıyla birlikte ciddi bir dönüşüm geçirmiştir. Çin, ekonomik başarısını "Küreselleşme Stratejisi" (Going Global) ile pekiştirmeyi; bu sayede jeopolitik ve jeoekonomik güç unsurlarını içeren stratejik bir etki alanı oluşturmayı hedeflemektedir. Bu doğrultuda Çin, birçok uluslararası kuruluş ve anlaşmaya taraf olmuştur. 2001 yılında Dünya Ticaret Örgütü'ne (WTO) kabul edilmesi, KYBCS, Şanghay İşbirliği Örgütü ve Bölgesel Kapsamlı Ekonomik Ortaklık üyelikleri, Çin'in küresel bağlantı kurma çabalarının örnekleridir. Ancak bu oluşumların hiçbiri, Çin'e KYB kapsamında elde etmeyi hedeflediği kontrol düzeyini sunmamaktadır. KYB bu noktada büyük önem arz etmektedir; zira Çin bu girişimle projeleri seçme, finanse etme ve inşa etme süreçlerinde başat karar verici konumuna gelmekte, aynı zamanda inşaat, altyapı, metalurji yapı malzemeleri ve haberleşme ekipmanları gibi sanayi kollarındaki rekabet gücünü bu ülkelerde kullanabilmektedir (Khanna, 2016).

Üçüncü olarak, KYB projelerinin Çin merkezli yapısı hakkında çeşitli eleştiriler dile getirilse de, katılımcı ülkelerden gelen olumlu tepkiler yıllar içerisinde azalmamıştır. Bu olumlu yaklaşım, söz konusu ülkelerdeki ciddi altyapı yatırımı açığıyla ilişkilendirilebilir. Asya Kalkınma Bankası'nın tahminlerine göre, Güney Asya ülkelerinin altyapı yatırım ihtiyaçlarının GSYİH'lerinin %8,8'ine ulaşması beklenirken, bu oran 2030 yılına kadar Pasifik ülkeleri için %9,1'e yükselecektir. Ayrıca, altyapı yatırımları gelişmekte olan ülkelerde ekonomik büyümenin temel dinamiklerinden biri olarak değerlendirilmektedir. Çin'in tutumuna ilişkin tüm kuşkulara rağmen, ülkenin WTO üyeliği ve ihracattaki lider konumu, Çin hükümetine serbest ticaret yanlısı bir söylem inşa etme imkânı sunmuş ve bu söylem, endişeleri azaltmaya yönelik kullanılmıştır.

Teklif süreçlerini standartlaştırmaya yönelik tüm çabalara rağmen, Çin hâlâ teknik ve finansal sınırlamalar nedeniyle projelerde teknik standartlara sürekli uyum sağlamakta zorluklar yaşamaktadır.

2013'te iddialı bir başlangıç yapan Kuşak ve Yol Girişimi kapsamında Çin yatırımlarının büyüme hızında ciddi bir düşüş yaşanmıştır. 2014 yılında KYB kapsamındaki toplam Çin finansmanının yıllık büyüme oranı %244 seviyesindeydi;

ancak bu oran izleyen yıllarda sürdürülememiştir. Garcia-Herrero (2017), Çin'in döviz rezervlerindeki ciddi düşüş, Çin ekonomisinin yavaşlaması ve banka bilançolarında sorunlu kredilerin payının artmasının bu düşüşte büyük rol oynadığını vurgulamaktadır. Yazara göre, Çin yetkilileri tarafından belirlenen 3 trilyon dolarlık rezerv alt limiti nedeniyle, rezervler azaldıkça KYB'ye ayrılabilecek döviz fazlası da düşmektedir.

Çin'in projeleri finanse etme kapasitesinin azalmasına ek olarak, Çin'in bu projeleri nasıl yürüttüğüne dair ciddi eleştiriler de gündeme gelmektedir. Baltensperger ve Dadush (2019), KYB'nin büyük potansiyeline rağmen hedeflerin yeterince açık olmadığı, şeffaflık ve eşgüdüm eksikliği yaşandığı görüşündedir. Ayrıca, sahadaki uygulamalarda yaşanan uzun gecikmeler ve farklı gelişmişlik düzeylerindeki ülkelerin kredi geri ödeme koşullarının farklılığı, borç yapılandırma süreçlerine ilişkin endişeleri artırmaktadır. Çin'in 2017 yılında KYB kapsamında sağladığı kredi miktarının zirveye ulaştığı dönemde, Çin resmi kredi verenler arasında dünya lideri konumundaydı ve IMF veya Dünya Bankası'nın sağladığı rakamların çok üzerindeydi (Yu, 2024). Hurley ve Portelance (2019), Çin'in kredi uygulamaları ile Paris Kulübü (dünya genelindeki büyük alacaklı ülkeler topluluğu) arasındaki farklara dikkat çekmektedir. Bu eşitsizlik, Paris Kulübü gibi alacaklıları borç yükü altındaki ülkelere yönelik borç hafifletme programları başlatmaya zorlayabilir. Çin'in, alacaklı olarak küresel ölçekte kabul görmüş "oyunun kurallarına" uymaya gönülsüz olması, özellikle düşük gelirli ülkelerde borç geri ödemelerinin başarısız olması durumlarında çok taraflı kuruluşların Çin'in pozisyonunu net biçimde belirleyememesine neden olmaktadır.

Çin'in Sudan, Etiyopya ve Kenya gibi ülkelerin borçlarını silmesi veya Tacikistan ve Sri Lanka gibi ülkelerde borç karşılığında toprak tahsisi ya da uzun dönemli kiralama anlaşmaları yapması, Batılı dünyada alışılmış olmayan uygulamalardır. Ayrıca Cibuti, Kırgız Cumhuriyeti (Kırgızistan), Laos, Maldivler, Moğolistan, Karadağ, Pakistan ve Tacikistan gibi ülkeler, borç krizine girme riski yüksek ülkeler arasında gösterilmektedir. Ancak, borç ödeme riski taşıyan Avrupa ülkesi bulunmamaktadır.

