EKOIST Journal of Econometrics and Statistics,
EKOIST 2025, 43: 103–127

https://doi.org/10.26650/ekoist.2025.43.1663189

Submitted 23.03.2025
Revision Requested 06.07.2025
Last Revision Received 28.10.2025
Accepted 01.12.2025

EKOIST Journal of Econometrics and Statistics

Research Article

Open Access

Macroeconomic Dynamics and Regional Disparities in Informal Employment: The Case of Türkiye

Gözde Nalbant Efe [1] & Berat Kara [1]

[1] İstanbul Medeniyet University, Department of Public Finance, İstanbul, Türkiye

Abstract Informal employment constitutes a significant socio-economic challenge both globally and within the context of Türkiye. As conceptualised by the International Labour Organisation, informal employment encompasses work activities that fall outside the purview of national labour legislation, taxation systems, and social security frameworks. This phenomenon not only erodes workers' access to fundamental rights and protections but also undermines public revenues, distorts labour market dynamics, and hampers overall economic efficiency. This study aims to analyse the macroeconomic determinants of informal employment in Türkiye, with a specific focus on the regional and temporal variations observed over the period 2009-2021. Employing the spatial Durbin error model, the research identifies significant relationships between informal employment and key economic indicators. The results indicate that higher levels of GDP per capita, increased public expenditure, unemployment rates, and COVID-19 are correlated with a decline in informal employment. Notably, the findings reveal that neither the tax burden nor the inflation exerts a statistically significant impact on informal employment within the Turkish context during the examined period. This demonstrates that the influence of these factors may be context-specific or mitigated by other prevailing economic and institutional dynamics in Türkiye. The results also demonstrate that GDP per capita, unemployment, public expenditure and inflation of neighbouring regions have spillover effects on the IFE. The methodological approach adopted in this study underscores the importance of spatial and regional interactions in shaping informal employment trends.

Keywords Informal Employment · Regional Disparities · Spatial Panel Data Analysis

JEL Classification J46 · H30 · C31

Citation: Nalbant Efe, G. & Kara, B. (2025). Macroeconomic dynamics and regional disparities in informal employment: The case of Türkiye. *EKOIST Journal of Econometrics and Statistics*, 43, 103-127. https://doi.org/10.26650/ekoist.2025.43.1663189

Corresponding author: Gözde Nalbant Efe gozde.nalbant@medeniyet.edu.tr

Macroeconomic Dynamics and Regional Disparities in Informal Employment: The Case of Türkiye

Informal employment (IFE) is recognised as a significant issue due to its economic and social impacts at both national and international levels. The International Labour Organisation (ILO) defines IFE as *"working arrangements that are de facto or de jure, not subject to national labour laws, income taxation, or entitlement to social protection or certain other employment benefits"* (ILO, 2023). In Türkiye, the Social Security Institution (SSI) describes IFE as *"the failure to report or the incomplete reporting of the working days and earnings of individuals employed in legal jobs to the relevant authorities"* (SSI, 2024).

IFE poses a problem that severely stresses the financial resources of the state mainly in poor and developing nations. The hiding of informal workers' incomes from the tax authorities and social security services reduces the revenues collected by governments through taxes and social security contributions. This scenario not only limits the governments' ability to provide social security but also increases social transfer expenditures at the same time. The two-way pressure of informality on government budgets is a factor leading to the unsustainability of public budget balances and giving a further boost to the rising public debt.

The inability to adequately measure the informal sector with official statistics creates serious problems in policy design and implementation processes. This situation prevents the effective use of public resources, narrows the tax base, and reinforces the perception in society that the tax burden is not distributed fairly. Such perception weakens tax morale in the long term and leads to unfair competition for firms operating in the formal sector (Joshi et al., 2014; Rogan, 2019). As a result, the expansion of the IFE has negative effects not only on public finances but also on the general functioning of the economic structure.

IFE also causes serious rights losses and risks for employees. Individuals working informally are deprived of health insurance, retirement benefits, disability coverage, unemployment insurance, official permits, and other legal rights. This situation causes individuals to live a life deprived of long-term social security. Furthermore, IFE also exposes employees to disadvantages such as low job satisfaction, job insecurity and unsafe working conditions (OECD & ILO, 2019; ILO, 2018).

