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Regional income inequality and trade openness in Türkiye: A spatial econometric analysis

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Abstract

This study examines the relationship between regional inequality and trade openness in Türkiye's 26 NUTS-II regions from 2014 to 2022, employing spatial panel data models. Using the GINI coefficient as a measure of inequality, the analysis explores the influence of trade openness, labor force participation, population density, and average years of schooling per capita. Results indicate that trade openness has a significant negative impact on inequality, highlighting its role in reducing regional disparities through enhanced market access and economic opportunities. However, the labor force participation rate exhibits a marginally positive relationship with inequality, potentially reflecting disparities in job quality and access to skilled employment. Population density emerges as a key driver of inequality, with densely populated regions experiencing greater income disparities due to urbanization and economic concentration effects. Surprisingly, the average years of education do not significantly influence inequality, which may result from unequal access to quality education or its limited translation into equitable economic opportunities. The study also identifies significant spatial dependencies, with regional inequality influenced by conditions in neighboring regions. These findings emphasize the need for tailored policies addressing both local and interregional dynamics to reduce inequality effectively.

Keywords: Income Inequality, Trade Openness, Spatial Panel Data Analysis, Regional Economics **JEL Codes:** F14, F40, R13, R23

Türkiye'de bölgesel gelir eşitsizliği ve ticaret açıklığı: Mekânsal ekonometrik analiz

Öz

Bu çalışma, 2014-2022 yılları arasında Türkiye'nin 26 NUTS-II bölgesindeki bölgesel eşitsizlik ve ticaret açıklığı arasındaki ilişkiyi mekânsal panel veri modelleri kullanarak incelemektedir. Eşitsizliğin bir ölçüsü olarak GINI katsayısını kullanan analiz, ticaret açıklığının, iş gücüne katılımın, nüfus yoğunluğunun ve kişi başına düşen ortalama okullaşma yılının etkisini araştırmaktadır. Sonuçlar, ticaret açıklığının eşitsizlik üzerinde önemli bir olumsuz etkiye sahip olduğunu ve gelişmiş piyasa erişimi ve ekonomik fırsatlar yoluyla bölgesel eşitsizlikleri azaltmadaki rolünü vurguladığını göstermektedir. Bununla birlikte, iş gücüne katılım oranı eşitsizlikle marjinal düzeyde olumlu bir ilişki göstermektedir ve potansiyel olarak iş kalitesindeki ve vasıflı istihdama erişimdeki eşitsizlikleri yansıtmaktadır. Nüfus yoğunluğu, kentleşme ve ekonomik konsantrasyon etkileri nedeniyle yoğun nüfuslu bölgelerin daha büyük gelir eşitsizlikleri yaşamasıyla eşitsizliğin temel bir itici gücü olarak ortaya çıkmaktadır. Şaşırtıcı bir şekilde, ortalama eğitim yılı eşitsizliği önemli ölçüde etkilememektedir ve bu, kaliteli eğitime eşitsiz erişimden veya bunun adil ekonomik fırsatlara sınırlı şekilde dönüştürülmesinden kaynaklanabilir. Çalışma ayrıca, bölgesel eşitsizliğin komşu bölgelerdeki koşullardan etkilendiği önemli mekânsal bağımlılıklar olduğunu da tespit etmektedir. Bu bulgular, eşitsizliği etkili bir şekilde azaltmak için hem yerel hem de bölgeler arası dinamikleri ele alan özel politikalara olan ihtiyacı vurgulamaktadır.

Anahtar Kelimeler: Gelir Eşitsizliği, Ticaret Açıklığı, Mekânsal Panel Veri Analizi, Bölgesel İktisat **JEL Kodları:** F14, F40, R13, R23

Introduction

The relationship between trade openness and inequality has been a central theme in economic discussions, with globalization often celebrated as a catalyst for economic growth but criticized for its uneven distributional impacts. Globally, regions within countries demonstrate differing capacities to engage with global markets, resulting in varied economic and social outcomes. In Türkiye, as noted by Doğruel (2006), the dual economic structure of its regions has been a subject of debate since the early stages of planned economic development. This disparity is particularly stark between the industrialized western regions and the economically underdeveloped eastern provinces, offering a distinct context for exploring the implications of trade liberalization. Understanding whether trade openness contributes to regional economic convergence or deepens inequality is crucial for crafting

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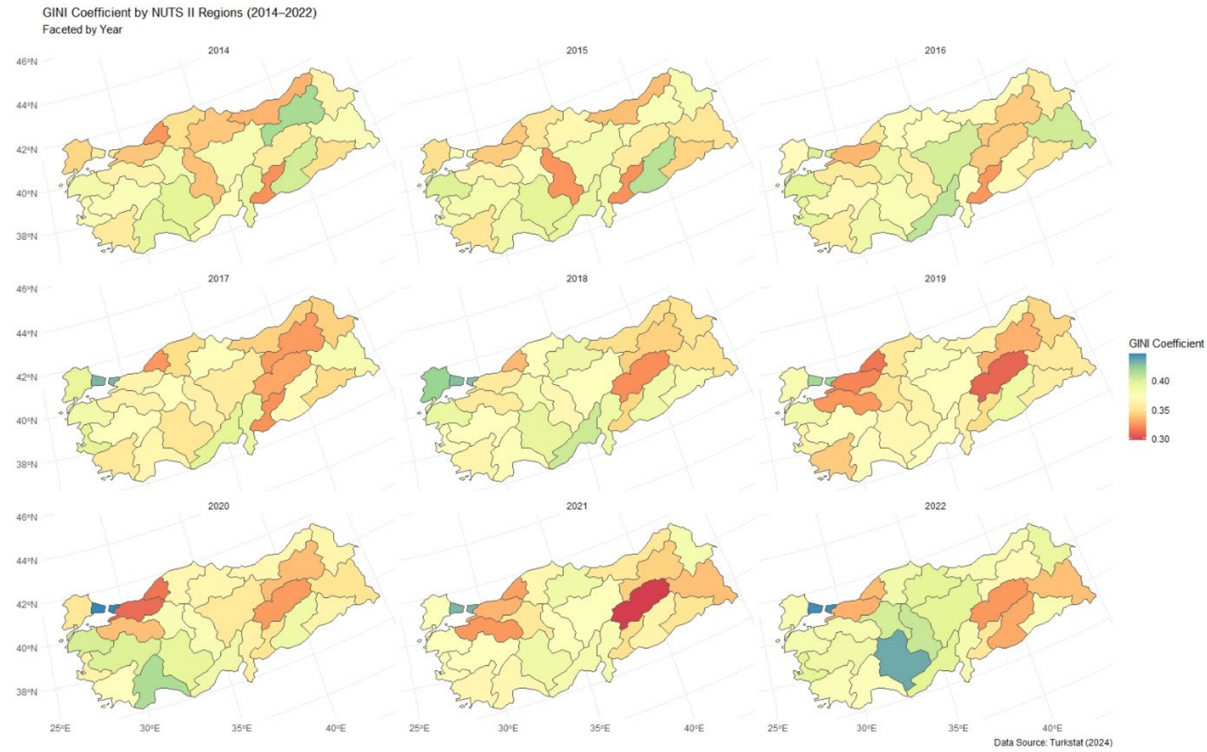
policies aimed at promoting balanced and inclusive growth.