KYB'ye ilişkin çok yıllı, ülke ve sektör kırılımına sahip resmi bir veri setinin olmaması, yukarıda bahsedilen sorunları daha da derinleştirmektedir. Garcia-Herrero

(2017), Çin hükümetinin Bretton Woods ilkelerine olan mesafesini göz önünde bulundurarak, Avrupa Kalkınma Bankaları ile kredi verme süreçlerinde iş birliğinin artırılmasını önermektedir. Böyle bir iş birliği, Çin'i piyasa ilkelerini benimsemeye yönlendirmek açısından fırsat penceresi olabilir. Her ne kadar Avrupa İmar ve Kalkınma Bankası (EBRD), Dünya Bankası ve Uluslararası Para Fonu (IMF) gibi kuruluşlarla belli ölçüde iş birliği bulunsa da, bu iş birlikleri Çin hükümeti üzerinde etkili olacak ölçüde güçlü değildir.

Fiziksel altyapı yatırımları ilk yıllarda ön planda olsa da, zamanla yeşil ve dijital teknolojileri içeren projeler de yaygınlaşmıştır. Yeşil İpek Yolu ve Dijital İpek Yolu projeleri, KYB'nin yeni bileşenleri olarak ilan edilmiştir. Haziran 2021'de Çin ile 28 ülke arasında KYB Yeşil Kalkınma Ortaklığı Anlaşması imzalanmış ve yenilenebilir enerji veya düşük karbonlu teknikler kullanan projelerin finansmanı hedeflenmiştir. 5G iletişim, e-ticaret, büyük veri ve kuantum hesaplama gibi dijital endüstrilerde faaliyet gösteren Çinli firmaların faaliyetleri, doğrudan devlet kurumları tarafından finanse edilmese de, Dijital İpek Yolu'nun (DSR) bir parçası olarak görülmektedir. Bu kapsamda örnekler arasında Huawei (dünyanın önde gelen 5G telekomünikasyon ekipmanı üreticisi), Alibaba (öncü e-ticaret firması), ByteDance (TikTok'un sahibi) ve Tencent (WeChat'in geliştiricisi) yer almaktadır. Çin hükümeti bu şirketleri, hem gelişmiş hem de gelişmekte olan ülkelere nüfuz etme aracı olarak görmektedir. Bu şirketlerin yurtdışı anlaşmalarını geliştirmek amacıyla Çinli kamu bankalarının sunduğu uygun kredi koşullarının kullanılması oldukça muhtemeldir.

Bu büyük yatırımlara rağmen, Ekim 2023'te düzenlenen üçüncü KYB Forumu'nda ilan edilen "küçük ama güzel" (small but beautiful) sloganı, Çin'in belirsizlik maliyetleri ve büyük ölçekli yatırımlarla gelen verimsizliklerle karşı karşıya kaldığını ortaya koymaktadır. Bu yeni anlayış, büyük projeler yerine küçük ama etkili projelerin tercih edilmesini vurgulamaktadır. Ayrıca COVID-19 pandemisi, Çin'e ihracat odaklı büyümenin tedarik zinciri sorunları nedeniyle tek öncelik olamayacağını göstermiştir. Bu nedenle bazı analistler, Çin içindeki projelerin de KYB kaynaklarıyla desteklenmesi gerektiğini savunmaktadır (Yu, 2024).

Son olarak, Ekim 2023'te düzenlenen 3. KYB Forumu'nda Çin Devlet Başkanı Şi Cinping, canlandırılan İpek Yolu'nun artık bir "hayat kurtaran yol" haline geldiğini ifade etmiştir. KYB'nin Avrasya'dan Latin Amerika'ya uzanarak 151 ülkeyi kapsaması ve 30'dan fazla uluslararası kuruluşla resmi anlaşmalar imzalanması büyük bir başarı olarak sunulmuştur. Hidro, rüzgar ve güneş enerjisine dayalı elektrik santralleri; Kuşak ve Yol Bilim, Teknoloji ve İnovasyon İş Birliği Eylem Planı; ve planlanan Küresel Yapay Zeka Yönetişimi Girişimi, KYB'nin ikinci on yılını (KYB 2.0) şekillendiren başlıca unsurlar olarak öne çıkmaktadır.

Çin'in iddialı açıklamaları sürse de, 2023 yılında düzenlenen forumda Yunanistan, Çek Cumhuriyeti, İtalya, Malezya, Filipinler ve İsviçre'nin ilk iki toplantıya katılmış olmalarına rağmen bu defa yer almamış olmaları dikkat çekicidir. IMF de toplantıya bir direktör göndermemiştir (Mardell, 2023). Aralık 2019'da Avrupa Komisyonu, üye devletleri 5G ağlarının siber güvenliği konusunda ulusal risk değerlendirmesi yapmaya çağıran bir rapor yayımlamıştır. Huawei ve ZTE şirketlerinin adı doğrudan zikredilmese de, AB yetkilileri olası sübvansiyonlar veya damping faaliyetlerinden kaynaklanabilecek baskın tedarikçilerden kaçınılması gerektiğini açıkça vurgulamıştır. Bu açıklamalarda ima edilen iki şirket olan Huawei ve ZTE, 2023 Eylül ayı itibarıyla 11 ülkede 5G ağlarında yasaklanmıştır. Bu ülkeler arasında Almanya (Çin'in AB'deki en büyük ticaret ortağı), Romanya, Estonya, Letonya, Litvanya ve Portekiz'in yer alması, bu tezin bakış açısından özellikle dikkat çekicidir; çünkü bu ülkeler Avrupa'da KYB'nin güçlü müttefikleri konumundaydılar.

Öte yandan, Malezya ve Endonezya hükümetleri, dijital ekonomilerini geliştirmek amacıyla Çinli firmalarla iş birliğini artıracaklarını resmi olarak beyan etmiştir. Bu bağlamda Çin, Batılı aktörlerin etkisini Asyalı aktörler yoluyla dengelemeye çalışmaktadır.

