İstanbul University Press

İstanbul İktisat Dergisi
Istanbul Journal of Economics

İstanbul İktisat Dergisi
Istanbul Journal of Economics,
IJE 2025, 75 (2): 262–287

https://doi.org/10.26650/ISTJECON2025-1507503

Submitted: 30.06.2024
Revision Requested: 06.11.2025
Last Revision Received: 09.11.2025
Accepted: 22.11.2025

Research Article

Open Access

Exploring Intra-Industry Trade Dynamics: Spatial Analysis of Türkiye's Provinces

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Abstract

This study investigates intra-industry trade (IIT) among the 81 provinces (NUTS-3) of Türkiye from 2004 to 2021 using Grubel-Lloyd's methodology with ISIC rev.4 - 4 digit data. Spatial autocorrelation analysis reveals significant clustering, with the western region demonstrating high-high IIT characteristics, whereas the eastern region exhibits low-low patterns, indicating regional disparities. Different spatial estimators, such as the spatial Durbin model (SDM), spatial autoregressive model (SAR), spatial error model (SEM), spatial autoregressive and autoregressive conditional heteroskedasticity model (SAC), and econometric models, are employed to explore spillover effects among cities. However, no statistically significant spillover effects are detected, suggesting IIT is linked to production fragmentation among Türkiye's cities. Hausman test results show that the most efficient estimators in the analysis are SAR, SEM, and SAC under fixed effects models. The time effects model yields the most significant results, indicating a positive relationship between GDP, GDP per capita, government spending, patent registrations, metropolitan status, and IIT. Conversely, a negative association is found with brand registrations. Trade openness, coastal access, border proximity, and landlocked status do not significantly impact IIT.

Keywords Intra-industry trade · regional economics · spatial panel data analysis

Jel Codes F14, R12

Citation: Şaşmaz, A. B. (2025). Exploring intra-industry trade dynamics: Spatial analysis of Türkiye's provinces. *İstanbul İktisat Dergisi–Istanbul Journal of Economics*, *75*(2), 262-287. https://doi.org/10.26650/ISTJECON2025-1507503

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Exploring Intra-Industry Trade Dynamics: Spatial Analysis of Türkiye's Provinces

Intra-industry trade (IIT) has gained importance, especially after the 1960s, and studies to explain this phenomenon have intensified (Greenaway & Milner: 1987: 39). Mutual and simultaneous trade of similar products between countries could not be explained by classical foreign trade theories and specialisation. This situation enabled IIT to be among the new foreign trade theories. The globalisation movement in the world, trade liberalisation and the resulting global value chains have increased the share of IIT. Today, IIT accounts for 25% to nearly 50% of the total trade in the world depending on the industrial classification (Krugman et al., 2022: 210). Broda and Weinstein (2006) found that welfare gains only from variety growth increased by 2.8% of the US GDP. Ruffin (1999) notes that IIT is more beneficial than inter-industry trade due to the stimulation of innovation and exploitation of scale economies. Ruffin (1999) also states that productive factors exhibit limited mobility across industries, primarily transitioning within industries. Consequently, IIT is observed to be less disruptive than inter-industry trade.

The most used index for calculating IIT was developed by Grubel & Lloyd (1971). After the development of this index, different methodologies have been created for measuring IIT, and studies have been conducted to theoretically explain IIT. However, while the determinants of IIT are well documented in cross-country analyses, studies at a subnational (NUTS-III/provincial) level remain scarce, particularly for Türkiye. Furthermore, to my knowledge, no existing study has combined a comprehensive provincial-level IIT analysis for Türkiye’s 81 provinces with a robust spatial econometric framework to investigate spatial dependencies, clustering, and potential spillover effects. This study seeks to fill this significant gap.

This subnational focus is increasingly relevant as competitiveness between regions and cities has gained importance, and cities have begun to be among the pioneers and determinants of innovation. In the analysis of international trade, analyses are conducted assuming that resources, demand, and supply are distributed homogeneously within a country. However, in practice, there may be significant differences between regions in countries. This situation causes the welfare increase obtained from IIT not to be distributed equally within the country. However, this regional heterogeneity is often overlooked. Therefore, examining the determinants of IIT at the local level will guide policymakers in eliminating the development gap among cities and regions.

Cities, acting as integral hubs in global and regional supply chains, play a crucial role. Analysing IIT at the city level enables a detailed exploration of supply chain dynamics, highlighting dependencies, vulnerabilities, and opportunities that might be obscured in broader national or international analyses. Trade policies, typically formulated at the national level, have profound implications for cities. Investigating IIT within cities unveils the localised impacts of global or national policies, shedding light on how cities adapt to navigate a dynamic economic landscape.

Considering the benefits brought by the increase in IIT, this phenomenon should also be considered in the policies developed for the regions. In this context, examining whether IIT forms clusters with other cities or regions and whether there is a spillover effect among them will also be important in terms of regional policies to be developed. In this study, IIT calculation of Türkiye's 81 provinces was conducted using ISIC rev.4–4-Digit data, and cluster, spillover effects, and determinants were examined using spatial statistics and different econometric tools for the 2004-2021 period.

Considering the gaps in the existing literature, this study aims to investigate how IIT spatially clusters across Türkiye's 81 NUTS-III provinces. It also examines whether there are statistically significant spatial spillover effects of IIT, suggesting that a province's IIT is influenced by its neighbours, and what the key provincial-level economic, demographic, and innovation-related determinants are that drive IIT dynamics in Türkiye.

The study is organised as follows. Section 1 continues with the conceptual framework and the development of the econometric hypotheses. Section 2 details the data, the Grubel-Lloyd IIT calculation, and the spatial econometric methodologies employed. Section 3 presents and discusses the results, covering the Moran’s I test, LISA cluster analysis, and findings from the spatial panel data models. The final section concludes the paper by summarising the key findings, discussing their implications, and offering recommendations for policy and future research.

Conceptual Framework

Empirical research on IIT between different countries and country groups is well documented. However, at the city and regional levels, these works are scarce. To my knowledge, the earliest work for examining IIT at the local level was conducted by Hanson (1996). The author examined US-Mexico integration, its impact on the border economy, and IIT. This study shows that trade shifts manufacturing activities towards border cities, implying the significance of transport costs in shaping firm location decisions. Yoshida (2008) studied the IIT between Korea and Japanese sub-regions and calculated Grubel-Lloyd index for 41 regions of Japan. The author found that the Grubel-Lloyd index at the regional level more likely captures the effect of the fragmentation of the production, and the IIT is pervasive even though it is restricted. Brodzicki et al. (2020) calculated the IIT between Spanish and Polish NUTS-2 regions and identified its determinants for the 2005-2014 period. Utilising a semi-mixed effect model estimated with the PPML method, the study explores traditional and unorthodox factors, such as regional path dependence, quality of regional institutions, and regional status, jointly and disjointly estimating models for all Spanish and Polish regions. Liu and Liang (2023) found a positive correlation between urbanisation and foreign trade.

Theoretical framework in this area is also underdeveloped. However, from the many empirical studies and theories emphasised for cross-country analysis, several assumptions for the regional and city-level IIT can be drawn, and differences can be pointed out.

At the city or regional level, IIT will be lower than at the country level. This is simply related to trade overlap. A certain product and/or product group can be produced and sold in/from different cities or regions. Therefore, trade of a certain product or product group will be concentrated in that particular city or region. The same can be said for imports. This situation will cause an inter-industry trade pattern to be realised.

At the sub-national level, there can be local clusters of production. Final products from these clusters can be sold from one main city, especially those with ports and/or those near borders. This can distort the IIT calculations.

Differences in culture and income levels among cities can influence diverse demand patterns, particularly impacting IIT patterns in city and regional level analyses. Such effects are best examined through sub-national level analysis, where heterogeneity among cities is evident. In contrast, cross-country analyses treat countries as singular units, making it challenging to observe city-level differences, though these variables are used to assess variations across countries.

Main triggers for IIT are demand and supply patterns. Factor endowment differences cause vertical product differentiation by use of various combinations. In the literature, love for variety explains the demand side, whereas scale economies are commonly used to explain the supply structure.

According to Yoshida (2008: 4, 10) restriction of IIT to the sub-national level yields intra-firm trade rather than the traditional results. Fujita et al. (1999) also noted that trade may induce a restructuring of internal economic geography, leading to a dual phenomenon characterised by the dispersion of manufacturing activity at a broader scale and the agglomeration of particular industries. Therefore, the observed IIT implies the fragmentation of production among regions. Although this is true for the trade among regions, it can be a different story for regional trade to country groups or the total trade to the world. Since total trade from a city or region to the world not only captures the intra-firm trade but also final products demanded by the consumers in a broader context. In this case, one of the main determinants of the IIT would be the amount of intermediate goods and existence of the manufacturing sector. Due to the nature of the manufacturing sector, certain inputs might have to be imported for production. In the same manner, certain outputs would be exported, and this trade cycle increases the IIT more than the other sectors. But, if the trade mainly consists of the primary products in a certain region, the IIT index most likely will yield lower results. Primary products depend on natural endowments with raw materials and climate, so trade of these products will have an inter-industry trade pattern (Grubel and Lloyd, 1971: 506). Also, differentiation of these products is difficult compared to intermediate products or manufacturing sector products.

If the IIT analysis is limited to the foreign trade of regions, it is possible to have high index values even in the primary products. Due to high transportation costs relative to scale economies and seasonality, high IIT values can be seen in the trade of certain products that include building materials (such as stone, sand, and gravel), perishable foods, and electricity among border regions (Grubel and Lloyd, 1971: 507). However, when analysing the trade of a border region with a country group or the world, some primary products with a relatively higher IIT index in trade with a neighbouring region or country may exhibit an inter-industry pattern, primarily due to the region's demand structure.