The study of trade-inequality dynamics in Türkiye is particularly relevant given the country's active participation in global trade and its persistent regional imbalances. This study offers a contemporary perspective by examining the period from 2014 to 2022, a time characterized by evolving global trade dynamics and domestic economic challenges. The analysis leverages the GINI coefficient to measure income inequality, offering a comprehensive assessment of regional economic disparities. Utilizing spatial panel data analysis, it delves into the nuanced interplay between trade openness and income inequality across Türkiye's 26 NUTS-II regions.

Figure 1. GINI Coefficient by NUTS-II Regions (2014-2022)



Source: Data obtained from Turkstat (2024) and illustrated by the author.

As illustrated in Figure 1, The GINI coefficient in Türkiye shows an increasing trend in 2022 compared to 2014, highlighting a rise in inequality. However, regional disparities exhibit a distinct pattern. The GINI coefficient is relatively lower in the eastern and southeastern regions, whereas Istanbul stands out as one of the regions with the highest levels of inequality. Interestingly, neighboring regions to the east and south of Istanbul display significantly lower inequality levels. In particular, the TRB1 region, comprising Malatya, Elazığ, Bingöl, and Tunceli, records some of the lowest GINI coefficients. Notably, 2023 data reveal a sharp increase in inequality in the TR52 region of Konya and Karaman. These regional and temporal variations underscore the necessity of examining inequality using panel data analysis at the regional level, rather than relying solely on aggregate time series analysis. Additionally, the findings highlight the importance of considering spatial interdependencies, such as the influence of neighboring regions, when analyzing regional inequality dynamics.

This article seeks to fill a critical gap in the literature. While there are several studies related with the inequality in Türkiye, no research has directly measured the impact of trade liberalization on inequality in Türkiye using spatial econometric approaches. By employing the GINI coefficient as a direct indicator of inequality and incorporating spatial dependencies, this study captures the complexities of regional interactions and trade impacts more comprehensively than earlier works. The findings aim to contribute to the broader discourse on globalization and inequality by offering evidence-based insights into Türkiye's regional development. They hold significant implications for policymakers striving to balance the benefits of trade liberalization with the need for inclusive growth.

1. Theoretical and Empirical Perspectives

The relationship between trade openness and inequality, particularly at the regional level, has been a focal point in economic discourse. While globalization and trade liberalization are often promoted for their potential to boost overall economic growth, their distributional consequences remain contentious. A central concern is whether trade openness exacerbates or mitigates regional inequalities, especially in countries with diverse socioeconomic and infrastructural conditions.

Theoretical perspectives offer competing narratives. Proponents of trade liberalization argue that it can reduce inequalities by enabling regions to specialize in sectors where they hold comparative advantages, thereby enhancing productivity and raising incomes across regions. However, trade openness may also lead to uneven development, with production and investment disproportionately attracted to metropolitan areas within larger countries, while smaller or rural regions face challenges in competing effectively in the global market (Krugman, 1991). The relationship between a country's factor endowments and trade policies significantly influences its ability to achieve welfare improvements or economic growth. According to Grossman and Helpman (1991), the outcomes—whether prioritizing welfare or growth—depend on the country's factor intensity. On one hand, trade openness is theorized to foster regional and income equality by enabling specialization based on comparative advantages. Dollar and Kraay (2002) emphasize that economic growth generally benefits the poor proportionally, suggesting that growth-enhancing policies should be central to poverty reduction strategies. However, they also acknowledge that the distributional effects of growth and its supporting policies must not be overlooked. While growth alone is not sufficient to address all aspects of poverty, its inclusive benefits make it a crucial component of any effective poverty alleviation framework. Winters (2004) explores the relationship between trade openness and education incentives in skill-scarce economies, as guided by Stolper-Samuelson (1941) theory. The theory suggests that in such economies, trade liberalization might decrease the returns to skill, reducing incentives for education. However, modifications to the model, such as incorporating multidimensional Stolper-Samuelson effects, endogenous growth theories, or skill biases in tradable sectors, could re-establish a positive link between trade openness and education returns. Moreover, trade openness could enhance educational technologies by facilitating the import of advanced techniques and equipment or enabling access to higher education abroad, albeit with concerns about potential brain drain. Also, mechanisms, amplified by foreign direct investment (FDI), can increase wages, technology transfer, and skill development, potentially benefiting less-developed areas (Lipsey, 2002; Blomström et al., 2000).

However, critics argue that trade openness can exacerbate regional inequalities by disproportionately favoring regions with superior pre-existing conditions, such as better infrastructure, a highly skilled workforce, and closer proximity to trade hubs. Rather than fostering regional convergence, trade liberalization and economic integration have often led to increased polarization, with benefits concentrating in more developed areas while leaving lagging regions further behind (Kanbur & Venables, 2005). These regions, better positioned to integrate into global value chains, attract more investment and reap greater gains from trade, leaving less-developed regions further behind. This aligns with the core-periphery theory, where economic activity becomes concentrated in a few "core" regions, exacerbating disparities with the "periphery" (Krugman & Venables, 1995). Moreover, trade liberalization may expose weaker regions to competitive pressures, leading to job losses and reduced income levels. Unequal distribution of trade benefits also arises when high-skill industries thrive while labor-intensive or import-competing sectors stagnate (Wood, 1994).