KYB olmasa bile, AB-Çin ekonomik ilişkilerinde kaçınılmaz sorunlar ortaya çıkmaktadır. Bu sorunların başında gelen konulardan biriyle ilgili olarak Herrero ve Xu (2017), Çin devletine ait işletmelerin, Çin ile AB arasında yapılabilecek herhangi bir ikili yatırım anlaşması açısından önemli bir engel oluşturduğunu ifade etmektedir. Çin hükümetinin sanayi politikası nedeniyle bu şirketler imalat sektörüne odaklanmaktadır. Hükümet yetkililerinden gelen ekonomik olmayan emirler doğrultusunda faaliyet göstererek kapasite fazlası ile çalışabilmekte ve iflas riski taşımamaktadırlar. Çin hükümetinin bu şirketlere verdiği sübvansiyonlar ve uygun krediler, Çinli firmaların küresel rekabet gücünü daha da artırmaktadır. Ayrıca bu firmalar, "Çin İmalat 2025" gibi düzenlemeler ve özel destek programları ile Çin ana karasındaki yabancı firmalara karşı korunmaktadır. Bu yapısal özellikler, Çin menşeli devlet şirketlerinin hem Avrupa'daki hem de Çin içindeki Avrupalı firmalar için açık bir rekabet riski oluşturmasına neden olmaktadır.

Avrupalı firmaların eşit şartlarda rekabet edebilmesi için Herrero ve Xu (2017), AB'nin Çinli firmaların Avrupa'daki varlıkları edinmesini engellememesini ya da bu firmalara yaptırım ve kısıtlamalar uygulamamasını önermektedir. Çünkü bu tür bir adım, Çin hükümetinden çok daha güçlü bir destek tepkisi alınmasına neden olabilir. Bunun yerine, Avrupa otoritelerinin Çin ana karasında Çinli firmaların sahip olduğu ayrıcalıklı piyasa erişimine nüfuz edecek yollar bulması gerektiği ifade edilmektedir. Enerji, altyapı, kamu hizmetleri ve finans gibi sektörlere erişimde yaşanan zorluklar, bir diğer öneriyi beraberinde getirmektedir: AB otoriteleri, Çinli firmaların küresel piyasa ilkeleriyle uyum sağlamasını teşvik etmek ve daha fazla serbestleşmeyi hayata geçirmek için uluslararası baskı uygulamalıdır. Örneğin, Çin'in OECD üyeliğine destek verilmesi, Çin'in WTO üyeliğinin politika yapım sürecini değiştirmeye yetmediği göz önüne alındığında, pratik bir adım olabilir.

Çin'in KYB kapsamındaki etkisi göz önüne alındığında, bu öneriler AB'nin Çin hükümetiyle doğrudan çatışmak yerine, rekabet politikası ve uyuşmazlık çözüm mekanizmaları gibi politika araçlarını kullanarak projelerin dışsallıklarını yönetmesi gerektiğini ima etmektedir. AB-Çin arasındaki mevcut anlaşmazlıklar incelendiğinde, AB'nin çoğunlukla bu yolu tercih ettiği ve "AB-Çin Bağlantı Platformu" gibi alternatif yol haritaları inşa etmeye çalıştığı görülmektedir.

Mardell (2018), tutarlı bir yaklaşım ihtiyacını vurgulayarak AB için KYB ile ilgili üç temel risk ortaya koymaktadır. İlk risk, Çin'in AB üyesi ülkeler üzerinde siyasi etki kurma potansiyelidir. Bu etki, AB'nin uyum politikaları açısından ciddi bir tehdit olarak görülmektedir. İkinci risk, KYB bağlamında sıkça dile getirilen borç sorunudur. Borçlarını geri ödeyemeyen AB ülkelerinde altyapı projelerinin Çin tarafından devralınma ihtimali, ekonomik bütünlüğü tehdit edebilir ve AB'nin daha güçlü üyelerinden mali destek gerektirebilir. Üçüncü risk ise Çin'in Avrupa'nın çevresel, sosyal ve ekonomik standartlarına uyum sağlayabilme kapasitesine yönelik şüphelerdir. Bu riskler 2018 yılında dile getirilmiş olsa da, KYB'nin zamanla daha fazla yeşil projeyi içermeye başlamasına rağmen, teknik uyum—örneğin Belgrad-Budapeşte demiryolu gibi örneklerde olduğu gibi—halen sorun olmaya devam edebilir.

2012 yılında Çin, 5 Balkan ülkesi ve 11 AB üyesi olmak üzere 16 Orta ve Doğu Avrupa (CEE) ülkesi ile bir bağlantı platformu kurmuştur. Küresel finansal kriz öncesinde Çin ile bu ülkeler arasındaki ticaret hacmi artış göstermekteydi. Kriz sonrasında bu ülkeler de Çin ile iş birliğine ilgi göstermiştir. 2019'da Yunanistan'ın katılımıyla platform "17+1" adını almıştır. Ancak 2022'de Estonya, Letonya ve Litvanya platformdan ayrılmış ve şu anda yapı "14+1" olarak bilinmektedir. Çin'in bu ülkelere olan ilgisi, ortak komünist geçmişe ve kriz sırasında Çinli firmaların düşük maliyetle varlık edinmelerine dayanmaktadır (Garcia-Herrero & Hu, 2017). Avrupa Komisyonu (2018) da Çin'in bu ülkelerle olan ilişkilerinin AB'nin uyum politikalarını tersine çevirebileceğini belirtmektedir. Daha somut olarak, Çin'in kredi verme uygulamaları, kamu ihaleleri sürecinde bu ülkelere yaptığı baskılar, Çin'den ithal edilen girdilerin ve iş gücünün kullanımında ısrar etmesi ve projelerin şartlarını Brüksel'deki AB merkezi ile değil, katılımcı ülkelerle müzakere etmesi, potansiyel sorun alanları olarak sıralanmaktadır.

Yalnızca 14+1 İş Birliği Platformu üyeleri değil, genel olarak Avrupa'ya yönelen KYB projelerinin payının özellikle COVID-19 pandemisi sonrasında nasıl değiştiğini görülmektedir. KYB bağlantılı yatırım projelerini çekme konusunda Sırbistan başı çekmektedir. Daha önce de belirtildiği gibi, Sırbistan AB üyesi değildir ve bu durum KYB projelerinin ülkeye girişini kolaylaştırmıştır. Budapeşte-Belgrad demiryolu hattının Macaristan ayağında yaşanan başarısızlığa rağmen, Macaristan hâlâ Avrupa'daki KYB yatırımlarında ikinci sıradadır. Portekiz'in üçüncü sırada yer alması ise şaşırtıcı değildir; çünkü Portekiz'in Çin ile Makao üzerinden tarihsel ilişkileri bulunmaktadır ve 1999 yılında bu bölgeyi Çin'e barışçıl biçimde devretmiştir. Sektörel açıdan bakıldığında, ulaşım ve enerji yatırımları Çin'in Avrupa'daki yatırımları içinde en büyük iki payı oluşturmaktadır.