Studies focusing specifically on Türkiye, while not at the provincial level, provide context. These studies have primarily used cross-country panel data to identify national-level determinants. For instance, market size and development represented by GDP and GDP per capita, respectively, were found to be significant positive determinants by Emirhan (2005), Şentürk & Kösekahyaoğlu (2014), Şaşmaz (2024). Çepni & Köse (2003) also confirmed the positive impact of average per capita income. Furthermore, Çepni & Köse (2003), Şentürk & Kösekahyaoğlu (2014) and Şaşmaz (2024) identified trade openness and economic integration with the EU as significant positive drivers. A consistent finding in this national-level literature is that geographic distance acts as a significant negative determinant, a proxy for transport costs. This paper builds upon these findings by moving the analysis from the national to the provincial level and introducing a spatial dimension.

Econometric Hypotheses for City-Level IIT

As pointed out by Brodzicki et al. (2020), empirical literature on IIT at the regional level is quite limited. There is a debate about which variables and hypotheses should be used because the determinants of regional IIT may differ from those used in cross-country analysis. Additionally, data at the city and/or regional levels may not be accessible or may not exist. For this reason, FDI cannot be used as an explanatory variable due to the non-existence of data at the city level in this study.

The distance between trading partners is also another commonly used variable to explain IIT. In this study, where the trade activities of Türkiye's 81 cities with countries worldwide are analysed, assigning a single distance value proved impractical due to the uneven distribution of trade from each city to various countries globally. As a result, a distance value representing the world average was not used in the trade analysis.

A similar situation arises with the size of economies and development levels, typically accounted for by including the GDP and GDP per capita of trade partners in the model. In this study, only the GDP and GDP per capita of Turkish cities are used. Since the analysis examines total trade with the world and does not conduct cross-country comparisons, partner GDP metrics are excluded, as they would represent global GDP and GDP per capita for each segment. This exclusion prevents biased results, as the cities analysed do not trade with every country.

Although research on the determinants of IIT at the local or regional levels is limited, it is possible to adapt variables and hypotheses commonly used for cross-country analysis. Despite the aforementioned limitations, eight hypotheses have been identified to test the relationship between selected variables and IIT.

Hypothesis 1: As economic size increases, IIT will increase..

This hypothesis is built on foundational trade theories. On the supply side, a larger economic size (proxied by GDP) implies a larger domestic market. This allows local firms to specialise in specific product varieties and exploit economies of scale, which reduces costs, fosters greater product differentiation, and therefore increases IIT (Loertscher and Wolter, 1980: 283). On the demand side, a larger economy generally supports a wider and more sophisticated range of consumer preferences. As firms specialise in producing distinct varieties to meet this diverse demand, and consumers seek differentiated products, the simultaneous export and import of these products, in other words, IIT, is expected to rise.

Many empirical studies utilise proxy variables derived from GDP or GDP itself. Given that GDP reflects economic size, it stands as a fundamental variable in cross-country analyses of IIT. In these studies, various measures are employed to represent the market size of trading countries, including average GDP, GDP of trade partners, minimum and maximum GDP values, and GDP differences. By using the GDP data of respective countries, researchers aim to observe the influence of economic size on IIT across countries.

Havrylyshyn & Civan (1983), Emirhan (2005), Yoshida (2013), Şentürk & Kösekahyaoğlu (2014) and Şaşmaz (2019), Şaşmaz (2024) utilised GDP data from host and partner countries and found a positive correlation between GDP increase and IIT. Ambroziak (2012) found a similar positive correlation between GDP and IIT for both horizontal and vertical IIT.

There are several studies that use maximum and minimum GDP values of trade partners. Blanes (2005) observed the positive impact of minimum and maximum GDP values, while Thorpe & Leitão (2013) noted the positive impact of minimum GDP values but observed statistically insignificant results with maximum GDP values on the IIT. Sohn & Zhang (2005) concluded that the minimum GDP value has a negative impact on horizontal IIT but a positive impact on vertical IIT. Conversely, they found that the maximum GDP value does not affect horizontal IIT and negatively affects vertical IIT. In the studies conducted by Hayakawa et al. (2017) and Turkcan & Ates (2010), where the average of total GDP was utilised, a positive relationship was observed between GDP increase and IIT. Turkcan and Ates (2011) specifically concluded that this increase positively impacts vertical IIT, whereas Jambor (2014) found positive effects on both vertical and horizontal

IIT. Okubo (2007) and Zhang & Clark (2009) revealed a negative impact of market size differences on IIT, whereas Reganati and Pittiglio (2005) noted negative effects on low-quality vertical IIT but positive effects on high-quality vertical IIT.

Generally, when examining the studies, it becomes evident that an increase in GDP tends to increase total IIT. Conversely, disparities in GDP tend to diminish IIT. In this study, for the local level, a positive impact of an increase in GDP on IIT is expected.

Hypothesis 2: As citizens' purchasing power increases, IIT will increase..

In line with the Linder (1961) hypothesis, the demand structure of a country is related to its per capita income. Consumers in low-income countries tend to purchase standardised products, whereas consumers with higher income would most likely demand differentiated products (Hellvin, 1996: 23). Demand and therefore, the trade of differentiated products would increase the IIT. This hypothesis is tested for cities in Türkiye using their per capita GDP to examine the IIT pattern. Indeed, cross-country studies on Türkiye by Çepni & Köse (2003), Emirhan (2005), and Şentürk & Kösekahyaoğlu (2014) confirmed a positive relationship between average per capita income levels and IIT.

GDP per capita serves as a crucial metric for measuring income level disparities between countries. In studies conducted by Lee & Lee (1993), Bergstrand (1990), Somma (1994), Wakasugi (1997), Hurley (2003), Kandogan (2003), Thorpe & Zhang (2005), Yoshida (2013), and others focusing on IIT between countries, GDP per capita differences have been calculated using various equations and employed as proxies to explore income level differences. The hypothesis in these studies suggests that increasing income level disparities lead to a decrease in IIT. Hirschberg et al. (1994) used GDP per capita of the trading country as a variable, while Ambroziak (2012) incorporated GDP per capita data from both partner and home countries. In cross-country analyses, GDP per capita is commonly employed to assess how changes in consumer income affect IIT demands. In this study, which focuses on Turkish cities as cross-sections, the GDP per capita of each city serves as a representation of consumer demand. Recognising that not all cities engage in trade with every country worldwide, total intra-industry foreign trade was calculated using the world chosen as the trade partner. However, given that trade levels vary across cities and countries, using the world average may yield biased results. Therefore, only the per capita GDP of the cities was used.

Hypothesis 3: As government spending per capita increases, IIT will increase..

Government spending per capita captures health, education, law, security, social work, investments such as infrastructure, urban, economic development, cultural and recreational facilities, and administrative costs.

In cross-country analyses, there is evidence, although limited, that government spending bolsters IIT by influencing the competitive dynamics, market structure, and trade patterns within industries and across borders. Anwar (2001) asserts that under certain conditions, public infrastructure spending can cause an increase in IIT. Łapińska etal (2019) found a positive relationship between general government expenditure on health and IIT of pharmaceutical products. According to Najafi et al. (2021), there is a positive relationship between government size and IIT.

While there are limited articles exploring the correlation between IIT and government spending, to my knowledge, no studies have investigated this relationship at the local level. However, there exist articles that delve into the association between growth and IIT. Ojede et al. (2018) observed a positive impact on growth from spending on productive higher education and highways in U.S. states. Marica et al. (2021) highlighted the significant role of infrastructure and capital expenditure in the growth rates of Italian regions. Brakman et al. (2002) demonstrated that government spending can influence a country's attractiveness for mobile production factors. Barattieri et al. (2023) identified significant positive effects on industries and their supply chains resulting from sector-specific government purchases. From these works, it can be deduced that government spending may cause an increase in IIT by inducing economic growth at either the local or national level. Therefore, a positive impact of government spending on IIT is expected.

Hypothesis 4: IIT will increase as the number of brand registrations increases..

The number of brand registrations is used as a proxy for horizontal product differentiation. Theoretically, a high number of brand registrations in a city signals a vibrant market where firms are actively competing by creating distinct product identities. This differentiation is a core driver of IIT, as it leads to the production and trade of numerous varieties (e.g., different brands of the same product) within the same product category, appealing to diverse consumer tastes (Linder, 1961).

Hypothesis 5: As the number of patent registrations increases, IIT will increase.. According to Loertscher and Wolter (1980: 284), IIT tends to increase in scenarios where there is a high degree of product differentiation coupled with limited market entry due to significant barriers. Moreover, economies of scale may exist within narrow product lines. Linder's (1961) concept of "representative demand" suggests that countries may specialise in particular varieties of products. In cases where substitutes exist in consumption patterns, patents and trademarks can serve as barriers to market entry. Such intellectual property protections can prevent local firms from imitating imported products for local markets, consequently stimulating trade and enhancing IIT. Therefore, a positive correlation is anticipated for both hypotheses.

Hypothesis 6: As trade openness increases, IIT will increase..

Trade openness and trade liberalisation are other common determinants of IIT. In cross-country analyses of IIT, researchers such as Balassa (1986), Çepni & Köse (2003), Xing (2007), Şentürk & Kösekahyaoğlu (2014), Şaşmaz (2019) and Şaşmaz (2024) have found evidence supporting the positive impact of trade openness and trade liberalisation.

In different studies focused on regional economies, authors such as Pernia & Quising (2003), González Rivas (2007), and Arabiyat et al. (2020) have utilised the trade openness variable similarly to cross-country analyses by dividing trade by GDP. The results of these studies indicate a positive correlation between trade openness and growth. Although there has not been much work related to trade openness at the local level due to the scarcity of intra-industry literature at this level, it can be deduced from the results of these studies that trade openness can have a positive impact on IIT. The main reason behind this intuition is that economic growth can stimulate the creation of new varieties of products, which can then be commercialised and subject to foreign trade. On the other hand, Brülhart (2011) asserts that the impact of trade openness on spatial concentration and regional inequality is indeterminate. In this study, the same variable is used to examine the relationship between IIT and trade openness.