IFE is frequently linked to lower salaries, scanty unionisation chances, and increased poverty risk. All these factors work against the workers' economic and social well-being, and at the same time, the government's safety and benefits in the formal sector remain unavailable to them. Usually, when IFE is widespread in a certain industry, the occupational health and safety standards are not up to par, which then puts the workers' lives and health at greater risk. Therefore, informal workers are not only suffering from economic insecurity but also from the lack of basic human rights (Dereli, 2011; Uslu, 2021; Benavides et al., 2022; Tansel & Acar 2016).

The negative consequences of IFE have been the main concern in academic discussions, but note that IFE can also, in the short run, particularly in developing countries, perform positive economic functions. The informal sector serves as a source of income for many people who cannot find jobs in the formal sector and also by providing them with work experience and specific professional skills (Dereli, 2011; OECD & ILO, 2019). They are therefore allowed to become part of the economic system. Studies have indicated that informality in labour contributes positively to the Gross Domestic Product (GDP) in developing nations. The informal sector is responsible for the advancement of economic activities and the stabilisation of employment rates through its production complementing that of the formal sector (Sultana et al., 2022; Charmes, 2016).

Although IFE might provide a temporary boost to the economic system, its negative effects would mainly be seen in the future goals such as the expansion of the formal economy, the fight against poverty, equality of income, and sustainable taxation and public policies. This has led to the issue of informality being considered a priority in the agendas of both international organisations and national governments (ILO, 2015, 2018, 2023; OECD, 2019, 2023, 2024). Informality and the related problems cannot be just neglected since they would negatively impact the whole economy, and on top of that, there would be no fair redistribution of wealth and social welfare. To make effective solutions, one has to thoroughly examine the structural reasons behind informality. Such studies will not only bring about quick fixes to the economic problems that are prevalent but also serve as the groundwork for a more sustainable and inclusive economic system that will last for a long time.

The 2019 statistics show that 58% of the world's employees are informally employed with varying proportions of informality according to country income groups. Up to 16% are informally employed in high-income countries, which increases to around 50% in upper-middle countries and up to 80-90% in lower-middle and low-income countries (ILO, 2023). In Türkiye, the informal employment rate has shown a decreasing trend, going from 44% in 2009 to 35% in 2019 to 29% in 2021 (SSI, 2022), which means that policies and programmes to reduce the informal economy have been effective; however, high rates of informal employment and more comprehensive and sustainable solutions to the problem still need to be formulated and implemented.

In Türkiye, formally employed people have certain tax obligations, including income and stamp tax, unemployment insurance premiums and social security premiums based on earnings. The informal employed population also detracts from the prime tax revenues of the central government and the premium revenues collected by the social security institution. Empirical evidence of lost revenues has been reported in the literature. For example, Uslu (2021) and Kutbay (2018) found that an increasing rate of informal employment will negatively affect the collection of income and stamp taxes. Similarly, Karaaslan (2010) reports that uncollected taxes and tax premium revenues lost because of informal employment units, is roughly 10% of Türkiye's GDP. These findings show that combating informality is crucial in increasing public sector revenues. Reducing informality through effective policies and control mechanisms will not only increase revenues but also ensure the establishment of a fairer tax system.

The present research delves into the study of macroeconomic factors from a broad set of variables that makes it prominent in the literature and tries to find the basic dynamics affecting the IFE in Türkiye. The variables included in the study determine how IFE is shaped at the national and regional levels and form a foundation for crafting more pragmatic policies in this area. In this regard, real per capita GDP, the unemployment rate, inflation, state expenditures and tax burdens, and dummy variables during and after the COVID-19 period have been identified. The dummy variables are included to observe the possible effects of the epidemic on the IFE, to learn about the dynamics of the period, and to evaluate the results in a more holistic manner. The research is based on data with respect to 26 regions of Türkiye classified according to the Nomenclature of Statistical Territorial Units (NUTS-2) for the period spanning 2009 to 2021.