KYB'nin küresel etkileri üzerine birçok çalışma yapılmıştır. Kohl (2019), 64 ülke için 2002-2011 dönemine ait verilerle BRI'nin tedarik zinciri ticareti üzerindeki etkilerini incelemiştir. Yapısal yerçekimi modeliyle, BRI kapsamındaki ulaşım yatırımları ve olası STA'ların ticaret maliyetlerinde ve mesafelerde yol açacağı düşüşler analiz edilmiştir. Mesafelerde %15, %30 ve %50 oranındaki düşüşlerin serbest ticaret anlaşmalarından daha fazla ticaret hacmi artışı sağladığı bulunmuştur. Genel denge çerçevesinde, yalnızca doğrudan değil aynı zamanda dolaylı (diğer destinasyonların etkisiyle oluşan) etkiler de hesaba katılmıştır. Çin ve Rusya'nın, AB pazarına erişim kolaylaştıkça, AB'den daha fazla fayda sağladığı ve bu durumun AB'nin bölgesel uyum politikaları üzerinde olumsuz etkiler yaratabileceği belirtilmektedir.

Wang ve arkadaşları (2020), BRI ülkelerinde ulaştırma altyapısının ekonomik büyüme üzerindeki etkilerini 2007–2016 döneminde hem ülke hem de bölge düzeyinde analiz etmiştir. Coğrafi, kültürel, ekonomik ve kurumsal mesafeyi dikkate alan mekânsal ağırlık matrisi kullanılarak yapılan analizlerde, altyapının yol uzunluğu ve demiryolu uzunluğu ile ölçülmesi tercih edilmiştir. Altyapı yatırımları için parasal değil fiziksel ölçüm kullanılmıştır. Mekânsal otokorelasyon testleri, kişi başına GSYİH'nın komşu ülkelerde karşılıklı olarak pozitif etki yarattığını göstermektedir. Demiryolu için bu otokorelasyon coğrafi ve kurumsal olarak güçlüdür, karayolunda ise sadece kurumsal yakınlık anlamlı bulunmuştur. Bölgesel düzeyde, Güneydoğu Asya ve Orta ve Doğu Avrupa'da demiryolu ve karayolu yatırımları pozitif etki yaratmaktadır. Güney Asya'da yalnızca demiryolu pozitif etki sunarken, Batı Asya ve Kuzey Afrika'da demiryolu yatırımı büyümeyi negatif etkilemektedir. Dolaylı (yayılma) etkiler, Orta ve Doğu Avrupa'da pozitifken, Orta Asya ve BDT ülkelerinde negatiftir. Bu negatiflik, altyapısı zayıf ülkelerin yüksek kaynak kullanımı gerektiren demiryolu projeleri nedeniyle komşularla paylaşılan kaynakların azalmasına bağlanmaktadır.

Villafuerte ve arkadaşları (2016), KYB projesinin Asya ülkelerindeki GSYİH, refah ve ihracat üzerindeki etkilerini ölçmek amacıyla GTAP modelini kullanmaktadır.

GTAP, mükemmel rekabet varsayımı altında çalışan, sabit ölçek getiri varsayımına dayanan ve karşılaştırmalı statik özellikte küresel bir hesaplanabilir genel denge modelidir. Model, tüm ülke ve bölgeler arasındaki ikili ticaret ilişkilerini dikkate alır. Çalışmada Çin, Asya ülkeleri arasında KYB'den en çok fayda sağlayan ülke olarak öne çıkarken; onu Moğolistan ve Pakistan takip etmektedir. Orta ve Güneydoğu Asya bölgeleri de projeden ciddi kazanç elde eden bölgeler arasında yer almaktadır.

Zhai (2018), Villafuerte ve ark. (2016)'nın kullandığı GTAP modelinin aynı sürümünü alarak analiz kapsamını genişletir ve KYB'nin Avrupa Birliği (AB), ABD, Japonya ve Avustralya üzerindeki etkilerini de ayrı ayrı değerlendirir. Ancak Zhai'nin çalışması üç temel noktada farklılaşır. Birincisi, Zhai dinamik bir genel denge modeli kullanarak, KYB kaynaklı yatırımların zaman içindeki birikimli etkilerini ve sermaye oluşum sürecini analizine dâhil eder. İkincisi, firma düzeyindeki heterojenlik modele eklenmiş ve firmalar arası kaynak tahsisi ile ticaretin kapsam marjlarındaki farklılıklar göz önünde bulundurulmuştur. Üçüncüsü, KYB'nin ticaret maliyetlerini ve altyapı yatırımlarını nasıl etkilediğine dair ilişkiyi varsaymak yerine, bu ilişkinin ampirik temeller üzerine kurulu olması gerektiği savunulmuştur. Çünkü altyapı yatırımları, KYB projesinin merkezinde yer almakta ve oldukça esnek bir ilerleyişe sahiptir.

Zhai, üç kademeli senaryo altında KYB'nin etkilerini 2015–2029 dönemi için simüle eder. İlk senaryo yalnızca KYB'nin yatırım değişikliği etkisini kapsarken; ikinci senaryo buna ticaret maliyetlerindeki azalmayı da ekler. Üçüncü ve en kapsamlı senaryo ise, enerji altyapısı yatırımlarının doğurabileceği pozitif dışsallıkları da içeren tam uygulama durumudur. Zhai'nin bulguları, Villafuerte ve ark. (2016) ile büyük ölçüde örtüşmektedir: Güneydoğu Asya ülkeleri büyük kazanımlar elde ederken, ihracattaki en büyük artış Vietnam'da, ardından Singapur'da gözlenmiştir. Pakistan da özellikle üçüncü senaryo altında kayda değer ihracat artışıyla öne çıkmaktadır.