Empirical evidence reflects this theoretical dichotomy. Studies in Mexico (González Rivas, 2007) highlight the nuanced effects of trade openness on regional disparities. While trade liberalization benefits regions with lower levels of education, potentially reducing regional inequality, it simultaneously provides even greater advantages to regions with higher levels of income and superior infrastructure. This dual impact reveals a complex dynamic: although trade might initially help lagging regions, the overarching effect often tilts toward increasing inequality, as more developed regions capitalize more effectively on the opportunities brought by trade. The predominance of these latter effects underscores the challenges of ensuring equitable development through trade policy, especially in contexts of significant initial regional disparities. Topalova (2010) analyzes the impact of India's 1991 trade liberalization on poverty and consumption growth, revealing highly uneven outcomes. While trade reform significantly reduced poverty overall, rural areas heavily reliant on sectors exposed to tariff reductions experienced less poverty alleviation and slower consumption growth compared to less exposed regions. Regions with inflexible labor laws faced heightened adverse effects, while those with more dynamic labor markets benefited more from liberalization.

Further compounding the debate are findings on the skill-biased technological change induced by globalization, which exacerbates wage gaps between skilled and unskilled workers, particularly in developing countries (Krusell et al., 2000; Acemoglu, 2002). The Heckscher-Ohlin model and Stolper-Samuelson theorem further predict that trade benefits factors abundant in an economy. This can often amplify inequalities in labor-scarce or capital-rich countries. In such contexts, trade openness tends to favor export-oriented or high-skill industries, while sidelining less competitive sectors, intensifying disparities.

2. Literature Review

Examining the literature on Türkiye reveals numerous studies addressing *inequalities*. Dincsoy and Ichiminami (2006) evaluate Türkiye's regional development targets using the Neoclassical Growth Model. The study suggested that there was a convergence trend in the distribution of per capita income at the NUTS-I level in the post-1997 period.

Gezici (2006) examines new regional statistical units (NUTS-2) and their implications for development policies for 1980-2001 period. The analysis highlights the persistence of economic peripherality in eastern regions despite decreasing overall inequalities.

Rich provinces in the west exhibit strong spatial spillovers, though these effects remain localized. The study advocates for the use of NUTS-2 regions as administrative units to facilitate targeted development planning and reduce disparities.

Gezici and Hewings (2007) conduct a spatial analysis of interregional and intra-regional inequalities using Theil indices. Their results show that while overall regional inequalities declined from 1980 to 1997, spatial dependence increased, driven by clustering effects in developed western provinces. These provinces not only amplified interregional inequalities but also contributed to spillovers that benefited neighboring regions.

Yıldırım et al. (2009) analyze regional income inequality and convergence dynamics using spatial econometric techniques for 1987-2001 period. The study demonstrates the utility of geographically weighted regression, which reveals significant regional variation in convergence speeds. Their findings suggest that spatial clustering of inequality is a crucial factor, challenging traditional beta convergence models.

Elveren (2010) examined wage inequalities in the Turkish manufacturing sector between 1980 and 2001. The study analyzed inequality trends by using Theil's T statistic based on regional (NUTS-1 and NUTS-2) distinctions and drew attention to the increasing regional wage inequalities in the private sector since the late 1980s. It was determined that differences between regions in particular were one of the main factors in the increase in inequalities.

Karahasan (2015) evaluated regional inequalities in Türkiye at the NUTS-II level, especially between 2003 and 2008, based on spatial differences and wage income differences. The study revealed that spatial dependency and heterogeneity played an important role in the ongoing inequalities. Wage income data and spatial statistics were used in the analyses at the NUTS-II level.

Duran and Erdem (2017) analyze the impact of trade liberalization on regional income disparities in Türkiye between 2004 and 2011. This study departs from traditional approaches by disaggregating trade into exports and imports and incorporating spatial spillovers. The findings indicate that regional inequalities declined during the study period. However, while export-led liberalization supported growth in poorer regions, imports had the opposite effect, underlining the need for a nuanced understanding of trade's impact on regional economies.

Focusing on economic convergence, Doğan and Kındap (2019) use sigma and beta convergence methods to evaluate interregional income gaps in Turkish NUTS-2 regions. They find that income disparities narrowed during economic recessions but widened during periods of growth. Spatial econometric analysis reveals significant spatial autocorrelation in income distribution, suggesting that regional spillovers play a critical role in convergence dynamics.

Karaalp-Orhan (2020) examined regional inequalities in Türkiye within the framework of economic, demographic and social indicators as of 2007. Socio-economic analysis methods were used in the study. The research revealed that the TR10-Istanbul region played a leading role in industrialization and development, but income inequality and poverty rates were also high in this region. In addition, the long-standing development differences between the west-east and coastal-inland parts of Türkiye were underlined.

Duran et al. (2024) examined socioeconomic development and income inequalities in Türkiye with long-term data sets (1963-2017 and 1975-2021) and emphasized the importance of spatial heterogeneity. The study used β-convergence method, spatial regressions, geographically weighted regression (GWR) and nonparametric regression methods. The findings indicate that while there is a general convergence trend at the country level, this trend is not valid for all regions.

Ustaoğlu (2024) investigates regional inequality in Türkiye using nighttime light (NTL) data from the Suomi National Polar-orbiting Partnership (NPP)-Visible Infrared Imaging Radiometer Suite (VIIRS) alongside socio-economic statistics. Employing Gini, Atkinson, and Theil indices, the study demonstrates that urban nightlights strongly correlate with economic activity, while rural nightlights are less associated with agricultural output. Regional inequalities were found to be increasing in Türkiye's northwest, south, and southeast regions, suggesting urban-focused economic growth exacerbates spatial disparities. This work highlights the potential of NTL data as a proxy for measuring urban inequality. Terzioğlu (2013) provides an additional perspective by analyzing the dynamic relationships among domestic debt stock, foreign trade volume, and benchmark interest rates in Türkiye, emphasizing the interplay between economic structure and macroeconomic indicators, which indirectly affect regional inequalities.

Spatial panel data analysis has gained prominence in recent years due to its ability to capture both spatial and temporal dependencies, making it an essential tool for understanding complex regional dynamics and spatial interactions. This approach is particularly valuable in fields like regional economics, urban studies, and environmental research, where spatial spillovers and heterogeneity play critical roles. Pioneering works such as Anselin (1988) introduced key concepts of spatial lag and error models, establishing the groundwork for spatial econometrics. Elhorst (2003, 2014) expanded this framework to panel data, formalizing methods for estimating spatial effects with fixed and random components. Baltagi et al. (2003) emphasized the biases introduced by ignoring spatial dependence in panel models, while Debarsy and Ertur (2010) advanced dynamic spatial panel models, integrating spatial and temporal lags. LeSage and Pace (2009) provided a Bayesian perspective, highlighting direct and indirect effects of spatial interactions. Together, these works form the backbone of spatial panel data methodology, enabling more nuanced analyses of spatial and temporal phenomena.