Türkiye is a socio-economically unequal country to a great extent inter-regionally because economic activities are centralised in certain regions and especially in metropolitan cities (Acar et al., 2019). Regions vary and group significantly in terms of macroeconomic factors such as informal work, per capita income, unemployment, etc. Upon viewing the influence of spatial variables over IFE, thought should be given with consideration being made under models that observe the spatial effect along with dependency. The spatial panel data analysis was accordingly performed in this study.

The findings indicate that the real GDP per capita, unemployment rate, public expenditures, and the COVID-19 pandemic exert a negative effect on IFE. In contrast, the tax burden and inflation show no substantial impact on IFE. Moreover, the results reveal notable spatial spillover effects of real GDP per capita, public expenditures, unemployment and inflation on IFE. This indicates that IFE in Türkiye is significantly shaped by macroeconomic factors with spatial differentials needing to be accounted for since the analysis process.

This study is structured as follows: The next section reviews the literature on the macroeconomic determinants of IFE, highlighting the findings and methodologies of previous studies. The dataset and variables used in the analysis are introduced in the third section, detailing their sources and construction. The fourth section outlines the econometric methodology employed, with particular emphasis on the spatial panel data models and the rationale for their selection. In the fifth section, the results of the analysis are presented, focusing on the relationships between macroeconomic variables and IFE. The discussion and policy recommendations are provided in the sixth section, offering insights into the implications of the findings for addressing IFE in Türkiye. The paper concludes with a summary of the key findings and directions for future research.

Literature Review and Hypothesis

Upon reviewing the literature, it becomes evident that research into the causes of IFE provides a comprehensive framework for understanding this phenomenon. The significant effects of various economic, demographic, sociological, institutional, and political factors on IFE are highlighted. Regarding economic factors, the economic growth rate, unemployment rate, inflation, tax burden, public expenditures, and the economic shocks emerge as particularly significant (Ihrig & Moe, 2001; Bosch et al., 2012; Bolukbas, 2018; Hazans, 2011; Caro & Nicotra, 2016). Regarding demographic factors, population growth, age, education level, and gender have been extensively discussed (Basol & Yalcın, 2020; Ozturk & Basar, 2018; Tansel et al., 2020; Aikaeli & Mkenda, 2013; Lehmann & Pignatti, 2007). Sociological factors are examined through urbanisation and migration trends (Torgler & Schneider, 2007; Caro & Nicotra, 2016). Among institutional indicators, the development of financial and labour markets is discussed, especially focusing on labour regulations such as employment protection laws, minimum wage, and unionisation (Almeida & Carneiro, 2012; Bosch et al., 2012; Galli & Kucera, 2004; Hazans, 2011; Perry et al., 2007; Capasso & Japelli, 2013). Policy factors are analysed through political stability, polarisation, governance quality, and corruption (Torgler & Schneider, 2007; Jonasson, 2011; Elgin & Ertürk, 2019).

A substantial body of literature explores the determinants of IFE. Given the numerous factors discussed in the previous studies, this research specifically focuses on the relationship between IFE and macroeconomic variables. Accordingly, the following literature review will concentrate exclusively on scholarly works addressing macroeconomic factors.

Munir and Pollin (2009) investigated the relationship between IFE, inflation, and GDP growth in Malaysia from 1970 to 2005. Their analysis demonstrated a statistically significant positive effect of GDP on IFE, whereas inflation had no significant effect. Volchik et al. (2020), who examined 80 regions in Russia from 2010 to 2016, further corroborated the substantial influence of GDP on IFE. Their findings revealed a significant relationship between unemployment, GDP per capita, and IFE, although they found no relationship between migration and IFE. Additionally, Ortiz and Torres (2024) analysed the factors influencing IFE in Mexico from 1980 to 2022, concluding that increases in taxes, unemployment, and the minimum wage positively affected IFE.

There have also been studies conducted for a single country that have addressed the effect of the tax burden on the IFE. For example, Nikulin (2023) analysed the relationship between IFE and tax burden through surveys conducted with SMEs in Poland in 2018. As a result, no statistically significant relationship was found between the tax burden and IFE, confirming the assumption that the tax level is not the main driver of informal activities. Conversely, Caro and Nicotra (2016) found a different result in their study prepared for Italy. The results of the analyses conducted for the 2011-2012 period showed that the tax burden and public employment had a positive effect on IFE, while GDP was negatively related to IFE.