Ancak Zhai'nin çalışmasında, Herrero ve Xu (2016) ile çelişen bir sonuç da bulunmaktadır. AB'nin KYB kapsamındaki kazançlarının, model kapsamındaki diğer ülkelere kıyasla oldukça sınırlı olduğu ifade edilmiştir. Özellikle Çin ve

Rusya'nın AB'ye yönelik artan pazar erişiminden daha fazla fayda sağladıkları ve bu durumun AB'nin bütünleşme politikaları açısından olumsuz sonuçlar doğurabileceği belirtilmektedir.

Zaman ve Tanewski (2024), firma düzeyindeki verileri kullanarak Ar-Ge, inovasyon ve ihracat arasındaki eşzamanlı ilişkiyi, özellikle firma büyüklüğünün rolüne odaklanarak ampirik olarak test etmektedir. Büyük firmalar için inovasyonun, Ar-Ge ve ihracat arasındaki çift yönlü ilişkiye aracılık ettiğini bulmaktadırlar: Ar-Ge, inovasyon yoluyla ihracatı etkilerken, ihracat da artan inovasyon sayesinde Ar-Ge'yi teşvik etmektedir. Bu bulgular, hem "ihracat için öğrenme" hem de "ihracatla öğrenme" etkilerini desteklemektedir. Buna karşın, küçük ve orta ölçekli işletmeler (KOBİ'ler) için böyle bir eşzamanlılık gözlemlenmemektedir. Bu da, küçük firmaların ihracata başlamadan önce inovasyon yapmadıklarını ve ihracat yoluyla inovasyon çıktılarında anlamlı bir artış elde etmediklerini göstermektedir. Bu durum, yukarıda değinilen "başabaş rekabet" (neck-to-neck competition) argümanını desteklemektedir. Başka bir deyişle, daha üretken ve rekabetçi firmalar, artan ticaret dinamikleri karşısında inovatif davranışlarını değiştirme konusunda daha yüksek bir eğilim göstermektedir. Çalışma, firma büyüklüğüne göre farklılaştırılmış inovasyon ve ihracat politikalarına ihtiyaç olduğunu vurgulamakta ve büyük firmaların teknolojik yetkinlik ile uluslararasılaşma arasındaki etkileşimden daha fazla fayda sağladığını öne sürmektedir.

Özetle, artan pazar büyüklüğü, yoğunlaşan rekabet, ürün değiştirme davranışı, üretimin yurtdışına kaydırılması (offshoring) ve ithalat yoluyla öğrenme gibi kanalların ticaret ile inovasyon arasında işlediği öne sürülmektedir; ancak bu ilişkinin yönü ve anlamlılığı konusunda literatürde bir uzlaşı bulunmamaktadır. Ticaretin sunduğu genişleyen fırsatların etkisi, firmaların faaliyet gösterdiği pazardaki başlangıç konumlarına, verimlilik düzeylerine ve rekabet güçlerine bağlıdır.

Ticaretin inovasyon üzerindeki etkisine yönelik çalışmalar, KYB'nin öncelikle ticaret ve devamında da inovasyon üzerindeki etkilerini anlamakta son aşamayı oluşturmaktadır. Aghion ve arkadaşları (2018), Fransız firma düzeyindeki verileri kullanarak ihracat şoklarının firmaların yenilikçi faaliyetleri üzerindeki etkisini analiz etmektedir. Ayrıca firmaların ihracat talep şoklarına verdikleri farklı tepkileri, aralarındaki verimlilik farklarına bağlamaktadırlar. Pazar büyüklüğündeki artış yenilikçi faaliyetleri desteklerken, artan rekabet özellikle düşük verimliliğe sahip firmaların yenilik kapasitesini olumsuz etkilemektedir. Bu tür bir durumda, yüksek verimliliğe sahip firmalar üzerindeki etki kaçınılmaz olarak daha güçlü olmaktadır. Çalışmada, ihracat ile inovasyon arasındaki ilişkiye dair endojenliğin mümkün olabileceği vurgulanmaktadır. Bu sorunu ele alabilmek için, bir firmanın doğrudan kontrolü dışında olan, ihracat yaptığı ülkelerdeki toplam talep koşullarındaki değişimlere yanıt veren firma düzeyinde ihracat göstergeleri geliştirilmektedir. Başka bir deyişle, odakta olan Fransız firmanın ihracat yaptığı ülkelere yönelik ithalat talebindeki değişiklikler gözlemlenmektedir. Bu değişiklikler, firmanın toplam ihracatındaki ürün ve hedef ülke paylarıyla ağırlıklandırılarak, firmanın etki edemeyeceği ihracat destinasyonlarındaki dinamikleri yansıtan bir gösterge elde edilmektedir. Yenilikçi faaliyetlerin bir göstergesi olarak kullanılan patent verilerine dayanan analizler, daha verimli firmaların artan ihracat kapasitesinden fayda sağladığı yönündeki yaygın görüşü desteklemektedir. Buna karşın, düşük verimli firmalar artan rekabetin olumsuz etkilerine maruz kalmaktadır.

Bahsedildiği üzere, KYB doğrudan yalnızca belirli güzergâhlardaki ülkeleri hedeflese de, etkisi bu ülkelerin çok ötesine uzanmaktadır. Avrupa için KYB, haksız rekabeti tetikleyerek, küresel ticaret ortamını değiştirerek ve AB merkezli geleneksel altyapı ve kurumsal ağları bypass eden alternatif yapılar oluşturarak dolaylı ancak önemli baskılar yaratmaktadır. Çinli firmalar—çoğu zaman devlet desteği ve diplomatik teşviklerle—Avrupa'nın geleneksel ihracat veya ortaklık pazarlarında giderek daha fazla yer almaktadır. Aynı zamanda, Avrupa tedarik zincirlerinin dışında yeni lojistik merkezleri, satın alma anlaşmaları ve yatırım akışları ortaya çıkmakta, bu da bazı AB şirketlerini küresel üretim ve dağıtım ağlarının merkezinden uzaklaştırmaktadır.