Although the use of spatial models in economic research has gained prominence in recent years, such studies remain less prevalent compared to traditional panel data and co-integration analyses, particularly in Türkiye. One primary reason for this is the limited availability of data at local and regional levels, which often hinders the application of spatial methods. Additionally, there is a gap in the understanding and recognition of the positive impact spatial analysis can have, particularly in accounting for spatial dependencies. Spatial analysis, however, offers valuable insights and can be applied across various fields to examine spatial relationships and dependencies. To better contextualize the significance of spatial approaches, this section highlights examples from the Turkish literature, illustrating the growing use of spatial models. This study contributes to the literature by exploring the nexus between income inequality and trade openness in Türkiye, providing a novel perspective on the interaction between these two critical factors.

Spatial panel data analysis has been widely applied to understand regional economic and demographic dynamics in Türkiye. İğdeli (2020) analyzed the determinants of regional housing demand in NUTS-II regions for 2010–2017, finding that income, industrialization, population growth, and enterprise numbers significantly influenced housing demand. Similarly, Doğaner (2022) examined the relationship between economic growth and housing demand using 2019 data, identifying GDP as a key driver with notable spatial autocorrelation. Ondes and Kizilgol (2020) explored internal migration across Türkiye's NUTS Level 1 regions for 2008–2017, emphasizing the spatial relationships of migration flows and the roles of income, employment, and agricultural productivity. These studies collectively highlight the role of spatial interdependencies in understanding housing and migration dynamics.

Several studies emphasize the spatial effects of infrastructure and policy measures on regional development. Koç et al. (2019) assessed the impacts of agricultural supports and credits on regional agricultural output, finding that credits enhanced value-added while supports produced mixed outcomes. Elburz and Cubukcu (2021) investigated transport infrastructure's role in regional growth (2004–2014), showing that road investments promoted spatial economic activity and reduced disparities. Additionally, Celebioglu (2020) simulated the economic impact of mega-city lockdowns due to COVID-19, demonstrating significant economic spillovers from Istanbul and Izmir to neighboring regions and beyond. Terzioğlu et al. (2020) analyzed the spatial effects of urban innovation on urbanization, finding that research and development and environmental activity indicators negatively affect urbanization, while health investments, infrastructure, and individual savings positively influence urban growth. These findings underline the importance of infrastructure and policy in shaping regional economies.

Environmental and eco-efficiency issues have also been explored using spatial panel data methods. Karahasan and Pınar (2022) tested the environmental Kuznets curve hypothesis using SO_2 emissions from 2004 to 2019, revealing a U-shaped relationship between economic development and environmental degradation, contrary to the hypothesis. Yücel and Terzioğlu (2022) evaluated eco-efficiency in Türkiye and Europe, showing that spatial interdependencies significantly influence environmental innovation and policy effectiveness. Yücel and Terzioğlu (2023) examined sustainable development and eco-innovation in Türkiye and European countries (2010–2018) using a dynamic spatial panel data approach. Their findings highlight significant spatial relationships between eco-innovation and related indicators, emphasizing the need for countries to integrate eco-innovation policies with development strategies to enhance sustainability. These studies provide insights into the spatial dimensions of environmental challenges and sustainability.

The relationship between economic growth, inequality, and regional disparities has been another focus of spatial analysis. Akçagün (2017) examined provincial income convergence during 1991–2009, highlighting distinct spatial relationships influenced by political and economic changes. Orhan and Gülel (2016) studied regional unemployment disparities in Türkiye (2008–2012), identifying spatial interactions with labor force participation, youth population share, and agricultural employment. Demirci and Tatoğlu (2024) investigated unemployment determinants (2014–2022), finding that regional growth and enterprise numbers reduced unemployment, while university graduate increases and poverty rates exacerbated it. These works highlight the complex spatial interplay of economic and demographic factors.

Studies also have addressed sector-specific and spatially dependent phenomena. Eralp (2023) examined electricity consumption and economic growth in Türkiye's industrial sector (2004–2019), revealing an inverted-U relationship driven by sectoral transitions and renewable energy adoption. Tunay and Silpagar (2007) explored regional inflation convergence in Türkiye, identifying rapid convergence and robust spillover effects. Yıldırım and Kantar (2020) analyzed road traffic accident rates (2013–2018), finding significant spatial clustering influenced by motor vehicle numbers and road lengths. Additionally, Tatlı and Tatoğlu (2022) explored the spatial determinants of internal migration in 2014, highlighting significant clustering and heterogeneity among provinces. These studies collectively underscore the breadth of spatial panel data applications in addressing diverse regional challenges.

In Türkiye, where significant regional disparities coexist with substantial trade integration, this relationship becomes particularly pertinent. Türkiye's economic landscape is characterized by stark contrasts between its industrialized western regions and less-developed eastern provinces. As trade liberalization progresses, questions arise as to whether it has acted as a force for regional convergence or exacerbated existing disparities. This study seeks to contribute to this critical discourse by employing spatial panel data analysis to investigate the dynamics of trade openness and inequality across Türkiye's 26 NUTS-II regions from 2014 to 2022. In doing so, it provides nuanced insights into the intersection of globalization and regional development in a diverse and rapidly evolving economic context. By focusing on a more recent timeframe, it offers a fresh perspective compared to earlier studies, which predominantly examine the early 2000s. This contribution is significant as it delves into the dynamics between regional inequalities and trade openness in a contemporary context.

Existing literature on regional inequality in Türkiye is diverse, exploring different perspectives. However, no study to date has directly analyzed the impact of trade liberalization on inequality in Türkiye using spatial panel data methods. Most studies have favored approaches like sigma-beta convergence, with spatial panel data analysis rarely utilized. An exception is the work by Duran and Erdem (2017), which examines the trade-inequality relationship using regional per capita real Gross Value Added (GVA) as a proxy for inequality. Their analysis incorporates variables such as total exports and imports, population, and the proportion of university graduates, offering an indirect assessment of the trade-inequality link through regional economic disparities.

3. Dataset, Methodology and Model Selection

Data for GINI, labour participation and necessary data to calculate trade openness, population density, average education time per person obtained from Turkstat (2024). GINI data has time and geographical constraints which only allows to access NUTS-II regions for the period of 2014-2022. Therefore, explanatory variables are also obtained or calculated for NUTS-II regions.