Panel studies have a significant place in the literature analysing the determinants of IFE. Hazans (2011) analysed IFE in 30 European countries for the period 2004-2009 and found that GDP had a positive effect on IFE. On the other hand, it was determined that the effect of GDP per capita on IFE was positive in eastern and southern Europe and negative in western and northern Europe. Adekoya and Biala (2023) also determined a similar relationship between GDP and IFE. The study, which examined the factors affecting the IFE in 16 countries in West Africa, showed that the unemployment rate, GDP per capita and population had a negative effect on the IFE. Inflation and tax burden were not significant in the analysis.

Herwartz et al. (2015) also confirmed the inverse influence of GDP on IFE. The analyses carried out in 2007-2008 in some European countries found that IFE was negatively impacted by GDP and public employment, whereas tax and unemployment rates had a positive impact. In the same vein, Williams (2014) looked into IFE through a survey of European countries in 2007. It was concluded that GDP per capita negatively impacted IFE while tax rates and public expenditures were statistically insignificant. Similarly, Elgin and Uras (2013) investigated the IFE of 152 countries over a period of nine years (1999-2007). They were able to identify that GDP per capita, public debt, and interest rates were the primary determinants of IFE.

Although the negative effect of GDP is frequently detected, Vidović and Ritan (2022) found the opposite. In this study, the macroeconomic determinants of the IFE in 42 developing and underdeveloped countries were analysed using the 2017-2019 data obtained from the ILO and other international organisations. The results showed that the key macroeconomic variables had a weak explanatory power on the IFE. However, it was determined that unemployment and exports had a decreasing effect on the IFE, while the GDP growth rate had an increasing effect. On the other hand, the tax burden, government expenditures and inflation did not have any effect on the IFE.

The literature on the macroeconomic determinants of IFE has a remarkable accumulation, especially in Türkiye. For instance, Bolukbas (2018) analysed the IFE in Türkiye based on monthly data for the period 2010-2017. As a result, a mutual causality relationship was determined between IFE and economic growth. However, no link was determined to youth unemployment. Dam et al. (2018) investigated IFE from 2002 to 2016 and concluded that unemployment positively affects IFE. Additionally, they found no significant effect of growth or inflation on IFE.

The studies conducted in Türkiye indicate that there is a strong connection among IFE, unemployment, and inflation. For example, Eralp (2022b) looked into the IFE phenomenon from 2009 to 2020, giving more attention to regional factors. The output of the investigation noted that inflation, youth unemployment, and female unemployment led to a fall in IFE, while the COVID-19 pandemic caused a decline, too, but it was severe. Eralp (2024) was later to do another research that used the same regional data over the same period to prove that there was a reverse relation between economic growth and IFE. The findings indicated that the rate of nonagricultural unemployment exerted a positive influence on IFE, whereas inflation had a negative impact. Likewise, interpreting the results of their study as at first glance, it would be easy to take the (Çelik et al., 2021) findings of negative correlation between IFE, inflation and then economic growth along with the positive co-movement of unemployment and IFE for the period starting in the year 2004 and ending in 2020.

Dalgıc (2023) examined the link between IFE and a range of economic indicators in Türkiye between 2006 and 2019 and highlighted the association of IFE with GDP per capita, population increase and unemployment as main economic indicators. Eralp (2022a) also pointed out a similar connection between GDP and IFE but concentrated on sectoral and regional IFE rates from 2009 to 2020. The analysis outcomes indicated an inverted U-shaped correlation between IFE and GDP. Uslu (2021) assessed IFE for the years 2006-2020 and concluded that the rise in IFE led to a decline in tax revenues and economic growth, and the impacts were more pronounced in the short run.

The literature has brought forth different findings concerning the influence of macroeconomic variables on IFE. The variations can be attributed to the time frames of the studies, the geographic area covered, the research methods, and the type of data employed. To illustrate, numerous researchers assert that GDP has a marked effect on IFE (Munir & Pollin, 2009; Volchik et al., 2020; Caro & Nicotra, 2016; Hazans, 2011; Adekoya & Biala, 2023; Herwartz et al., 2015; Williams, 2014; Elgin & Uras, 2013; Vidović & Ritan, 2022; Bolukbas, 2018; Eralp, 2024; Celik et al., 2021; Dalgıc, 2023; Eralp, 2022a; Uslu, 2021). Conversely, Dam et al. (2018) found that the association was not significant.