Bu genel değişim, AB'yi ve AB'deki firmaları daha önce hiç olmadığı kadar dış baskılara karşı kırılgan hale getirmiştir. KYB, küresel rekabet dinamiklerini değiştirerek Avrupalı firmaların stratejik konumunu zayıflatırken, Avrupa dışı firmaların hızla büyümesine olanak tanımaktadır. Ticaret yolları yeniden yönlendirilmekte, tedarikçi ilişkileri yeniden yapılandırılmakta ve lojistik sorunlar yeni koridorlara taşınmaktadır. İstikrarlı talep, güvenilir altyapı ve öngörülebilir ortamlar üzerine kurulu AB işletmeleri için bu değişiklikler, özellikle inovasyonu, rekabet gücünü ve büyümeyi sürdürme açısından ciddi zorluklar teşkil etmektedir.

KYB'nin AB için en önemli sonuçlarından biri, Avrupa inovasyon ekosistemi üzerinde belirgin etkiler yaratmasıdır. AB'nin de sistemini kökten değiştirmeye hazırlandığı bir dönemde, bu etkinin analiz edilmesi kritik önemdedir. KYB'ye ilişkin projeksiyonlar, küresel değer zincirlerini değiştirmek ve teknoloji akışlarını Çin kurallarına göre yönlendirmekle ilgilidir. Ayrıca, KYB'nin kolaylaştırdığı küresel ticaret, AB firmaları üzerinde kendi geleneksel pazarlarında rekabet baskısı yaratabilir. KYB projelerindeki şeffaflık eksikliği, AB ülkelerinin mali sağlığı açısından tehdit oluşturabilir ve AB kurtarma planlarını gerektirecek durumlara yol açabilir.

Çin ve Avrupa Birliği (AB) arasında KYB ile ilgili girişimler de mevcuttur. Ulaştırma bağlantılarını geliştirmek amacıyla 2015 yılında Avrupa Komisyonu ile Çin Ulusal Kalkınma ve Reform Komisyonu arasında bir Bağlantı Platformu kurulmuştur. Bu platformun amacı, Trans-Avrupa Ulaştırma Ağı (TEN-T) ile Kuşak ve Yol Girişimi (OBOR) arasındaki çıkar çatışmalarını ortadan kaldırmak, piyasalara erişimde karşılıklılık ve şeffaflığı artırmak ve adil bir rekabet ortamı sağlamaktır.

KYB kapsamındaki yatırımlar tüm Avrupa ülkelerine yönelmiş olsa da, bazı çalışmalar yalnızca Avrupa Birliği (AB) ülkelerine odaklanmaktadır. Fardella ve Prodi (2017), Yunanistan'daki Pire Limanı'nın inşasının—KYB projesi kapsamında gerçekleşmiştir—Adriyatik Denizi kıyısındaki İtalyan limanları üzerindeki etkisini incelemektedir. Yazarlar, Pire Limanı'nın inşasının İtalyan limanlarının önemini tehdit ettiğini öne sürmektedir. Bu risk, Yunanistan'daki demiryolu inşaatlarıyla ve Mısır ile Cezayir'de yeni limanların geliştirilmesiyle daha da artabilir. Verlare ve van der Putten (2015), KYB projelerinin AB bölgelerine nüfuz etmesine karşılık olarak, AB üye ülkelerinin ortak ve uyumlu bir yaklaşım benimsemelerinin, bireysel tutumlara kıyasla çok daha yüksek faydalar sağlayacağını belirtmektedir.

Tüm zorluklara rağmen, AB ile Çin'i ortak araştırma ve yenilik faaliyetlerinde bir araya getirmeye yönelik çeşitli girişimler de bulunmaktadır. Bu faaliyetlerin en yenileri, Ufuk Avrupa Programı (2021-2027) kapsamındadır. Çin ve AB, gıda, tarım, biyoteknoloji ve iklim değişikliği alanlarında iş birliği yapmayı hedeflemektedir. Bu amaçla, Ufuk Avrupa ile Çin Bilim ve Teknoloji Bakanlığı arasında eş finansman mekanizması kurulmuştur.

Bir firmanın inovasyon kapasitesi yalnızca kendi yenilikçi çabalarıyla belirlenmez; aynı zamanda yakın çevresindeki firmaların bilgi üretim süreçlerinden de etkilenir. Bu bağlamda bilgi dışsallıkları, bir firma tarafından üretilen bilginin ücretsiz şekilde diğer firmalar tarafından kullanılması anlamına gelir (Venuvinod, 2011; akt. Doyar, 2023). OECD (2015, 2018), bilgiyi üçe ayırır: kodlanmış, örtük ve somutlaşmış bilgi. Kodlanmış bilgi; yayınlar, patentler, veritabanları ve Ar-Ge çıktıları aracılığıyla toplanan, sistematik ve biçimsel dille aktarılabilen bilgiyi ifade eder. Buna karşılık örtük bilgi, doğrudan algıya dayalıdır ve kişisel deneyimlere bağlı olduğundan doğrudan iletişim olmadan aktarılması zordur. Bu nedenle, nitelikli işgücünün hareketliliği ve firmalar arası ağlar, örtük bilginin aktarımı açısından kritik önem taşır.

Literatürde üç tür bilgi dışsallığı tanımlanır. İlki "MAR dışsallıkları" olarak bilinir ve Marshall, Arrow ve Romer'in isimlerinin baş harflerinden gelir. MAR dışsallıkları, esas olarak tekelleşmiş piyasa yapıları ile aynı sektördeki firmaların yerel yoğunlaşmasını ve uzmanlaşmasını ifade eder. İkinci tür dışsallık, Jacobs (1969) tarafından ortaya atılmıştır ve tamamlayıcılığın önemli olduğu sektörlerle daha ilgilidir. Çeşitlilik, firmaları yenilik yapmaya teşvik eder ve bu, rekabetçi piyasa koşullarında daha kolay gerçekleşir. Bu türdeki bilgi dışsallıkları, sektörler arası bilgi yayılımını ifade eder.

Üçüncü tür dışsallık ise Porter (1990) tarafından geliştirilmiştir ve ilk iki türün bir birleşimi olarak görülür. Yani sektörel uzmanlaşmadan kaynaklanan bilgi dışsallıkları rekabetçi bir yapı altında daha da verimli hale gelir.

Bilgi dışsallıklarının aktarımı ekonomik aktörler arasında en az düzeyde etkileşim gerektirdiğinden, aktörler arası "yakınlık" kavramı, bu sürecin analizinde kritik hale gelir. Hangi tür yakınlığın bilgi yayılımında daha güçlü bir çarpan etkisi yarattığı ise literatürde oldukça tartışılan bir konudur.