Table 1. Data Description for Variables Used in the Analysis

Variable	Name	Description
GINI	GINI coefficient	Obtained from Turkstat (2024). Used as dependent variable to examine the inequalities.
TO	Trade openness	Export, import and GDP data obtained for each region and year. Trade openness calculated by using the formula: $TO = \frac{X + Y}{GDP}$
pop_dens	Population density	Population density is calculated by dividing the population of each NUTS-II region by its respective area in km². Area for each NUTS-II region calculated by aggregating province data obtained from Republic of Türkiye Ministry of National Defence (2024).
edu_time	Average education time per person	Obtained from Turkstat (2024) as NUTS-III and aggregated by NUTS-II regions.
lab_part	Labour participation	Obtained from Turkstat (2024).

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The general spatial panel model for analyzing the relationship between regional inequality (as measured by the GINI coefficient) and the independent variables can be expressed as:

$$y_{it} = \rho W y_{it} + X_{it}\beta + \theta W X_{it} + \lambda W \varepsilon_{it} + \varepsilon_{it} \qquad (1)$$

Where:

y_{it} : Dependent variable (GINI) for region i at time t.

ρ (rho): Spatial autoregressive parameter, capturing the influence of neighboring regions' GINI values.

W: Spatial weight matrix, defining the spatial relationships between regions.

X_{it}: Vector of independent variables for region i at time t, including:

TO: Trade openness,

lab_part: Labor participation rate,

pop_dens: Population density,

edu_time: Average years of education.

β: Coefficients for the direct effects of the independent variables.

θ (phi): Coefficients for the spatial lag of the independent variables (WX_{it}), capturing spatial spillovers of the explanatory variables (used in SDM).

λ (lambda): Spatial error parameter, reflecting spatial dependence in the error term (used in SEM and SARAR).

ε_{it} : Random error term, assumed to be independently and identically distributed.

Before the estimation process, several stages are undertaken to determine the most efficient model and estimator. Prior to estimation Likelihood Ratio (LR) test, Hausman (1978) test, AIC/BIC criteria, correlation matrix for coefficients, heteroskedasticity and autocorrelation tests are applied to obtain best, linear, unbiased estimator. These stages combine theoretical justifications with empirical findings to ensure a robust selection.

The Likelihood Ratio test is employed at two stages of the analysis. In the first stage, the test evaluates whether the model should be specified as pooled OLS, individual fixed effects, time fixed effects, or a combination of both. In subsequent stages, it is applied to determine the efficiency of spatial econometric models such as SAR, SDM, SEM, and SARAR.

The LR test is used to compare nested models, where one model (the restricted model) is a simplified version of the other (the unrestricted model). By comparing the fit of these models, the test assesses whether the additional complexity of the unrestricted model is justified. If the unrestricted model does not exhibit a significant improvement in fit over the restricted model, the restricted model is preferred for its parsimony.

The test statistic is calculated based on the difference in log-likelihoods between the models and is expressed as (Wooldridge, 2002, pp. 397):

$$LR = -2(lnL_R - lnL_U) \tag{2}$$

or,

$$LR = 2[loglikelihood\ of\ unrestricted\ model - loglikelihood\ of\ restricted\ model] \tag{3}$$

Null hypothesis ($H0$): The simpler (restricted) model is sufficient. The LR statistic follows a chi-squared distribution with degrees of freedom equal to the difference in the number of parameters between the two models. This provides the basis for determining whether the unrestricted model offers a significantly better fit.

Table 2. Tests for Individual and Time Fixed Effects

Statistical Test	Statistic	p-Value	Hypothesis Test
LR Test for Individual Fixed Effects	177.3753	0.000	H0: no individual effects - Accepted
LR Test for Time Fixed Effects	7.665638	0.467	H0: no times effects - Rejected

Source: Own calculations.

The likelihood ratio (LR) test for individual effects confirms the presence of significant individual-specific (regional) heterogeneity, supporting the inclusion of spatially varying effects. However, the LR test for time effects fails to reject the null hypothesis, suggesting that time-specific factors do not significantly influence the outcome variable (GINI).

Hausman (1978) test is used to determine whether fixed effects (FE) or random effects (RE) is the appropriate model specification. Hausman test examines if the random effects assumption (independence of individual-specific effects and regressors) holds. Null hypothesis (H0) of Hausman test is random effects are consistent and efficient. Test statistic can be illustrated as follows:

$$H = (\beta_{RE} - \beta_{FE})'[Var(\beta_{FE}) - Var(\beta_{RE})]^{-1}(\beta_{RE} - \beta_{FE}) \tag{4}$$

Where β_{RE} and β_{FE} are coefficients from RE and FE models, Var is the covariance matrix, H follows a $\chi 2$ distribution under H0.

Table 3. Hausman Test for Random and Fixed Effects Selection

Model Name	Hausman Test p-Value	Hypothesis Test
SAR	0.2817	H0: Random Effects - Accepted
SDM	0.8468	H0: Random Effects - Accepted
SEM	0.5994	H0: Random Effects - Accepted
SARAR	0.8468	H0: Random Effects - Accepted

Source: Own calculations.

The Hausman test results favor the random effects specification for all models (SAR, SDM, SEM, SARAR). This implies that unobserved individual effects are not correlated with the regressors, justifying the use of random effects in the spatial panel framework.

The Akaike (1974) information criterion (AIC) and Bayesian information criterion (BIC) by Schwarz (1978) are also utilized to select the best-fitting model. Similar to the Likelihood Ratio Test, these criteria favor simpler models unless the added complexity significantly improves the model's fit. Among the competing models, the one with the lowest AIC or BIC value is considered the most appropriate.

AIC can be written as:

$$AIC = -2 \, x \, Log - Likelihood + 2 \, x \, k \quad (5)$$

Where k is the number of parameters in the model.

BIC can be written as:

$$BIC = -2 \, x \, Log - Likelihood + k \, x \ln(n) \quad (6)$$

Where n is the sample size.