Hypothesis 1: As GDP per capita increases, the IFE ratio decreases.

There is often a significant relationship between the unemployment rate and IFE (Volchik et al., 2020; Ortiz & Torres, 2024; Caro & Nicotra, 2016; Adekoya & Biala, 2023; Herwartz et al., 2015; Vidović & Ritan, 2022; Dam et al., 2018; Eralp, 2024; Celik et al., 2021; Dalgıc, 2023). However, Bolukbas (2018) found no significant relationship between unemployment and IFE.

Hypothesis 2: As the unemployment rate increases, the IFE rate increases.

The effect of inflation on IFE is also controversial. While some studies suggest that inflation has a significant effect on IFE (Eralp, 2022b; Eralp, 2024; Celik et al., 2021), others do not find this relationship significant (Munir & Pollin, 2009; Adekoya & Biala, 2023; Vidović & Ritan, 2022; Dam et al., 2018).

Hypothesis 3: As inflation increases, the IFE rate increases.

Tax burden is an important factor studied in different countries and periods. Some studies demonstrate that the tax burden significantly affects IFE (Ortiz & Torres, 2024; Caro & Nicotra, 2016; Herwartz et al., 2015; Uslu, 2021). However, Nikulin (2023), Adekoya and Biala (2023), Williams (2014), and Vidović and Ritan (2022) found this relationship insignificant.

Hypothesis 4: As the tax burden increases, the IFE rate increases.

Public expenditures were examined by some studies, but the effect on IFE was found to be insignificant (Williams, 2014; Vidović & Ritan, 2022).

Hypothesis 5: As public expenditures increase, the IFE rate decreases.

The COVID-19 pandemic, which has global economic and social impacts, has also affected IFE dynamics. The impact of the COVID-19 pandemic on IFE has been discussed in the literature with different findings. Eralp (2022b) found that the pandemic period had a negative impact on IFE in Türkiye. In contrast, Williams and Kayaoglu (2020) provided evidence that the pandemic had an increasing effect on the IFE rates due to the economic difficulties. These different findings reveal that the impact of the pandemic on IFE may vary depending on the economic and institutional structures specific to the countries and the policies implemented during the pandemic.

Hypothesis 6: During the COVID-19 pandemic, the IFE rate decreased.

There is a wide variety of sources that provide different viewpoints and they all point that the dynamic analysis of IFE should be conducted comprehensively through the lens of macroeconomic determinants. The current investigation enhances the existing knowledge pool by considering the spatial variables and thereby acknowledging the large socio-economic differences between various areas in Türkiye. Urban clusters are the ones that attract the most economic activity, while some regions remain disadvantaged for a long time, which is visible in their labour market situation as well as in their access to social safety nets. Moreover, the IFE of one area may be subject to the influence of economic and policy transfer from its neighbouring regions. We employ spatial econometric techniques in this research to ascertain whether IFE is affected not only by the national situation but also by the regional context and inter-regional links, thus yielding significant implications for policy formulation.

Hypothesis 7: Regional dynamics affected the IFE rate in Türkiye.

Data Set

This research applies an extensive dataset to study the determinants of IFE in Türkiye, emphasizing macroeconomic and spatial dynamics. In the analysis of 2009-2021 within 26 different regions, the study merges together major economic variables such as real GDP per capita, the rate of unemployment, inflation, government spending, and tax burden. In addition, dummy variables are included to show the peculiar impact of COVID-19 on IFE dynamics due to the fact that curfews were enacted in Türkiye in 2020 and 2021 to halt the spread of the virus. The timeframe of 2009–2021 was chosen because there are several important regional indicators, especially in the case of IFE, that only have availability up to 2021. Similarly, the study is done at the NUTS-2 level, because most of the regional variables employed in the study along with IFE data are not publicised at the level of provinces. This comprehensive dataset serves as a solid ground for understanding the interplay between regional economic conditions and IFE, as expressed in the table below, rendering profound insights into the structural factors that shape the labour market of Türkiye.