Hypothesis 7: The city becoming a metropolitan will increase IIT..

Metropolitan cities play a crucial role in shaping economic dynamics at the city level, as underscored by the OECD (2006: 87). Their positive impact is multifaceted, encompassing enhanced accessibility to underdeveloped regions, the facilitation of a diversified division of labour, the stimulation of healthy competition, and the promotion of specialisation within industries. Moreover, agglomeration effects inherent in metropolitan areas reduce transaction costs by eliminating intermediaries between customers and suppliers, thereby fostering smoother trade interactions. The synergy among companies, public authorities, research institutions, and educational centres generates positive externalities that further bolster economic activity. Additionally, the substantial presence of physical capital, including robust building stocks and well-developed infrastructure facilities, contributes to the conducive business environment. Metropolitan cities also accumulate substantial social capital through diverse local communities and civic groups, which enhances networking and collaboration opportunities. However, caution must be exercised regarding potential negative impacts, as noted by the OECD (2006: 91-92). These include congestion costs arising from traffic, pollution, compromised water and air quality, diminished green spaces, and elevated noise levels. Furthermore, challenges such as poor infrastructure quality and social and fiscal cohesion deficits could impede the realisation of the full potential of metropolitan cities.

Brodzicki and Uminski (2018) emphasise the role of metropolitan cities in foreign trade and have found a positive correlation between them. Brodzicki et al. (2020: 5) stated that the metropolitan status of a region can trigger IIT due to having a larger and more dense population with diversified economic structures. Metropolitan cities can possess more qualified human resources, which can positively affect factor endowment and, consequently, IIT. Moreover, having a large population with diverse cultures and backgrounds can stimulate the demand side of trade, as per Krugman's (1979) theory of the "love of variety." Therefore, a positive relationship between being a metropolitan city and IIT is expected.

Hypothesis 8: Having a border with another country or having a sea coast will increase IIT, whereas having a landlocked status will reduce IIT..

Location theory provides insights into the spatial organisation of economic activity and helps policymakers, businesses, and urban planners understand the factors driving location decisions and their implications for economic outcomes. It seeks to explain the location patterns of economic activity. As Franksen and Grattan-Guinness (1989) discussed, the earliest contribution to location theory in spatial economics dates back to the publication of Lame and Clapeyron in 1829.

IIT and location theory are interconnected concepts that shed light on the spatial organisation of economic activity, patterns of specialisation, and the factors driving international trade and investment flows. Krugman (1991) demonstrates how agglomeration economies and firms' location decisions affect trade patterns by shaping the spatial distribution of economic activity. Brülhart (2011) emphasises that areas with lower transportation costs to foreign markets, such as border or sea regions, have the greatest gain from trade liberalisation. Cross-country studies for Türkiye such as Çepni & Köse (2003) and Şentürk & Kösekahyaoğlu (2014) utilise distance as a proxy for transport costs and find a significant negative relationship with IIT.

Brodzicki et al. (2020) employed dummy variables to capture the effects of being landlocked, having access to the coast, and having a border with a foreign country. In this study, factors such as having a border with another country, access to the coastline, and being landlocked were also used as control variables due to their time-invariant nature. Border trade can potentially increase IIT in primary goods (Grubel and Lloyd, 1971), thereby possibly exerting a positive impact on regional-level IIT. Export-oriented firms may also select these locations to facilitate easier access to trade, thereby potentially fostering IIT. A landlocked city is expected to experience lower trade gains due to relatively higher transportation costs. However, being landlocked may prompt the city to leverage its abundant factors. Consequently, it is also conceivable for a city to use its unique resources to concentrate on certain industries, contributing to IIT. Having access to the sea can similarly be regarded as another determinant for trade, akin to border trade. Firms may restructure their production processes to manufacture final goods near ports to mitigate transportation costs. Additionally, it is plausible to use imported goods as inputs for production processes.

IIT Analysis and Econometric Methodology

This section outlines the empirical strategy of the study. It details the data sources, the methodology for calculating the Grubel-Lloyd index, and spatial econometric models employed to test the hypotheses.

Data and Econometric Methodology

Data used in the analyses in this study and their description are given in Table 1.

Table 1

Variable Overview: 2004-2021 Analysis Period[1]*,*

Variable	Name	Source	Notes	Access date
gdp	Gross Domestic Product	Turkstat (2023)	Given that GDP data are current, denominated in the Turkish lira, and not provided in real value, a deflator was employed to adjust for inflation. The natural logarithm of the real GDP data was calculated and used in the analysis.	25.01.2023
gdppc	Gross Domestic Product Per Capita	Turkstat (2023)	Given that GDP per capita data are current, denominated in the Turkish lira, and not provided in real value, a deflator was employed to adjust for inflation. The natural logarithm of the real GDP per capita data was calculated and used in the analysis.	26.01.2023
gov_spend	Central Government Spending per capita	Republic of Türkiye Ministry of Treasury and Finance (2023)	Given that central government spending data are currently denominated in Turkish lira and not provided in real terms, the yearly data were first divided by the population for the corresponding year. Secondly, a deflator was employed to adjust for inflation. The natural logarithm of the real central government spending per capita data was calculated and used in the analysis.	11.02.2023
iit	Intra Industry Trade	Turkstat (2023) Own Calculations (See Appendix Tables)	Export and import data were taken from Turkstat TL. IIT was calculated using the standard Grubel-Lloyd Index.	26.01.2023
brand_reg	Brand Registration	Turkstat (2023)	-	18.01.2023
patent_reg	Patent Registration	Turkstat (2023)	-	18.01.2023
trade_open	Trade Openness	Turkstat (2023)	Calculated by the author based on the data obtained from Turkstat using the following equation: (X + M) / GDP	26.01.2023
metropolitan	Metropolitan City	-	Dummy based on the date when the city achieves metropolitan status. Yetkin (2020) summarised the chronological order of cities becoming metropolitan. Prior to the year 2004, which marks the beginning of the analysis, there were 16 metropolitan cities,	-

[1]The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Variable	Name	Source	Notes	Access date
			and after 2012, an additional 14 cities were granted metropolitan status.	
coast	Coastal City	-	Dummy based on the geographic location of the city on the map.	-
border	Border City	-	Dummy based on the geographic location of the city on the map.	-
landlocked	Landlocked City	-	Dummy based on the geographic location of the city on the map.	-

The generalised regression form can be formulated as follows:

$$IIT_{it} = \beta 0 + \beta 1 gdp_{it} + \beta 2 gdppc_{it} + \beta 3 gov\_spend_{it} + \beta 4 brand\_reg_{it} + \beta 5 patent\_reg_{it}$$

$$+\beta 6 trade\_open_{it} + \beta 7 metropolitan_{it} + \beta 8 coast_{it} + \beta 9 Border_{it} + \beta 10 landlocked_{it} + \epsilon_{it}$$

where i represents city, and t denotes year. This form shows a simple pooled OLS approach; however, classical econometric approaches and models often disregard spatial autocorrelation, which causes biased results (LeSage & Pace, 2009). This problem occurs more often when the number of spatial units is high. Therefore, in recent years, spatial econometrics has gained attention and has started to be used in empirical analysis. One of the aims of this study is to use spatial estimators to achieve relatively unbiased results and to analyse spillover effects. To be able to use the spatial econometric methods, the dependent variable should have spatial dependence, which can be observed with Moran's I test.

In order to analyse the spatial relationship, spatial weights matrices are used and commonly denoted by W. These spatial weights matrices are used to include the spatial distance among spatial units to the econometric model. There are two common methodologies to create these matrices: contiguity matrix and distance-based matrix. The contiguity matrix contains information about whether a spatial unit is adjacent to another. If two spatial units are not neighbours, $w_{ij} = 0$, if they are $w_{ij} = 1$. To create the contiguity matrix, it is necessary to identify neighbourhood relationships, which can be accomplished using various methods, including those derived from chess piece movements such as the bishop, queen, and rook. These methods categorise neighbourhood relations based on the specific movement patterns of the respective chess pieces: the Rook method accounts for horizontal and vertical movements, the Bishop method for diagonal movements, and the Queen method encompasses relationships in both horizontal-vertical and diagonal directions.

Distance-based matrices have the information of distances between two spatial units. Euclidean or straight line distances can be calculated using coordinates. However, these distances can be used when the coordinates can yield meaningful results because the curvature of the Earth should be taken into account. To overcome this issue, the arc or great circle distance, which includes an approximation of the Earth's shape, can be used (Anselin, 2020).

With either of these two methodologies, a basic spatial econometric model can be expressed as follows:

$$y = \rho W_1 y + X\beta + \varepsilon \tag{1}$$

$$\varepsilon = \lambda\, W_2 \varepsilon + \mu \tag{2}$$

where y denotes the vector of variables, ρ denotes coefficient for spatially lagged dependent variables, W denotes the spatial weights matrix, β denotes a K-dimensional vector of parameters associated with exogenous variables X, ε and μ denote vector of independently distributed random terms, λ denotes the coefficient in a spatial autoregressive structure for the disturbance term. (Anselin, 1988: 34-35)

Spatial Autoregressive Model (SAR) and Spatial Durbin Model (SDM) are the two most common models used in spatial analysis. SAR models have certain constraints:

$$\rho \neq 0,\ \lambda = 0$$

It is also assumed that the autoregressive process is included in the dependent variable. This model can be expressed as follows:

$$y_t = \rho W y_t + X_t \beta + \mu + \varepsilon_t, \quad \mu \sim N\left(0, \sigma^2 I\right) \tag{3}$$

SAR models account for spatial dependence by incorporating a term that represents the weighted average of the dependent variable in neighbouring spatial units. The model assumes that the value of a variable in a given location is influenced not only by its own characteristics but also by the characteristics of nearby locations. SAR models allow to analyse data where spatial interactions or spillover effects are present.