Boschma (2005), beş farklı yakınlık türü tanımlar: coğrafi, bilişsel, örgütsel, sosyal ve kurumsal yakınlık. Özellikle bilişsel yakınlık üzerine yaptığı tartışmalar, diğer tüm yakınlık türlerinin başarısının hangi zemine oturduğunu belirlemesi açısından önemlidir. Bilişsel yakınlık, benzer bilgi tabanına ve deneyime sahip bireylerin ya da firmaların birbirlerinden daha kolay öğrendiği anlamına gelir. Bu kavram, Cohen ve Levinthal (1990) tarafından geliştirilen "soğurma kapasitesi" ile yakından ilişkilidir. Soğurma kapasitesi, bir firmanın dışarıdan gelen yeni bilgiyi tanıma, özümseme ve ticarileştirme yeteneğidir ve dinamik bir yapıya sahiptir. Firmaların bilgi düzeyi, yani yetenekleri, ortak bir dili konuşmaları ve bilimsel ya da teknolojik gelişmelerden haberdar olmaları, yeni bilginin değerini fark etmeleri ve bu bilgiyi nasıl içselleştireceklerini belirleyen unsurlardır. Firmaların bu kapasiteyi artırması, yaptığı her yenilikçi faaliyetle daha da mümkün hale gelir; çünkü bilgi doğası gereği kümülatiftir. Bilgi yayılımı ve bu yayılımın özellikle coğrafi ve teknik (ekonomik) yakınlık ölçütlerine duyarlılığı üzerine yapılan çalışmaların bir özeti, yakınlığın birçok durumda bilgi yayılımını ve inovasyonu hızlandırdığını ortaya koysa da, aşırı yakınlığın sektör kilitlenmeleri, yeni pazarlar veya kaynaklar için rekabet gibi sorunlara yol açarak firmaların sektörden çıkmasına ya da inovasyon göstergelerinde duraklama dönemlerine neden olabileceğini de göstermektedir. Bu nedenle, yakınlığın etkisinin yönü hakkında kesin bir sonuca varmak zordur.

Bu tez, KYB'nin firmaların AR-GE ve inovasyon faaliyetleri üzerindeki etkisinin gelişmiş ticaret olanakları aracılığıyla gerçekleştiğini varsaymaktadır. Bu bağlamda üç araştırma sorusu ortaya konmaktadır: Birincisi, Çin'in Kuşak ve Yol Girişimi (KYB), Avrupa firmalarının yenilikçi kararları ve faaliyetleri üzerinde anlamlı bir etkiye sahip midir? İkincisi, bu etkinin mekânsal bir boyutu var mıdır? Üçüncüsü, KYB'nin etkisi zamanla ve firmaların pazar yönelimine bağlı olarak değişmekte midir?

Bu sorular ışığında, tez Çin'in KYB'sinin Avrupa inovasyon ekosistemi üzerindeki etkisini 2012-2018 döneminde Topluluk İnovasyon Anketi (CIS) kapsamında 12 ülkeden firma düzeyinde verileri kullanarak incelemektedir. 2014, 2016 ve 2018 CIS verileri, Çin KYB'sinin etkilerinin de modele dahil edildiği MMK çerçevesi içinde analiz edilmektedir. Mairesse vd. (2005) tarafından geliştirilen MMK çerçevesi, Crepon vd. (1998) tarafından tanıtılan CDM çerçevesine dayalı olup denklem sayısını dörtten beşe çıkarır. CDM ve MMK çerçeveleri tezde birbirinin yerine kullanılmakta olup her ikisini yönlendiren ortak bir mantık vardır: firmaların inovasyon girdileri (Ar-Ge faaliyetleri), inovasyon çıktıları ve verimlilikleri arasındaki ilişkiyi üç blok üzerinden modellemek. Bu yapı "Ar-Ge, inovasyon ve verimlilik ilişkisi (RIP)" olarak da adlandırılmaktadır. Eurostat tarafından sağlanan CIS verisi panel yapıda olmadığından panel veri teknikleri kullanılamamaktadır. Bu nedenle KYB'nin ilk beş yılını kapsayan üç anket dönemi ile zaman etkileri üç kesit analizi üzerinden incelenmiştir.

CIS mikro verilerine ek olarak, Dünya Bankası'nın KYB Küresel Veriseti ve CEPII'nin yardımcı veri kaynakları kullanılarak yeni bir veri seti oluşturulmuştur. Aghion vd. (2018) yaklaşımı izlenerek dışsal talep şoku değişkeni inşa edilmiştir. Bu değişken MMK çerçevesine firmaların pazar yönelimiyle birlikte entegre edilerek KYB'nin etkisi yerel/ulusal, AB-EFTA ve AB dışı pazarlar açısından analiz edilmiştir.

Bu tez literatüre üç önemli katkı sunmaktadır: Birincisi, teorik katkıdır. KYB gibi küresel bir projenin firma düzeyindeki inovasyon dinamikleri üzerindeki etkisini analiz eden ilk çalışmadır. Literatürde KYB'nin firma düzeyinde etkilerini ele alan çalışmalar bulunmakla birlikte, bunlar genellikle Çinli firmalara odaklanmakta ve firmaların yenilik kararlarını sistematik olarak açıklayan yapısal modellere yer vermemektedir.

İkincisi, yöntemsel katkıdır. Bu tez, geleneksel CDM/MMK çerçevesini mekânsal bağımlılık içerecek şekilde dönüştüren ilk çalışmadır. Önceki çalışmalar, dışsallıkların varlığını varsaymakla birlikte, tüm bloklarda mekânsal ağırlık matrislerini kullanan entegre bir yapıya sahip değildir. Üçüncü katkı ise ampiriktir. KYB'nin ticaret maliyetleri üzerindeki etkisini yansıtan yeni bir veri seti oluşturulmuş ve sadece CIS mikro verileri kullanılarak CDM literatüründe ilk defa böyle bir uygulama gerçekleştirilmiştir.