Table 1
Variables

Variable	Acronym	Definition	Source
Informal Employment	IFE	The ratio of informal workers to formal workers (%)	Social Security Institution (2022)
GDP per capita	GDP	Logarithm of real GDP divided by the regional population	Turkish Statistical Institute (2023)
Unemployment	UNP	The ratio of the unemployed to the total work-force (%)	Turkish Statistical Institute (2023)
Inflation	INF	Annual Consumer Price Index (%)	Turkish Statistical Institute (2023)
Public Expenditures	EXP	Ratio of central government public expenditures to regional GDP (%)	Ministry of Treasury and Finance (2023) and Turkish Statistical Institute (2023)
Tax Burden	TXB	Ratio of central government tax revenues to regional GDP (%)	Ministry of Treasury and Finance (2023) and Turkish Statistical Institute (2023)
COVID-19	C20	"1" if 2020, "0" otherwise	
	C21	"1" if 2021, "0" otherwise	

The addition of these variables has many benefits regarding the research of IFE dynamics. The use of real GDP per capita, which is deflated by the corresponding regional inflation rates and then transformed into a logarithmic scale, allows for the very careful examination of the impact of economic development on IFE after the regional cost-of-living differentials have been controlled for. The amount of public spending and taxation as a percentage of regional GDP allows for the examination of the role of fiscal policy in shaping employment structures. These changes make the dataset much stronger and thus allow the researchers to be more precise when estimating the connection between macroeconomic factors and IFE.

Methodology

The primary focus of spatial econometrics is to consider the location effects of data spread over a geographic space. Nearby observations in cross-sectional data sets tend to cluster, which violates the assumption of independence critical to traditional econometric methods (Tobler, 1970; LeSage & Pace, 2010). When distinguishing between spatial and traditional econometrics, it is essential to consider the spatial effects in regional science (Anselin, 1988a). Spatial dependence (autocorrelation) is the correlation among observations of a variable strictly attributable to the proximity of those observations in geographic space (Fisher & Wang, 2011). When analysing spatial data, neglecting spatial autocorrelation can lead to inconsistent and biased results (LeSage & Pace, 2010).

Spatial weight matrices are used to incorporate spatial interactions in the models when spatial autocorrelation is present. The spatial weight matrix W is a positive N×N matrix where the rows and columns correspond to the cross-sectional observations. The W_{ij} element of this matrix indicates the strength of the interaction between location i and location j.

$$W_{ij} = \begin{cases} 1 & if\ i\ is\ contiguous\ to\ j \\ 0 & otherwise \end{cases} \tag{1}$$

As a rule, $W_{ij} = 0$ in the diagonal elements of the matrix. For ease of estimation and interpretation, spatial weights are often standardised so that the sum of each row and column equals one (Anselin et al., 2008).

The weight matrix can be generated according to the distance between units or neighbourhood relationships. Based on the joint edges and corners of the units, different neighbourhoods are classified as castle, bishop, and queen neighbourhoods (Gumprecht, 2005). This study uses a standardised spatial weight matrix of 26x26 dimensions based on the queen neighbourhood.