On the other hand, SDM has three components: a dependent variable with a spatial lag, explanatory variables with a spatial lag, and explanatory variables in relationship with spatial units. It can be expressed as follows (Belotti et al., 2017):

$$y_t = \rho W y_t + X_t \beta + W Z_t \theta + \mu + \varepsilon_t, \quad \mu \sim N\left(0, \sigma^2 I\right) \tag{4}$$

Here, θ represents the vector of coefficients associated with the spatially lagged independent variables, and Z is the matrix of spatially lagged independent variables.

SDM extends the SAR model by including spatially lagged values of the independent variables. SDM incorporates spatially lagged independent variables to account for spatial spillover effects in the explanatory variables.

Fixed effects spatial autocorrelation (SAC, also known as SARAR) model can be referred to as the SAR model with spatially autocorrected errors. It allows for a spatially autocorrelated error in the SAR model (Belotti etal., 2017):

$$y_t = \rho W y_t + X_t \beta + \mu + v_t \tag{5}$$

$$v_t = \lambda M v_t + \varepsilon_t \tag{6}$$

In this model, M denotes a spatial weights matrix that is equal or not equal to W. M can encompass both direct and indirect spatial relationships. It may include elements from W or other forms of spatial interaction, depending on the specific model and its assumptions. v represents the error term associated with the spatially autocorrelated errors.

SAC models are used to address spatial heteroskedasticity, which occurs when the variance of the error term is not constant across spatial units. SAC models allow the error variance to be spatially correlated and vary across locations. (Kelejian & Prucha, 2010)

Spatial error model (SEM) is a special case of the SAC model where it focuses on the error term: (Belotti et al., 2017)

$$y_t = X_t \beta + \mu + v_t \tag{7}$$

$$v_t = \lambda M v_t + \varepsilon_t \tag{8}$$

SEM accounts for spatial dependence by assuming that the error terms in the regression model are spatially correlated. Unlike SAR and SDM, SEM does not assume spatial dependence in the dependent or independent variables. Instead, it models spatial dependence in the error term. (Anselin & Bera, 1998: 248)

It was derived from LeSage and Pace (2009) and Elhorst (2010) by Belotti et al. (2017) Wald test (test and testnl commands in Stata) and information criteria can be used to select the appropriate model for the analysis. Results of this study show that SAR, SEM, or SAC models are more appropriate compared with SDM. Hausman tests were carried out to select between random and fixed effects models. Results show that fixed effects models are more efficient for each estimator.[2]

The dependent variable IIT in the model is calculated with Grubel-Lloyd indices by using Microsoft 365 Excel. Stata 16 software and xsmle, xtmoran, and spmat packages are utilized for the econometric analysis. Xsmle package developed by Belotti et al. (2017) uses Driscoll-Kraay standard errors which is robust to disturbance being heteroscedastic, autocorrelated with MA(q), and cross-sectionally dependent (Hoechle, 2007:4). Package utilizes Quasi-Maximum Likelihood (QML) estimator and allows to make SDM, SEM, SAR, and SAC analysis. Xtmoran package used for the Moran's I test by Zihou et al (2022).

GeoDa 1.8 software was used for generating both for spatial weights matrix and cluster maps. Spatial weights matrix W is generated by using queen contiguity approach. Local indicators of spatial association (LISA) analysis was conducted to generate cluster maps.

Calculation of the IIT

IIT can be described as simultaneous export and import of similar products. Debates over IIT gained importance after the 1960s. Grubel and Lloyd's (1971) seminal work for developing an index to calculate this phenomenon paved the way for many empirical and theoretical studies and discussions. Grubel-Lloyd index is expressed as follows:

$$\mathbf{GL_i} = \frac{(\mathbf{X_i} + \mathbf{M_i}) - |\ \mathbf{X_i} - \mathbf{M_i}\ |}{\mathbf{X_i} + \mathbf{M_i}}\ \mathbf{x\ 100} \tag{9}$$

where i represents the industry and X and M represent export and import, respectively.

Formula (10) can be adapted for the aggregation of specific sectors at any level.

$$\mathbf{GL_i} = \frac{\sum_{\mathbf{i}}^{\mathbf{n}} (\mathbf{X_i} + \mathbf{M_i}) - \sum_{\mathbf{i}}^{\mathbf{n}} |\ \mathbf{X_i} - \mathbf{M_i}\ |}{\sum_{\mathbf{i}}^{\mathbf{n}} (\mathbf{X_i} + \mathbf{M_i})}\ \mathbf{x\ 100} \tag{10}$$

where n denotes the number of industries at selected level of aggregation.

Results of both indices are between 0 and 100, where the former shows total inter-industry and the latter shows total IIT. Table 5 in the Appendix shows the IIT indices of this study.

Moran's I Test

One of the most common tests to identify spatial autocorrelation is developed by Moran (1950a, 1950b) (Eq. 11). In order to analyse the spatial effects and use spatial analysis methods, the result of the Moran I test coefficient has to be statistically significant. The value of Moran I coefficient can be between −1 and 1. A positive and significant coefficient implies positive spatial interdependence. In the case of negative spatial dependence, dissimilar regions surround each other. Values close to +1 and −1 show strong positive

[2]Results are available upon request.

and negative spatial autocorrelation, respectively. On the other hand, a value of 0 indicates that there is no spatial correlation. Null hypothesis of Moran's I test is spatial randomness.

where e denotes a vector of OLS residuals, N denotes the number of observations, $S_0 = \sum\sum w_{ij}$ denotes the sum of spatial weights matrix elements. Durbin-Watson statistics can be seen as a special version of Moran's I (Arbia et al., 2021). While Durbin-Watson statistic is commonly used to test the presence of autocorrelation in the residuals in regression analysis, similarly Moran's I test is utilized for identifying the presence of spatial clustering and dispersion.

Local Indicators of Spatial Association (LISA)

By utilising local Moran's I tests, the LISA approach is suggested by Anselin (1995). The LISA approach allows the illustration of high and low spatial relationships among spatial units. LISA emphasises specific locations and informs whether neighbouring units have similar or dissimilar values. While providing information, LISA examines the spatial units under four categories: High-high, low-low, low-high, high-low. High-high and low-low categories show positive and negative autocorrelation, respectively. Low-high and high-low categories refer to spatial units adjacent to clusters but are the opposite of the negative or positive spatial autocorrelation outcome in the cluster. In other words, if the cluster in question has spatial neighbor(s) with a statistically significant and different effect, they are either low-high or high-low category. This categorisation helps to examine the relationship among clusters and their outliers; therefore, it is possible to uncover patterns that cannot be noticed when treating the data as a whole.

Spatial Data Analysis Results and Discussion

This section presents the empirical findings. It begins by establishing spatial autocorrelation with the Moran's I test, then visualises regional clusters via LISA analysis, and finally discusses the determinants of IIT based on the spatial panel data model results.

Moran's I Test

The results of the Moran's I test, given in Table 2

Table 2

Moran's I Test Results: 2004-2021

Year	I	E(I)	Sd(I)	Z	P-value
2004	0.4379	−0.0125	0.0675	6.6728	0.0000
2005	0.4422	−0.0125	0.0674	6.7470	0.0000
2006	0.3910	−0.0125	0.0675	5.9781	0.0000
2007	0.3933	−0.0125	0.0677	5.9903	0.0000
2008	0.2573	−0.0125	0.0679	3.9732	0.0001
2009	0.4399	−0.0125	0.0680	6.6508	0.0000
2010	0.2526	−0.0125	0.0676	3.9211	0.0001
2011	0.2327	−0.0125	0.0676	3.6273	0.0003
2012	0.3153	−0.0125	0.0678	4.8343	0.0000
2013	0.2433	−0.0125	0.0679	3.7675	0.0002
2014	0.1424	−0.0125	0.0678	2.2838	0.0224
2015	0.1783	−0.0125	0.0680	2.8048	0.0050

Year	I	E(I)	Sd(I)	Z	P-value
2016	0.3412	−0.0125	0.0679	5.2104	0.0000
2017	0.4166	−0.0125	0.0677	6.3382	0.0000
2018	0.3108	−0.0125	0.0677	4.7742	0.0000
2019	0.3270	−0.0125	0.0679	5.0036	0.0000
2020	0.1899	−0.0125	0.0671	3.0171	0.0026
2021	0.1545	−0.0125	0.0671	2.4900	0.0128

Source: Own calculations.