Table 4. Likelihood Ratio Test and AIC/BIC Criterion for Model Selection

Statistical Test	Statistic	p-Value	Hypothesis Test
LR Test (SAR ve. SDM)	-0.05427981	1.000	H0: The restricted model (SAR) is valid – Accepted
LR Test (SAR vs. SEM)	1.375774	0.502637	H0: The restricted model (SAR) is valid – Accepted
LR Test (SAR vs. SARAR)	0.05427981	1.000	H0: The restricted model (SAR) is valid – Accepted
LR Test (SDM vs. SARAR)	0	1.000	H0: The restricted model is valid (SDM) - Accepted
SAR – Criterion Analysis	AIC: -1186.675 BIC: -1169.398		
SDM- Criterion Analysis	AIC: -1186.729 BIC: -1169.452	Based on the AIC and BIC criterion, SDM model is efficient. However, the difference between SDM and SAR too small to make a certain decision.	
SEM- Criterion Analysis	AIC: -1185.299 BIC: -1168.022		
SARAR- Criterion Analysis	AIC: -1186.729 BIC: -1169.452		

Source: Own calculations.

The LR test comparisons reveal no significant differences between the SAR, SEM, and SARAR models, indicating that the simpler SAR model is appropriate and stable across different specifications. Model selection criteria, including AIC and BIC, suggest that the SDM model is the most efficient, closely followed by the SAR model. The minimal differences in these metrics imply that either model could be confidently applied. Considering both tests favor the SAR model, the analysis proceeds with this model, taking these results into account.

The coefficient correlation matrix is used to use the relationship between variables. The correlation matrix lists pairwise Pearson correlation coefficients (r) between independent variables. r ranges from -1 (perfect negative correlation) to 1 (perfect positive correlation), with r = 0 indicating no linear relationship.

In order to avoid multicollinearity in regression, the relationship between the coefficients of the variables must be below a certain threshold value. According to Ratner (2009, pp. 139-140), correlation coefficients between 0 and ±0.3 indicate a weak relationship, those between ±0.3 and ±0.7 represent a moderate relationship, and values above ±0.7 suggest a strong relationship.

Table 5. Correlation Matrix

	GINI	TO	lab_part	pop_dens	edu_time
GINI	1	0.248381	0.1644887	0.3741244	0.1840605
TO	0.2483805	1	0.2065698	0.5952191	0.2292757
lab_part	0.1644887	0.20657	1	0.2309393	0.3688156
pop_dens	0.3741244	0.595219	0.2309393	1	0.337395
edu_time	0.1840605	0.229276	0.3688156	0.337395	1

Source: Own calculations.

The correlation matrix reveals moderate positive correlations between GINI (income inequality) and the independent variables. Among these, population density (r=0.374) and trade openness (r=0.248) show the strongest relationships with GINI. Importantly, correlations among independent variables are low to moderate (r<0.6), alleviating concerns about multicollinearity that could affect model estimations.

Heteroskedasticity and autocorrelation tests are applied to ensure that the significancy of the estimation results are robust.

Table 6. Heteroskedasticity and Autocorrelation Tests

Breusch and Pagan (1971) Test for Heteroskedasticity		
BP Test Statistics	**p-Value**	**Hypothesis**
5.69	0.2234	H0: No heteroskedasticity - Accepted
Wooldridge (2002) Test for Autocorrelation		
F-Stat	**p-Value**	**Hypothesis**
24.65	0.00	H0: No serial correlation - Rejected

Source: Own calculations.

Diagnostic tests were conducted to assess the presence of autocorrelation and heteroskedasticity in the panel data. The Wooldridge test for autocorrelation rejected the null hypothesis of no serial correlation (p-value < 0.01), indicating the presence of autocorrelation. To address this, standard errors were clustered by region ID (NUTS-II). The Breusch-Pagan test for heteroskedasticity did not reject the null hypothesis of homoskedasticity (p-value = 0.223). Adjusting for autocorrelation did not alter the statistical significance or magnitude of the estimated coefficients.

Spatial panel data models differ from conventional panel data in that it explicitly incorporates spatial relationships among observational units into the analysis. While traditional panel data accounts for variations across time and entities, spatial panel data models address the influence of geographic or spatial proximity by integrating spatial dependence and spatial heterogeneity. In this paper, we use four spatial econometric models: the Spatial Autoregressive Model (SAR), the Spatial Durbin Model (SDM), the Spatial Error Model (SEM), and the Spatial Autoregressive Model with Autoregressive Errors (SARAR) to analyze the factors influencing inequality (GINI) across Türkiye's NUTS-II regions over the period 2014–2022.

In this study, spatial dependence is modeled using a row-standardized contiguity matrix based on the queen contiguity criterion. The queen contiguity criterion defines spatial neighbors based on shared boundaries or vertices. The spatial weights matrix W is the key difference between standard panel and spatial panel approaches. If regions i and j are contiguous $w_{ij} = 1$, otherwise $w_{ij} = 0$. To ensure comparability and to interpret the spatial effects consistently, the contiguity matrix is row-standardized. Row standardization transforms each row of W such that the sum of weights for each region equals 1.

The Spatial Autoregressive Model (SAR) is a commonly used spatial econometric model that incorporates spatial dependence in the dependent variable. It assumes that the value of the dependent variable in one region is influenced by the values of the dependent variable in neighboring regions (Anselin, 1988). The SAR model is specified as:

$$y = \rho W_y + X\beta + \epsilon \tag{7}$$

Where y is the dependent variable, W is the spatial weight matrix (defines spatial relationships between regions), ρ is the spatial autoregressive parameter (spatial dependence in the dependent variable), X is the matrix of independent variables β is the coefficient vector for the independent variables, ϵ is the error term. The SAR model is typically used when there is strong spatial dependence in the dependent variable but no significant spatial correlation in the error term.

Elhorst (2014) asserts that SAR and SEM models are limited and special emphasis should be given to SDM model. The Spatial Durbin Model extends the SAR model by including spatial lags not only of the dependent variable but also of the independent variables. This model accounts for the fact that the explanatory variables in one region can influence not only the dependent variable in that region but also the dependent variable in neighboring regions. The SDM is specified as:

$$y = \rho W_y + X\beta + WX\theta + \epsilon \tag{8}$$

Where, WX represents the spatial lag of the independent variables, and θ is the corresponding coefficient vector for these spatial lags. The SDM model is useful when there is both spatial dependence in the dependent variable and spillover effects from the independent variables across regions.

$$y = X\beta + \mu + v \tag{9}$$

The Spatial Error Model (SEM) assumes that the spatial dependence arises from the error term rather than the dependent or independent variables. In other words, the model accounts for unobserved factors that are spatially correlated and affect the dependent variable (LeSage & Pace, 2009). The SEM can be specified as (Belotti et al., 2017):

$$v = \lambda M v + \varepsilon \tag{10}$$

Where the error term v_t follows a spatial autoregressive process: $v = \lambda M v + \varepsilon$, λ is the spatial autocorrelation coefficient for the error term, u is the normally distributed error term. The SEM is appropriate when there is spatial dependence due to unobserved heterogeneity across regions that is not captured by the independent variables.