Analiz iki yaklaşım üzerinden yürütülmektedir. İlk yaklaşımda geleneksel MMK çerçevesi Heckman seçim modeli ile tahmin edilmiştir. İkinci yaklaşımda ise bu çerçeve, coğrafi ve ekonomik yakınlığı temsil eden mekânsal bağımlılık yapılarıyla genişletilmiştir. Ekonomik yakınlık, Eurostat'ın Figaro girdi-çıktı tabloları kullanılarak hesaplanmıştır.

Analiz bulguları dikkat çekicidir. İlk yaklaşıma göre, KYB ulusal pazarlara yönelmiş firmaların Ar-Ge harcamalarını artırırken, Ar-Ge faaliyetlerine başlama eğilimlerini azaltmaktadır. AB-EFTA ve AB dışı pazarlara yönelmiş firmalar için ise hem harcama düzeyinde hem de Ar-Ge'ye giriş kararlarında KYB'nin olumsuz etkileri görülmektedir. İnovasyon çıktısına dair sonuçlar da benzer doğrultudadır ancak etkilerin büyüklüğü daha sınırlıdır. Bu sonuçlar, KYB'nin ulusal pazarda faaliyet gösteren düşük verimliliğe sahip firmaların Ar-Ge faaliyetlerinden çekilmesine neden olabileceğini düşündürmektedir. AB-EFTA pazarlarına odaklanan firmalar içinse rekabet baskısının belirleyici olduğu ve bu firmaların küresel değişime karşı yeterince dirençli olamayabileceği yorumu yapılabilir.

İkinci yaklaşımdan elde edilen sonuçlar, birinci yaklaşım ile tutarlıdır. Mekânsal bağımlı terimler, odak firma çevresinde AB-EFTA ve AB dışı firmaların bulunması durumunda Ar-Ge harcamasının azaldığını göstermektedir. Bu da ilk modeldeki olumsuz etkinin yalnızca firmaya özgü değil, çevresel yapıya da yayıldığını göstermektedir. Yine de coğrafi yakınlığa dayalı modellerin daha sağlam sonuçlar verdiği gözlenmiştir.

İnovasyon çıktısı üzerindeki etki söz konusu olduğunda daha karmaşık bir tablo ortaya çıkmaktadır. KYB'nin dahil edilmesiyle çevresindeki firmalar dış pazarlara yönelmiş olan firmaların Ar-Ge harcaması azalmaktadır; ancak inovasyon çıktısı analizinde bu ilişkinin yönü tersine dönebilmektedir. Yani, çevresel etkinin pozitif ya da negatif olması duruma bağlı olarak değişmektedir. İlk etkinin yönünden bağımsız olarak, KYB'nin firma ilişkilerini bozabileceği açıktır.

Bu analizler üç araştırma sorusuna da yanıt vermektedir. İlk olarak, KYB Avrupa firmalarının inovasyon karar ve faaliyetleri üzerinde anlamlı bir etkiye sahiptir. Bu etkinin mekânsal bir boyutu da bulunmakta ve bu ikinci soruya olumlu yanıt oluşturmaktadır. Son olarak, etkinin zamanla ve firmaların pazar yönelimiyle değiştiği görülmektedir. Ancak bu farklılaşma, zaman içinde belirli bir artış ya da azalış yönünde sabit bir desen göstermemekte; daha ziyade pazar yöneliminin niteliği çerçevesinde istikrarlı şekilde farklılaşmaktadır.

Bu bulgular Avrupa Birliği'nin inovasyon politikaları açısından önemli çıkarımlar doğurmaktadır. Öncelikle, sadece ekonomik entegrasyonun veya coğrafi yakınlığın inovasyon sistemlerinin dayanıklılığını garanti etmediği anlaşılmaktadır. Firmalar, istikrarlı koşullarda kümelenmeden ve ağlardan fayda sağlasa da, bu avantajlar küresel jeopolitik ya da ekonomik şoklar karşısında zayıflayabilir veya tersine dönebilir. Bu bağlamda çevredeki firmaların kapasitesi belirleyici hale gelmekte; uyum sağlayabilen firmalar bilgi aktarımını desteklerken, katı ve yerelleşmiş yapılar bilgi yayılımını engelleyebilmektedir. Bu durum, küresel ticaret olanakları sayesinde sağlanması beklenen faydaların parçalı bilgi dışsallıkları ve yetersiz kolektif gelişmeyle sonuçlanmasına yol açabilir.

İkinci olarak, inovasyon politikalarının sadece bölgesel güçlü yanlara değil, firmalar arası ilişkisel ağ yapısına da odaklanması gerektiği ortaya çıkmaktadır. S3 gibi politika araçları bölgesel önceliklere göre tasarlansa da, yeni küresel bağımlılıklar ve şoklara karşı güncellenmeleri gerekmektedir. Bölgesel stratejiler sadece iç dinamiklere değil, firmaların ağ yönelimi, küresel bilgi zincirlerine entegrasyonu ve değişimlere hızlı tepki verebilme kapasitelerine göre yeniden şekillenmelidir. Fonlama yapıları da, firmaların bu risklere karşı güvende olduklarını hissedecekleri şekilde revize edilmelidir.

Üçüncü olarak, Ufuk Avrupa, Avrupa İnovasyon Konseyi ve ERA Hubs gibi sınır ötesi iş birliğini önceliklendiren politika araçları, dışsal şokların inovasyon kapasitesi üzerindeki etkisini gözeten bir perspektifle yeniden hizalanmalıdır. Firmaların yalnızca yenilik yapmalarını değil, aynı zamanda hem yerel hem küresel ağlarını geliştirmelerini teşvik eden mekanizmalar kurgulanmalıdır. Firmaların absorpsiyon kapasiteleri, bilgi akışına entegrasyonu ve tedarik zinciri kırılganlıkları gibi sistemik zayıflıkları belirlemek AB inovasyon ekosisteminin güçlendirilmesi açısından büyük önem taşımaktadır.

Eğer AB, değişen küresel dinamiklerin firma düzeyindeki inovasyon kararlarını etkileyebileceğini kabul etmezse, sadece bölgesel iç uyuma odaklanan politikalar, inovasyon eşitsizliklerini çözmek yerine derinleştirebilir. Bu nedenle, hem dirençlilik planlaması hem de bağımlılıkların azaltılmasına yönelik yaklaşımları içeren, daha dışa dönük ve uyarlanabilir bir inovasyon politikasına ihtiyaç vardır.

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