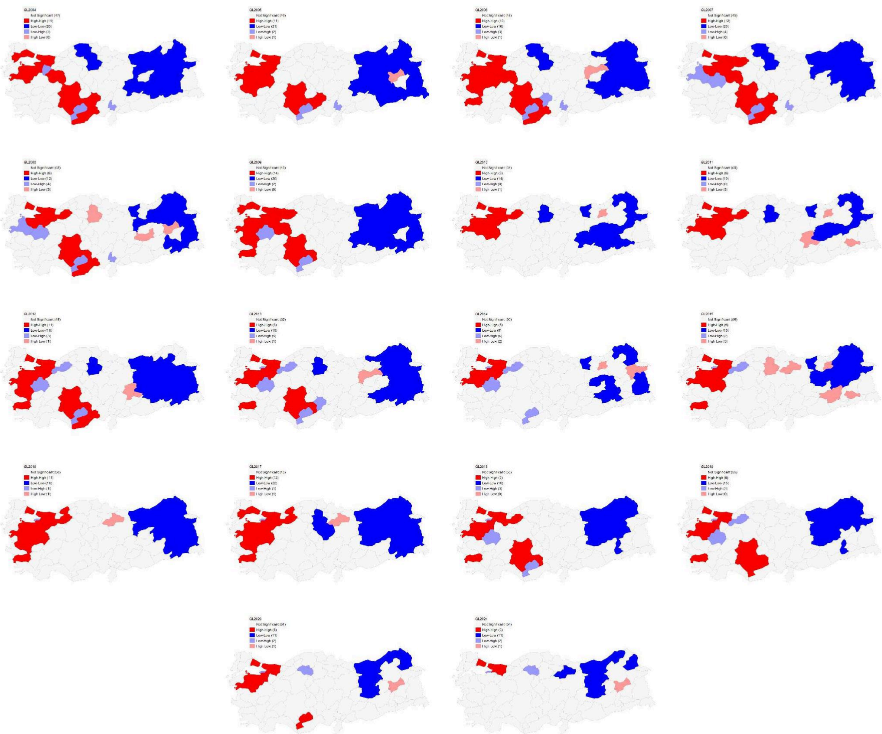
Local Indicators of Spatial Association (LISA) Analysis

The spillover effects of IIT and inter-industry trade are illustrated for each year spanning from 2004 to 2021, with the former represented by red and the latter by blue colours in Figure 1. Red indicates high-high areas where the IIT index value is high, whereas blue indicates low-low areas where the IIT index value is low. Light blue and light red represent low-high and high-low areas with opposite values adjacent to clusters with low and high IIT index values, respectively.

Although the pattern for each year for both types of trade slightly changes, it can be observed that the northwestern and partially western and middle-southern parts of Türkiye have IIT clusters. On the other hand, the northeastern, partially middle-northern, and eastern parts of Türkiye have inter-industry trade clusters. No other clusters are observed in the grey area, which encompasses more than half of the country.page

Figure 1

Figure 1. LISA Analysis Results: 2004-2021



The results of the LISA analysis are consistent with the findings of Fujita et al. (1999) and Yoshida's (2008) statement about the relationship between IIT and fragmentation of production. A study conducted by Celebioglu & Dall'Erba (2010) with 76 Turkish regions for the period of 1995-2001 indicates that the western part of Türkiye is significantly more developed than its eastern part. Compared with the East, the western part of Türkiye is more industrialised. In this analysis, there is a clear distinction between western and eastern IIT clusters, which correlates with the production structure in Türkiye.

Spatial Panel Data Analysis

To better understand, examine, and compare the determinants of IIT, OLS, SDM, SAR, SEM, and SAC (SARAR) models are employed with random, fixed, time-fixed, and individual-time-fixed effects with different sets of variables. The most striking result of the analysis is that IIT does not exhibit a spillover effect among the cities of Türkiye, as evidenced in Table 3. Although certain random and fixed effect models suggest a spillover effect when GDP and GDP per capita are excluded, this relationship dissipates once the individual effects are included.

In order to measure and observe the effect of GDP metrics in the analysis, a second analysis was conducted in which these variables were excluded, and the results are presented in Table 4. It is evident that excluding GDP metrics renders certain variables statistically insignificant, while some time-invariant variables become significant in certain models. This can be attributed to the fact that time-invariant variables are inherently captured by GDP metrics. Indeed, the characteristics of cities that remain constant over time are likely to influence their GDP.

Separate analyses were conducted to better understand these effects. The individual fixed-effects model may absorb the effects of GDP and per capita GDP, rendering these variables statistically insignificant. This is because GDP and per capita GDP are influenced by various unique, time-invariant characteristics of cities, which are accounted for by the individual fixed effect model's dummy variables. To observe this change and its effects, a second analysis excluded the GDP and per capita GDP variables. However, no model in the first table showed a pattern indicating the spillover of the IIT effect to other cities.

When the models are compared in terms of R2 values, it is evident that the models incorporating GDP and per capita GDP have higher explanatory power. The R2 values of individual-fixed effect and individual-time fixed effect models are lower than those of time-fixed effect models. The reason for this, as mentioned, may be that individual-fixed effect and individual-time fixed effect models absorb values that do not change over time and therefore affect the explanatory power of certain variables.

In recent articles, there is criticism of the use of the two-way fixed effects model, which includes both unobserved unit-specific and time-specific effects. Imai and Kim (2021) stated that the two-way fixed-effects model cannot be adjusted simultaneously to observe both unit and time-specific effects. Kropko and Kubinec (2020) emphasise that the use of estimators should align with the research question and do not recommend that applied researchers use the two-way model except in certain cases. In this study, random, individual-fixed, time-fixed, and individual-time fixed effects estimators were employed for comparison. However, it can be predicted that time fixed effects estimators would yield more meaningful results. This is because the cross sections in the panels in this study include 81 provinces of Türkiye. Therefore, the economic cycles, policy and political changes, technological advances, global events, environmental factors, and cultural and social trends of a single country affect all cities over time. Since Türkiye is a country where political, economic, and policy changes occur frequently, taking time effects into consideration will enable more accurate results to be achieved. Control variables, such as border, coast, and landlocked status, were used to account for time-invariant variables in the time fixed effects estimator.

Table 3

Spatial Panel Data Analysis Results

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	OLS	SDM RE	SDM FE	SDM FE	SDM FE	SAR RE	SAR FE	SAR FE	SAR FE	SEM RE	SEM FE	SEM FE	SEM FE	SAC FE	SAC FE	SAC FE
gdp	0.0626***	0.0665***	0.0386	0.0586***	0.0535	0.0676***	0.0151	0.0614***	0.00982	0.0684***	0.0159	0.0619***	0.00836	0.00429	0.0581***	0.00998
	(0.00486)	(0.0116)	(0.0925)	(0.0153)	(0.0935)	(0.0122)	(0.0750)	(0.0158)	(0.0933)	(0.0124)	(0.0754)	(0.0158)	(0.0920)	(0.0685)	(0.0165)	(0.0934)
gdppc	0.0936***	0.00818	−0.00826	0.0699*	−0.00840	0.0143	0.0118	0.0892***	0.0289	0.0192	0.0115	0.0990***	0.0303	0.0159	0.0681**	0.0287
	(0.00970)	(0.0406)	(0.0881)	(0.0386)	(0.0894)	(0.0297)	(0.0861)	(0.0330)	(0.0879)	(0.0292)	(0.0866)	(0.0281)	(0.0869)	(0.0766)	(0.0340)	(0.0883)
gov_spend	−0.0691***	−0.0124	0.0114	−0.0542**	−0.00181	−0.0164	0.0306	−0.0659***	−0.00445	−0.0176	0.0309	−0.0737***	−0.00477	0.0253	−0.0523**	−0.00441
	(0.00691)	(0.0291)	(0.0497)	(0.0266)	(0.0505)	(0.0176)	(0.0250)	(0.0253)	(0.0429)	(0.0178)	(0.0252)	(0.0241)	(0.0423)	(0.0194)	(0.0248)	(0.0432)
brand_reg	−4.53e-06**	1.04e-06	2.44e-06	−4.39e-06	1.21e-06	1.56e-06	2.82e-06	−4.92e-06*	1.95e-06	1.61e-06	2.86e-06	−4.96e-06*	1.81e-06	2.16e-06	-3.91e-06	1.97e-06
	(2.16e-06)	(1.86e-06)	(1.94e-06)	(2.95e-06)	(2.00e-06)	(1.91e-06)	(1.99e-06)	(2.94e-06)	(1.92e-06)	(1.90e-06)	(2.00e-06)	(2.90e-06)	(2.02e-06)	(2.70e-06)	(2.97e-06)	(2.09e-06)
patent_reg	0.000142*	1.32e-05	-2.74e-06	0.000144*	1.16e-05	-2.12e-06	−1.18e-05	0.000157*	1.41e-06	−1.38e-06	−1.22e-05	0.000157*	2.82e-06	-3.02e-06	0.000128	1.23e-06
	(7.95e-05)	(4.99e-05)	(5.06e-05)	(8.24e-05)	(5.01e-05)	(5.01e-05)	(4.72e-05)	(8.33e-05)	(4.54e-05)	(4.89e-05)	(4.73e-05)	(8.15e-05)	(4.70e-05)	(5.84e-05)	(7.92e-05)	(4.61e-05)
trade_open	−0.0216	−0.0329	−0.0329	−0.0273	−0.0377	−0.0328	−0.0290	−0.0160	−0.0346	−0.0333	−0.0291	−0.0198	−0.0347	−0.0280	−0.0128	−0.0346
	(0.0139)	(0.0348)	(0.0334)	(0.0526)	(0.0352)	(0.0346)	(0.0323)	(0.0519)	(0.0359)	(0.0346)	(0.0323)	(0.0517)	(0.0360)	(0.0323)	(0.0517)	(0.0359)
metropolitan	0.0365***	0.0261**	0.0260**	0.0451*	0.0259**	0.0248**	0.0256**	0.0385*	0.0258**	0.0249**	0.0256**	0.0374	0.0258**	0.0244*	0.0387*	0.0258**
	(0.00910)	(0.0117)	(0.0118)	(0.0235)	(0.0125)	(0.0115)	(0.0127)	(0.0232)	(0.0129)	(0.0115)	(0.0127)	(0.0232)	(0.0131)	(0.0128)	(0.0218)	(0.0129)
coast	−0.0120	0.00677	0	−0.0237	0	0.0316	0	−0.0114	0	0.0314	0	−0.0161	0	0	−0.0122	0
	(0.0160)	(0.0341)	(0)	(0.0425)	(0)	(0.0377)	(0)	(0.0394)	(0)	(0.0400)	(0)	(0.0418)	(0)	(0)	(0.0378)	(0)
border	0.00173	−0.00737	0	−0.0243	0	0.00113	0	0.00351	0	0.000283	0	0.000970	0	0	−0.000360	0
	(0.0146)	(0.0320)	(0)	(0.0387)	(0)	(0.0380)	(0)	(0.0362)	(0)	(0.0401)	(0)	(0.0384)	(0)	(0)	(0.0348)	(0)
landlocked	0.00458	0.0234	0	0.00224	0	0.0312	0	0.00547	0	0.0310	0	0.00130	0	0	−0.000987	0
	(0.0169)	(0.0350)	(0)	(0.0430)	(0)	(0.0416)	(0)	(0.0417)	(0)	(0.0438)	(0)	(0.0445)	(0)	(0)	(0.0397)	(0)
rho		0.0366	0.0117		−0.0589	0.0549	0.0141	0.0586	−0.0557					0.228	0.220	−0.0617
		(0.0372)	(0.0368)		(0.0402)	(0.0350)	(0.0376)	(0.0795)	(0.0390)					(0.344)	(0.168)	(0.200)
lgt_theta		−1.224***				−1.248***										
		(0.178)				(0.180)										
sigma2_e		0.00495***	0.00465***	0.00933***	0.00452***	0.00497***	0.00466***	0.00946***	0.00454***	0.00497***	0.00466***	0.00949***	0.00454***	0.00485***	0.00918***	0.00481***
		(0.00115)	(0.00108)	(0.00163)	(0.00104)	(0.00115)	(0.00108)	(0.00165)	(0.00104)	(0.00115)	(0.00108)	(0.00161)	(0.00104)	(0.00106)	(0.00165)	(0.00104)
lambda										0.0302	0.0139	−0.0327	−0.0546	−0.234	−0.289	0.00635
										(0.0369)	(0.0374)	(0.0809)	(0.0396)	(0.412)	(0.217)	(0.196)
ln_phi										0.0792						
										(0.303)						
Constant	-2.099***	-1.773***				−1.527***				−1.580***						
	(0.101)	(0.450)				(0.285)				(0.278)						
Observations	1,458	1,458	1,458	1,458	1,458	1,458	1,458	1,458	1,458	1,458	1,458	1,458	1,458	1,458	1,458	1,458
R-squared	0.543	0.528	0.321	0.548	0.454	0.518	0.334	0.545	0.472	0.514	0.337	0.542	0.475	0.257	0.546	0.472
Number of pids		81	81	81	81	81	81	81	81	81	81	81	81	81	81	81
City FE			YES		YES		YES		YES		YES		YES	YES		YES
Year FE				YES	YES			YES	YES			YES	YES		YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: Own calculations.