The SARAR model combines elements of both the SAR and SEM models. It models spatial dependence in the dependent variable and in the error term (Kelejian, 2008). This model is specified as:

$$y = \rho W_y + X\beta + \epsilon \tag{11}$$

$$\epsilon = \lambda W \epsilon + u \tag{12}$$

Where ρ captures spatial dependence in the dependent variable (as in SAR), λ captures spatial dependence in the error term (as in SEM), W is the spatial weight matrix, and u is the error term. The SARAR model is useful when both spatial dependence in the dependent variable and spatial autocorrelation in the error term exist.

4. Results and Discussion

The spatial panel data estimation results using the SAR and SDM models are presented in Table 7 and Table 8, respectively. Based on the LR test results and AIC/BIC criterion, the SAR and SDM models are identified as the most efficient for analyzing the data. The SAR and SDM models provide important insights into the determinants of inequality, as measured by the GINI coefficient, across regions. The intercept term is significant and positive in both models. The intercept suggests a baseline level of inequality that persists when all independent variables are at their average values. This baseline reflects inherent disparities not captured by the explanatory variables in the model.

Trade openness has a statistically significant and negative impact on inequality, indicating that increased trade integration reduces regional disparities. This finding aligns with theoretical expectations, as greater trade openness can enhance access to markets and job opportunities, particularly benefiting lower-income groups. This result consistently suggests that regions with greater integration into trade networks experience reduced income disparities, possibly due to broader economic opportunities and enhanced access to international markets. As a result, trade serves as a leveling mechanism, potentially reducing income inequality. Both models reinforce the importance of trade as a means to reduce inequality, with the SDM model suggesting that spatial spillovers of trade policies may be less pronounced than direct effects.

The labor participation rate shows a positive, marginally significant relationship with inequality, suggesting that higher workforce participation may slightly exacerbate income disparities. Autor et al. (2008) argue that increased labor participation does not uniformly reduce inequality, as many new jobs are concentrated in low-wage, low-skill sectors, amplifying disparities. The rising returns to education disproportionately benefit skilled workers, while unskilled workers often face stagnant wages, further widening the income gap. This dynamic may result from unequal access to quality jobs, where skilled workers gain more from employment opportunities than unskilled laborers. Moreover, increased labor force participation can intensify job competition in economies with abundant low-skilled workers, potentially suppressing wages for lower-income groups and contributing to inequality. Terzioğlu *et al.* (2015) further highlight the intricate interactions between employment, economic growth, and price levels, emphasizing the importance of labor market dynamics in understanding inequality.

Population density shows a positive and strongly significant association with inequality, suggesting that urbanization and the concentration of economic activities in densely populated areas contribute to greater income disparities. Glaeser et al. (2009) examined inequality in cities and found a positive relationship between population growth and area-level inequality. High population density often corresponds with urbanization, which can have mixed effects on inequality. Urban areas tend to have more diverse economies and better access to services, but they may also experience greater income disparity due to housing costs, access to better jobs, and regional inequalities. In densely populated areas, economic opportunities may be concentrated in certain sectors or regions, contributing to greater income inequality. Additionally, urban areas often see a growing divide between skilled and unskilled workers, with the skilled benefiting from higher wages and more job opportunities, while the unskilled are left behind. This can exacerbate overall income disparities.

Education time is widely acknowledged as a critical factor influencing income inequality. Higher levels of education are generally associated with a more skilled and productive workforce, which can reduce income disparities by offering individuals better job opportunities and higher wages. However, the relationship between education and inequality is complex. Barro (2000) found that different levels of education have varying effects on inequality. Primary education is negatively and significantly associated with inequality, while secondary education shows a statistically insignificant relationship. In contrast, higher education is positively and significantly linked to inequality. In this model, the average years of education do not exhibit a statistically significant effect on inequality. While education is theoretically expected to reduce inequality by enhancing skills and earning potential, this insignificance may reflect the influence of other factors, such as disparities in access to or the quality of education, which could offset its potential equalizing effects. In theory, increasing educational attainment can reduce inequality by improving access to well-paying jobs and promoting a more equitable income distribution. However, if the education system disproportionately benefits certain segments of the population (e.g., urban elites) or fails to translate into meaningful job opportunities, it may exacerbate disparities instead. This dynamic may help explain why education time does not have a significant impact on the GINI coefficient in the empirical model.

Table 7. Estimation Results for SAR Model

SAR MODEL	Coefficient	Std. Error	t-value	Pr(>|t|)		
(Intercept)	2.23E-01	2.75E-02	8.1088	0.00	***	
TO	-6.05E-06	1.45E-06	-4.1773	0.00	***	
lab_part	8.64E-04	4.97E-04	1.7401	0.08	x	
pop_dens	3.66E-05	7.54E-06	4.8604	0.00	***	
edu_time	-1.02E-03	1.95E-03	-0.5224	0.60	-	
Phi	0.91461	0.30673	2.9818	0.00	**	
Lambda	0.279824	0.075757	3.6937	0.00	***	
Impact Measures						
Variables/Impact	**Direct Coefficient**	**p-Value**	**Indirect Coefficient**	**p-Value**	**Total Coefficient**	**p-Value**
TO	-6.05E-06	0.00	-2.35E-06	0.02	-8.40E-06	0.00
lab_part	8.64E-04	0.11	3.36E-04	0.16	1.20E-03	0.11
pop_dens	3.66E-05	0.00	1.42E-05	0.02	5.09E-05	0.00
edu_time	-1.02E-03	0.60	-3.96E-04	0.65	-1.42E-03	0.61

Table 8. Estimation Results for SDM Model

SDM MODEL	Coefficient	Std. Error	t-value	Pr(>|t|)		
(Intercept)	2.06E-01	2.67E-02	7.70	0.00	***	
TO	-5.99E-06	1.44E-06	-4.17	0.00	***	
lab_part	8.37E-04	4.84E-04	1.73	0.08	x	
pop_dens	3.67E-05	7.50E-06	4.89	0.00	***	
edu_time	-1.06E-03	1.84E-03	-0.58	0.56	-	
phi	9.21E-01	3.11E-01	2.96	0.00	**	
rho	-0.069912	0.2944	-0.2375	0.81	-	
lambda	0.33213	0.22537	1.4737	0.14	-	
Impact Measures						
Variables/Impact	**Direct Coefficient**	**p-Value**	**Indirect Coefficient**	**p-Value**	**Total Coefficient**	**p-Value**
TO	-5.99E-06	0.00	-2.98E-06	0.36	-8.97E-06	0.06
lab_part	8.37E-04	0.07	4.16E-04	0.53	1.25E-03	0.27
pop_dens	3.67E-05	0.00	1.82E-05	0.35	5.49E-05	0.04
edu_time	-1.06E-03	0.60	-5.26E-04	0.75	-1.59E-03	0.66

*Significance codes: ***: p<0.001, **: 0.001≤p<0.010 , *: 0.01≤p<0.05, x : 0.05≤p<0.10, - : p≥0.1*
Standard errors are clustered by NUTS-II regions.
Source: Own calculations.