Table 4

Spatial Panel Data Analysis Results Without GDP Metrics

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	OLS	SDM RE	SDM FE	SDM FE	SDM FE	SAR RE	SAR FE	SAR FE	SAR FE	SEM RE	SEM FE	SEM FE	SEM FE	SAC FE	SAC FE	SAC FE
gov_spend	−0.0497***	0.0101	0.0165	−0.0363	0.00677	0.0362***	0.0490***	−0.0646*	0.00552	0.0403***	0.0498***	−0.0742*	0.00552	0.0367**	−0.0361	0.00552
	(0.00709)	(0.0374)	(0.0451)	(0.0401)	(0.0446)	(0.0132)	(0.0138)	(0.0363)	(0.0407)	(0.0133)	(0.0136)	(0.0414)	(0.0400)	(0.0154)	(0.0246)	(0.0408)
brand_reg	4.47e-06*	5.61e-06***	2.73e-06	6.03e-06**	1.54e-06	6.06e-06***	3.07e-06*	3.91e-06	1.99e-06	6.09e-06***	3.11e-06*	3.54e-06	1.84e-06	2.19e-06	5.00e-06**	2.02e-06
	(2.43e-06)	(1.75e-06)	(1.72e-06)	(2.59e-06)	(1.83e-06)	(1.75e-06)	(1.69e-06)	(3.28e-06)	(1.79e-06)	(1.78e-06)	(1.71e-06)	(4.01e-06)	(1.89e-06)	(2.51e-06)	(2.22e-06)	(2.03e-06)
patent_reg	0.000143	−4.63e-05	-3.88e-06	3.76e-05	1.07e-05	−5.45e-05	−1.04e-05	9.34e-05	1.62e-06	−5.41e-05	−1.08e-05	0.000114	3.26e-06	2.36e-07	1.39e-05	1.23e-06
	(9.17e-05)	(4.78e-05)	(4.81e-05)	(0.000134)	(4.83e-05)	(4.96e-05)	(4.92e-05)	(0.000159)	(4.67e-05)	(4.92e-05)	(4.92e-05)	(0.000186)	(4.87e-05)	(6.50e-05)	(8.71e-05)	(4.78e-05)
trade_open	0.00115	−0.0243	−0.0312	−0.00745	−0.0386	−0.0183	−0.0230	−0.00244	−0.0348	−0.0182	−0.0230	−0.00618	−0.0347	−0.0219	−0.00375	−0.0348
	(0.0160)	(0.0321)	(0.0320)	(0.0559)	(0.0350)	(0.0315)	(0.0310)	(0.0571)	(0.0346)	(0.0315)	(0.0310)	(0.0596)	(0.0346)	(0.0302)	(0.0413)	(0.0345)
metropolitan	0.149***	0.0400***	0.0273**	0.123***	0.0271**	0.0417***	0.0275**	0.137***	0.0256**	0.0418***	0.0276**	0.139***	0.0256**	0.0253**	0.0956***	0.0256**
	(0.00712)	(0.0117)	(0.0111)	(0.0248)	(0.0122)	(0.0116)	(0.0112)	(0.0249)	(0.0117)	(0.0117)	(0.0113)	(0.0255)	(0.0118)	(0.0113)	(0.0267)	(0.0117)
coast	0.0853***	0.0283	0	0.0503	0	0.0844	0	0.0674**	0	0.0895	0	0.0776**	0	0	0.0458	0
	(0.0174)	(0.0679)	(0)	(0.0329)	(0)	(0.0713)	(0)	(0.0296)	(0)	(0.0762)	(0)	(0.0340)	(0)	(0)	(0.0330)	(0)
border	0.00651	−0.0253	0	0.0189	0	−0.0387	0	0.00972	0	−0.0414	0	0.0136	0	0	−5.70e-06	0
	(0.0168)	(0.0693)	(0)	(0.0327)	(0)	(0.0741)	(0)	(0.0332)	(0)	(0.0788)	(0)	(0.0374)	(0)	(0)	(0.0343)	(0)
landlocked	0.0677***	−0.00309	0	0.0539	0	0.0241	0	0.0572	0	0.0256	0	0.0674*	0	0	0.0290	0
	(0.0189)	(0.0704)	(0)	(0.0362)	(0)	(0.0776)	(0)	(0.0371)	(0)	(0.0826)	(0)	(0.0408)	(0)	(0)	(0.0374)	(0)
rho		0.0645*	0.0124	0.0988	−0.0552	0.0792**	0.0168	0.269***	−0.0537					0.259	0.653***	−0.0640
		(0.0335)	(0.0375)	(0.0713)	(0.0405)	(0.0335)	(0.0377)	(0.0746)	(0.0406)					(0.233)	(0.102)	(0.226)
lgt_theta		−1.649***				−1.689***										
		(0.183)				(0.177)										
sigma2_e		0.00495***	0.00465***	0.0110***	0.00453***	0.00496***	0.00467***	0.0115***	0.00455***	0.00496***	0.00467***	0.0119***	0.00455***	0.00482***	0.00901***	0.00482***
		(0.00115)	(0.00107)	(0.00156)	(0.00103)	(0.00115)	(0.00108)	(0.00169)	(0.00104)	(0.00115)	(0.00108)	(0.00168)	(0.00104)	(0.00106)	(0.00146)	(0.00103)
lambda										0.0184	0.0126	0.231**	−0.0522	−0.271	−0.834***	0.0109
										(0.0375)	(0.0376)	(0.0905)	(0.0403)	(0.288)	(0.204)	(0.218)
ln_phi										0.874***						
										(0.303)						
phi																
sigma_mu																
sigma_e																
Constant	0.0823***	0.293				0.0910				0.101						
	(0.0192)	(0.202)				(0.0763)				(0.0804)						
Observations	1,458	1,458	1,458	1,458	1,458	1,458	1,458	1,458	1,458	1,458	1,458	1,458	1,458	1,458	1,458	1,458
R-squared	0.389	0.272	0.022	0.331	0.078	0.227	0.047	0.408	0.239	0.212	0.046	0.381	0.242	0.056	0.432	0.238
Number of		81	81	81	81	81	81	81	81	81	81	81	81	81	81	81
City FE			YES		YES		YES		YES		YES		YES	YES		YES
Year FE				YES	YES			YES	YES			YES	YES		YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: Own calculations.

Hypothesis 1: As economic size increases, IIT will increase..

The GDP variable has statistically significant positive effects on IIT in the time-fixed effect models. Additionally, a statistically significant and positive relationship is found solely for the GDP variable in the random effects models. These results are in line with theory, as GDP represents the size of the economy and is related to economies of scale. This shows that this variable, commonly used in cross-country analysis, yields the same results at the city level and is consistent with the findings of national-level studies for Türkiye (e.g., Emirhan, 2005; Şentürk & Kösekahyaoğlu, 2014; Şaşmaz, 2024).

Hypothesis 2: As citizens' purchasing power increases, IIT will increase..

Similarly, GDP per capita has statistically significant positive effects on IIT in the time-fixed effect models. This result is also in line with theory, as GDP per capita represents purchasing power and affects the demand side of trade. This finding is consistent with national-level studies on Türkiye, such as Şentürk & Kösekahyaoğlu (2014).

Hypothesis 3: As government spending increases, IIT will increase..

Per capita government spending includes public services such as health, education, law enforcement, security, social work, investments in infrastructure, urban and economic development, cultural and recreational facilities, and administrative costs. This variable is statistically significant in the models with GDP and GDP per capita included, while time-effects are controlled. Once GDP and GDP per capita are excluded, it also yields significant results under certain fixed-effects models.

The negative relationship observed in the individual-fixed effects models can be attributed to the time-invariant characteristics captured by these models. Within each city, persistent factors such as institutional frameworks, geographical location, or historical contexts might influence the observed negative relationship. This suggests that while controlling for these unchanging city-specific factors, an increase in government spending might, in certain city contexts, correspond to reduced IIT. Factors such as misallocation of resources or inefficiencies in spending within specific cities might contribute to this negative association.

The positive relationship observed in the time effects model underscores the temporal aspect of the relationship. Over the study period, as government spending fluctuates across cities and time, a general positive association emerges, indicating that, on average, higher government spending tends to coincide with increased IIT across cities. This situation aligns with the expectations outlined in the hypothesis.

In essence, considering the unique and time-invariant attributes of cities reveals that government expenditures decrease IIT. Conversely, excluding these characteristics and observing the impact of time across all spatial units shows an increase in IIT. Further studies on the time-invariant dynamics of cities are required for a deeper understanding, which is beyond the scope of this study.

Hypothesis 4: IIT will increase as the number of brand registrations increases..

The number of brand registrations in a city yields mixed results in the models with and without GDP and GDP per capita variables. When GDP-related metrics are controlled, only three estimators (OLS, SAR, and SEM time-fixed effects) yield a negative relationship between IIT and brand registration. This could imply that when controlling for economic size and wealth (as captured by GDP and GDP per capita), a higher number of brand registrations might signal a shift towards more differentiated or segmented markets for internal consumers, potentially reducing IIT.

On the other hand, when GDP-related metrics are excluded, results from eight estimators show a positive relationship. This shift in the impact might indicate that without considering economic size and wealth factors, a higher number of brand registrations could signify increased market dynamism, fostering IIT. Without the influence of GDP-related metrics, more brand registrations might reflect a competitive and vibrant market environment, encouraging trade within industries.

It should also be noted that the statistically significant results predominantly arise from time-effects models. This might imply that the relationship between brand registration and IIT can be better observed when collective temporal changes are considered. The broader scope of the time effects models might capture overarching trends that cannot be observed by models focusing solely on individual city-specific time effects. As a result, the analysis results do not coincide with the expectations in the hypothesis.

Hypothesis 5: As the number of patent registrations increases, IIT will increase..

The number of patent registrations in a city has a positive effect on IIT in the time effect models that include GDP and GDP per capita. In the random effects, individual-fixed effects, and individual time fixed effects models, as well as models without GDP metrics, yield statistically insignificant results. This implies that without considering the economic size or wealth captured by GDP metrics, the influence of patent registrations on IIT becomes less discernible or inconsistent across the 81 cities in Türkiye.

The positive and significant results in the time-fixed effects model show that a temporal trend across 81 cities in Türkiye might exist for the relationship between the number of patent registrations and IIT. Patent registration represents innovation and the use of new techniques in production and services. Therefore, patent registrations may foster the trade dynamic of cities over time, resulting in industry specialisation which can lead to an increase in IIT. The results support the expectation in the hypothesis.

Hypothesis 6: As trade openness increases, IIT will increase..

Although in cross-country analyses for IIT, the trade openness variable often yields statistically significant results, at the city level, no statistically significant effect is found. This may be related to the administrative differences between countries. In Türkiye, local jurisdiction is quite limited, so it is not possible for local administrators and mayors to make decisions that would create a significant impact on trade. Therefore, almost all trade-related incentives and regulations are managed by the central government. Additionally, regulations and laws regarding trade liberalisation would be the same for each city.

This finding presents a notable contrast to cross-country panel studies like Çepni & Köse (2003), Şentürk & Kösekahyaoğlu (2014) and Şaşmaz (2024), which all found trade openness to be a significant positive determinant of Türkiye's IIT. This divergence may underscore a key difference between national-level policy effects and the more granular, production-focused dynamics captured at the provincial level. At this level, the trade intensity of the local economy may not be the primary driver of IIT structure, which is more influenced by factors like metropolitan status and innovation.

In this study, the trade openness variable rather indicates trade intensity relative to production and services. Thus, having a more trade-based economy does not have any significant impact on the IIT of a city. Although the analysis results do not coincide with hypothesised expectations, it can be said that trade openness, which is a useful variable for cross-country analyses, is not as efficient for city and regional level analyses.

Hypothesis 7: The city becoming a metropolitan will increase IIT..

Being a metropolitan city can be identified as the most stable determinant to explain IIT at the city level. In the two tables, which show the results of several different estimators, the only statistically significant variable in almost every model is being a metropolitan city, with a positive coefficient. This result is in line with the work of Brodzicki et al. (2020).

Hypothesis 8: Having a border with another country or having a sea coast will increase IIT, whereas having a landlocked status will reduce IIT..

Having a border with another country has statistically insignificant effects on IIT. Normally, it is expected to have a higher degree of IIT due to transportation costs. However, at the city level, there is no such effect, which is not in line with the hypothesis. This may be related to the trade partners in the analysis. Different results may emerge if an analysis is conducted for IIT between two border cities.

Only two models show statistically significant results for being a landlocked city. Both of these models are analysed without considering GDP and GDP per capita. In these two models, coefficients are positive, indicating a positive relationship between being a landlocked city and IIT. The reason behind this relationship could be specialisation in certain sectors due to relatively high transportation costs. This specialisation may lead to an increase in IIT since only a few sectors are involved in trade. However, when the analysis is evaluated overall, it is observed that a city's being landlocked has no effect on IIT. This result shows that the hypothesis was not supported. Therefore, it can be concluded that transportation costs do not have a positive or negative impact on IIT.

Having access to the sea variable yields similar results. It is only statistically significant in the model without GDP and GDP per capita and in three models. Since trade is expected to be more intensified in coastal areas and ports, IIT would increase. However, in the overall evaluation of our results, it can be stated that there is no statistical relationship between having access to the sea and IIT.

In a study by Kurt and Çoban (2021), which analysed the determinants of IIT in the manufacturing industry between Türkiye and the European Union, it was found that the effect of having a common border on IIT was statistically insignificant. While having a border with a foreign country may be a relevant variable in analysing the determinants of IIT at the local level, it appears to lack statistical significance in country-level analyses in the case of Türkiye. In the same study, it was observed that sharing the same sea had a positive impact on IIT between countries. However, this variable differs from the analysis in our study. While the authors examined countries sharing the same sea, our study included every province with a coastline in the econometric analysis. Therefore, achieving similar results from an econometric perspective may not be feasible.

Furthermore, while this study's geographic dummies (border, coast) were insignificant, this contrasts with the findings of cross-country studies for Türkiye (Çepni & Köse, 2003; Şentürk & Kösekahyaoğlu, 2014), which consistently found that distance, a proxy for transport cost, is a significant negative determinant of IIT. This suggests that while simple geographic location, like border access, may not be a key determinant, the actual economic friction of transport costs, which is not measured in this provincial model, remains a critical factor in national trade patterns.

Conclusion

In this study, the IIT of Türkiye's 81 provinces is examined for the period of 2004-2021. Utilizing Grubel-Lloyd's (1971) methodology, IIT indices are calculated for each city. Moran's I test and LISA analysis are employed to analyse the existence of spatial autocorrelation among cities. The Moran's I test results demonstrate evidence of such spatial autocorrelation. LISA analysis reveals the presence of two distinct and statistically significant IIT clusters within Türkiye. The western region exhibits high-high characteristics, signifying a concentration of IIT. In contrast, the eastern region displays low-low characteristics, indicating a concentration, albeit at a lower level, showing an inter-industry trade pattern. This highlights the regional disparity between the Western and Eastern parts of Türkiye.

To gain a deeper understanding and examine the existence of a spillover effect of IIT among cities, different spatial estimators (SDM, SAR, SEM, and SAC) and models are utilized. According to the results, although there are IIT clusters in Türkiye, there is no statistically significant spillover effect among the cities. This may indicate that IIT is related to production fragmentation among cities in Türkiye. However, an increase or decrease in the IIT of cities does not have any effect on their spatial neighbours.

It is identified that the most efficient estimators are SAR, SEM, and SAC under the fixed-effects model. The comparison of the models shows that time-fixed effects yield more statistically meaningful results. According to these results, there is a positive relationship between GDP, GDP per capita, government spending, the number of patent registrations, being a metropolitan city, and IIT. On the other hand, a negative relationship is found with the number of brand registrations. Trade openness at the city level, having access to the sea, border, and being a landlocked city does not have any statistically significant impact on IIT.

An increase in GDP triggers IIT by facilitating economies of scale. GDP per capita, which represents the purchasing power of citizens, affects the variety of products demanded, thus having a positive impact on IIT. Government spending, which encompasses various areas including health, education, law, security, social work, investments such as infrastructure, urban and economic development, cultural and recreational facilities, as well as administrative costs, positively impacts IIT. The number of patent registrations is related to innovation, variety of products, and competition. The analysis shows that this variable also has an effect that increases IIT. Brand registrations are expected to have a similar effect; however, a negative nexus with IIT is found. The reason behind this result might be that registered brands are only effective in the internal market. Being a metropolitan city is a variable that is statistically significant and positive in almost every model. Metropolitan cities have more population, usually with a more diverse background; therefore, they can trigger IIT in terms of demand and supply. Border, sea, landlocked, and trade openness have a statistically insignificant impact on IIT.

The primary contribution and originality of this study lie in its highly granular NUTS-III level analysis. To my knowledge, this study is the first to apply a comprehensive spatial econometric framework to investigate the clustering and determinants of IIT across all 81 Turkish provinces. This approach yields compelling results that offer valuable insights for future research endeavours by treating each city as a small economy and considering the spatial relationship.