The SAR model also reveals strong spatial dependencies in inequality. The spatial autoregressive coefficient phi (ϕ) is significant and positive, highlighting that inequality in a region is influenced by the inequality levels of its neighbors. This suggests the presence of spatial spillover effects, where economic and social conditions in one region affect those in neighboring areas. Additionally, the spatial error coefficient lambda (λ) is significant, indicating that unobserved factors affecting inequality are also spatially correlated. This reinforces the importance of accounting for spatial dynamics to avoid biased or inefficient estimates.

Spatial dependencies play a key role in the SDM model. The spatial autoregressive coefficient phi (ϕ) is significant and positive, indicating that regional inequality is influenced by the inequality levels of neighboring regions. This highlights the importance of spatial spillovers, where economic and social dynamics in one region impact those in adjacent areas. The spatial error coefficient lambda (λ) is not statistically significant in this model, suggesting that unobserved spatially correlated factors are less critical here. The spatial lag of the dependent variable rho (ρ) is also insignificant, indicating that inequality in a region is not directly affected by the spatial lag of explanatory variables from neighboring regions in this specification.

When *direct, indirect and total impacts* are examined, it can be seen that the SAR and SDM models offer complementary insights into the determinants of regional inequality, emphasizing both local and spatial spillover effects. While the two models share some common conclusions, their differences highlight the varying treatment of spatial dependencies.

Trade Openness: Both models agree that trade openness has a significant and negative direct effect on inequality, indicating that increased trade activity within a region helps reduce disparities. This result aligns with the theoretical expectation that trade liberalization enhances economic opportunities and resource allocation within regions. However, the indirect effects differ between the models. The SAR model finds significant spillovers, suggesting that the benefits of trade openness in one region moderately extend to neighboring regions. In contrast, the SDM model reports insignificant spatial spillovers, implying that trade openness primarily influences inequality locally, with minimal interregional impact. Consequently, the total effects in the SAR model are slightly stronger and more robust than in the SDM model. This divergence reflects the SAR model's stronger emphasis on spatial spillovers in the dependent variable.

Labor Participation: For labor participation, both models indicate a positive direct effect on inequality, but the magnitude and significance differ. The SDM model suggests a slightly stronger and marginally significant direct effect, pointing to the possibility that increased labor force participation might exacerbate inequality within regions. This finding may stem from the unequal distribution of job opportunities or wage disparities. The indirect effects are insignificant in both models, indicating no meaningful spillovers to neighboring regions. The total effects remain weak and statistically insignificant, suggesting that labor participation's influence on inequality is primarily local and limited in scope. The consistency across models reinforces the localized nature of labor market dynamics.

Population Density: Both models consistently show that population density has a significant and positive direct effect on inequality, reflecting the concentration of disparities in densely populated areas. This result aligns with the idea that urbanization and agglomeration effects can amplify income gaps. However, the models differ in their treatment of indirect effects. The SAR model identifies significant spillovers, suggesting that densely populated regions can indirectly influence inequality in neighboring areas, possibly through economic interdependence or migration. Conversely, the SDM model finds no significant spillovers, attributing the effects of population density primarily to local conditions. The total effects are significant in both models but are stronger in the SAR model, emphasizing the broader spatial impact captured by the SAR framework.

Average Years of Education: Both models agree that average years of education have no significant effect on inequality, either directly or indirectly. This result challenges conventional expectations and may reflect the limitations of education as a short-term equalizer in the context of regional inequality. Structural factors such as mismatched skills, quality disparities in education, or unequal access to high-paying jobs may dilute the impact of education on reducing disparities. The lack of significance across models suggests that education's influence on inequality is neither local nor spatially diffuse in this dataset.

The SAR model generally attributes stronger spatial spillovers to variables such as trade openness and population density. These spillovers highlight the importance of considering interregional dependencies in understanding inequality dynamics. The SDM model, with its more flexible framework, downplays the role of spillovers, attributing most effects to local conditions. This divergence reflects differences in the underlying assumptions of the models, with the SAR model focusing on spatial interdependencies in the dependent variable and the SDM model capturing the influence of spatially lagged explanatory variables.

Overall, both models reinforce the importance of trade openness and population density in shaping regional inequality while highlighting the limited role of education and labor participation. The SAR model's emphasis on spatial spillovers provides a broader perspective, while the SDM model offers a more localized interpretation. These findings underscore the need for tailored policy interventions that address both local conditions and regional interdependencies.

Conclusion

This study examines the determinants of regional inequality in Türkiye's NUTS-II regions for the period of 2014-2022 using spatial panel data models. The spatial panel data analysis with the most efficient models SAR and SDM, reveal that trade openness and population density are critical drivers of inequality, while labor participation and education exhibit nuanced or limited roles. Trade openness consistently demonstrates a significant negative impact on inequality, emphasizing its role in reducing regional disparities through enhanced market access and economic opportunities. Population density, however, contributes positively to inequality, reflecting the challenges of urbanization and uneven economic growth in densely populated areas.

The study also highlights the importance of spatial dependencies in understanding regional inequality. The SAR model identifies significant spatial spillovers for trade openness and population density, suggesting that regional policies can have ripple effects on neighboring areas. In contrast, the SDM model indicates a more localized impact of these factors, with limited interregional spillovers. These findings underscore the need for policies that address both local and spatial dimensions of inequality, promoting inclusive growth while considering regional interdependencies.

Informed by these results, targeted policy interventions should prioritize enhancing trade openness, mitigating urbanization-driven disparities, and addressing labor market inequalities. Although education's impact is not statistically significant in this analysis, improving education quality and accessibility remains a long-term priority for equitable economic development. Future research should further explore the mechanisms driving these relationships and the role of unobserved regional factors.

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