Based on these findings, several policy recommendations can be suggested. First, the positive and robust impact of metropolitan status suggests that policies should focus on enhancing the economic infrastructure and diversified production capabilities of these large urban centres, as they are key drivers of IIT. Second, the positive link with patent registrations implies that regional innovation systems should be strengthened.

Policymakers could foster innovation by increasing R&D support and university-industry collaboration in provinces to boost the creation of high-value, differentiated products. Finally, the positive effect of government spending suggests that targeted public investments in infrastructure, education, and health can create a more conducive environment for sophisticated economic activity and, consequently, IIT.

The limitation of the study is the lack of access to data and data variety at the local level. Since the study shows that metropolitan cities positively affect IIT, specific variables and trade patterns related to these cities can be further examined. Undoubtedly, the results of these studies will guide policymakers to increase the competitiveness and prosperity of cities.

Peer Review: Externally peer-reviewed.

Conflict of Interest: The author have no conflict of interest to declare.

Grant Support: The author declared that this study has received no financial support.

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Grant Support	The author declared that this study has received no financial support.

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Appendix

Table 5

Grubel Lloyd Index Intra Industry Trade Values for the Period of 2004-2021 for the 81 Provinces of Türkiye

Year / Province	Adana	Adıyaman	AfyonKarahisar	Ağrı	Aksaray	Amasya	Ankara	Antalya	Ardahan	Artvin	Aydın	Balıkesir	Bartın	Batman	Bayburt	Bilecik	Bingöl	Bitlis	Bolu	Burdur	Bursa	Çanakkale	Çankırı	Çorum	Denizli	Diyarbakır	Düzce	Edirne	Elazığ	Erzincan	Erzurum	Eskişehir	Gaziantep	Giresun	Gümüşhane	Hakkari	Hatay	Iğdır	Isparta	İstanbul	İzmir
2004	43	0	6	0	8	0	44	45	0	0	19	11	0	0	1	7	0	0	15	0	48	34	8	6	14	0	10	17	0	0	0	21	18	0	0	0	38	0	20	37	38
2005	41	0	6	0	0	0	44	18	0	0	17	15	0	0	1	12	0	0	17	0	50	21	0	15	15	0	9	9	0	0	0	16	17	0	0	0	34	0	19	40	40
2006	43	0	16	0	5	0	49	24	0	0	19	13	0	11	0	13	0	0	24	0	51	12	0	6	20	5	17	6	0	12	0	24	21	2	0	0	28	0	13	42	44
2007	46	0	14	3	0	7	47	31	0	0	24	10	0	0	1	25	6	0	29	3	52	10	0	3	16	11	21	3	0	0	0	21	19	4	0	0	30	6	21	48	42
2008	43	4	14	13	3	11	45	34	0	0	25	14	17	0	10	16	0	0	20	1	49	11	0	15	19	0	37	4	20	0	0	24	26	3	0	0	37	0	20	52	45
2009	35	5	16	12	9	13	46	29	0	0	22	15	0	12	11	28	0	0	19	1	44	22	19	14	24	2	30	5	4	0	0	29	22	0	0	0	29	0	24	51	45
2010	38	4	15	11	2	7	47	25	0	0	26	16	0	6	83	19	0	0	22	1	48	17	0	11	21	2	26	2	0	0	0	45	24	2	0	0	21	0	14	45	47
2011	41	10	25	4	3	5	45	38	0	0	26	19	0	0	76	19	0	0	18	1	51	10	8	6	23	5	28	2	3	0	0	30	28	2	0	2	23	0	10	43	46
2012	36	8	9	3	9	5	49	36	0	0	21	20	0	0	0	21	0	0	11	0	49	6	0	13	26	6	30	0	0	0	12	35	28	2	0	2	29	0	7	49	48
2013	37	12	12	12	24	7	50	35	0	0	20	21	0	4	0	24	0	0	15	3	53	12	2	9	29	14	36	9	0	32	0	40	23	2	0	0	35	0	6	49	49
2014	41	15	8	17	20	5	50	34	0	0	24	25	0	11	68	24	0	0	15	0	54	23	0	21	26	15	38	20	0	0	0	40	22	4	0	0	24	0	11	51	48
2015	41	9	6	14	16	3	50	29	0	0	25	22	0	0	32	42	0	0	10	2	54	17	2	27	27	20	36	8	0	0	0	42	26	4	3	0	34	0	14	53	49
2016	40	9	11	5	6	0	44	26	0	0	25	20	22	0	0	30	7	0	16	0	51	23	8	29	28	12	39	11	2	0	0	37	27	3	0	0	36	0	8	55	48
2017	37	25	6	3	8	0	45	27	0	0	24	20	24	0	2	28	0	0	17	1	51	18	3	7	28	5	37	12	3	0	0	34	26	3	0	0	33	2	11	53	47
2018	35	26	16	12	10	4	42	38	0	3	22	25	5	9	0	25	1	13	19	4	50	26	4	12	30	12	43	9	3	4	5	37	23	7	0	5	31	8	10	51	49
2019	32	24	20	10	18	6	45	37	0	5	21	21	5	9	0	23	2	17	15	2	48	21	5	8	28	9	44	7	3	1	6	34	22	4	0	11	31	5	12	51	47
2020	34	27	12	11	19	7	48	36	0	4	20	24	3	9	5	19	3	16	16	3	52	29	4	22	29	7	35	6	3	4	5	37	25	6	0	28	36	5	11	51	46
2021	36	25	14	14	19	7	44	28	0	19	24	18	0	12	2	18	2	13	15	3	49	27	5	43	32	12	40	10	3	5	4	40	25	5	0	38	39	6	10	54	48

	K.Maraş	Karabük	Karaman	Kars	Kastamonu	Kayseri	Kırıkkale	Kırklareli	Kırşehir	Kilis	Kocaeli	Konya	Kütahya	Malatya	Manisa	Mardin	Mersin	Muğla	Muş	Nevşehir	Niğde	Ordu	Osmaniye	Rize	Sakarya	Samsun	Siirt	Sinop	Sivas	Şanlıurfa	Şırnak	Tekirdağ	Tokat	Trabzon	Tunceli	Uşak	Van	Yalova	Yozgat	Zonguldak
2004	6	0	6	0	0	21	16	6	0	0	36	29	16	4	16	3	41	0	0	0	12	1	0	2	18	8	0	0	0	9	0	30	24	1	0	14	0	16	0	12
2005	5	0	4	0	0	18	18	8	0	0	31	22	12	2	19	6	46	7	14	0	11	3	0	3	24	15	0	0	4	2	0	32	26	3	0	23	0	32	0	8
2006	5	0	7	0	2	23	9	16	8	0	30	28	13	1	14	9	39	17	0	0	11	6	0	0	29	12	0	0	5	16	1	37	21	5	0	23	0	19	0	10
2007	14	9	6	0	2	22	0	3	0	0	33	25	5	11	17	6	44	23	4	7	15	6	0	1	37	11	0	0	0	29	4	38	32	4	0	29	0	18	0	17
2008	9	14	8	0	3	23	0	24	0	0	31	27	10	10	18	4	39	11	20	0	9	5	0	3	32	8	0	0	0	21	2	35	43	4	0	26	0	17	11	29
2009	8	38	10	0	3	23	0	31	0	0	37	28	9	11	15	6	38	27	0	0	8	5	11	2	38	10	0	0	2	10	2	36	28	4	0	23	0	20	0	28
2010	14	52	10	0	0	22	0	16	0	0	43	29	16	12	20	5	32	23	0	0	14	4	8	1	39	10	15	0	3	9	2	40	40	3	0	28	12	15	0	21
2011	9	54	12	0	0	23	0	18	0	0	42	31	17	15	21	5	30	22	0	10	10	4	7	2	43	10	31	0	4	22	2	41	25	4	0	31	0	17	0	18
2012	8	50	12	0	7	21	9	19	0	0	37	33	13	15	15	7	30	29	0	11	15	4	10	4	47	14	0	0	2	18	2	43	29	3	0	25	0	17	0	15
2013	7	48	14	0	3	22	0	13	0	14	35	34	12	17	21	7	42	23	0	5	11	5	10	2	44	12	0	0	4	12	3	49	30	3	0	22	6	3	11	24
2014	10	50	9	0	5	21	0	9	0	7	38	31	12	15	22	6	43	26	0	10	3	3	4	2	43	14	0	0	2	10	6	49	30	3	0	23	13	3	27	29
2015	13	49	11	0	8	21	0	10	0	0	38	31	19	16	22	9	42	31	0	0	0	5	20	1	47	12	31	20	2	21	4	52	40	4	12	23	7	3	0	22
2016	14	52	10	0	4	20	0	13	0	4	43	27	18	21	23	6	45	33	0	0	4	7	18	0	36	14	10	22	3	21	4	49	30	4	0	18	6	5	0	17
2017	14	52	16	0	2	19	0	25	1	16	58	28	21	15	21	8	40	27	0	6	9	7	11	0	24	11	0	0	0	23	8	51	19	4	0	20	3	5	0	26
2018	14	52	15	0	11	27	13	23	1	10	60	28	15	21	25	9	42	37	0	11	16	11	9	4	24	12	3	19	7	28	8	47	15	9	3	18	29	5	17	24
2019	14	41	17	0	20	27	9	22	2	5	43	25	12	20	23	5	39	34	0	9	11	6	8	3	25	12	8	24	13	27	7	46	20	8	0	16	11	7	6	23
2020	16	32	21	2	42	24	15	23	2	3	59	27	11	21	25	6	40	26	76	17	14	8	10	5	26	12	10	22	12	23	5	43	9	9	5	16	17	7	8	19
2021	21	35	26	0	51	30	11	21	2	7	59	26	13	20	25	7	45	27	85	23	16	6	7	2	28	9	1	7	10	29	3	44	15	7	0	17	18	11	10	23