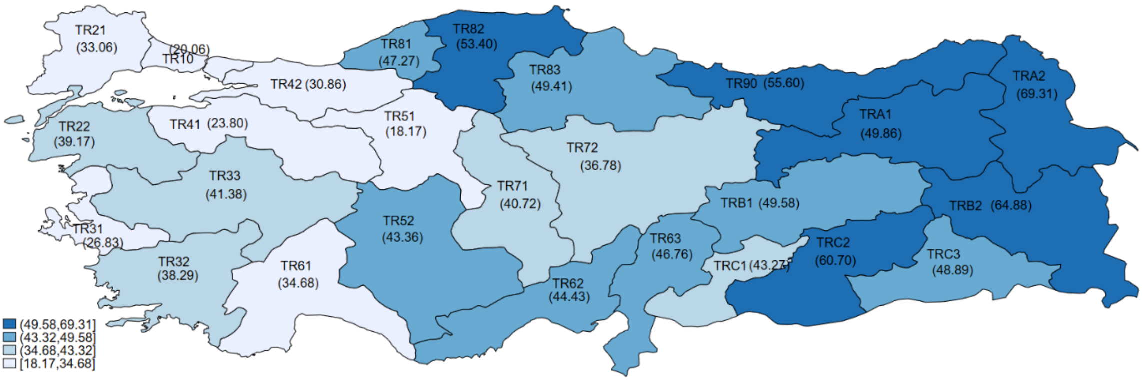
Spatial autocorrelation analysis

In the initial stage of spatial data analysis, it is essential to provide a priori information regarding whether the regional values of a variable are randomly distributed or exhibit spatial dependence. Observationally distributing classification maps such as quartiles or quantiles are frequently applied (Fisher & Wang, 2011). A quartile map depicting the average IFE from 2009 to 2021 over 26 areas of Türkiye is shown below.

The map uses a colour gradient to show the percentages of IFE. Higher percentages are represented by darker colours, and lower ones are represented by lighter ones. The northwest part of the country has the least IFE, while the southwest has the next lowest. On the other hand, the northeast and southeast regions contain high IFE. The map demonstrates that IFE rates are not scattered randomly but rather show a systematic way of distribution and strongly implies the existence of spatial autocorrelation.

Figure 1

Spatial Distribution Map of the IFE



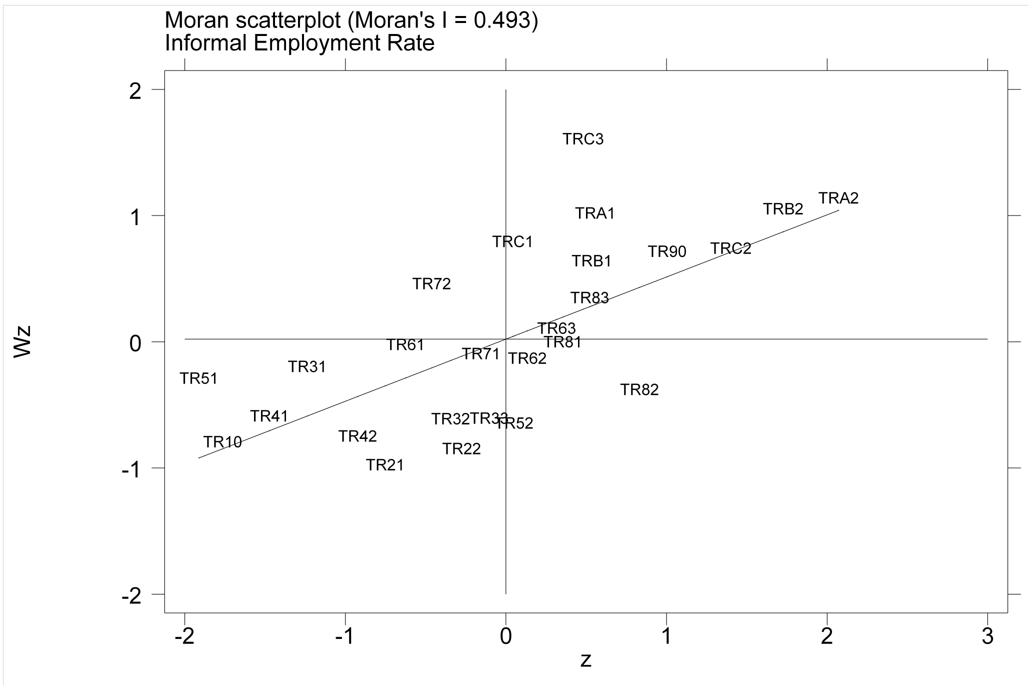
Source: Created by the authors in Stata 15.0

The Moran I statistic, which was introduced by Moran in 1950, is another common method for checking the existence of spatial autocorrelation. If the result of the Moran I test is significant and positive, then it implies that regions with high (or low) values are likely to be surrounded by areas with high (or low) values. When assessed locally, the test results provide region-specific information, whereas when evaluated globally, they provide insights into the overall spatial autocorrelation (Yerdelen Tatoğlu, 2022).

The presence and strength of the spatial autocorrelation can be visualised using a scatter plot. Figure 2 displays the scatter plot of the average IFE rates from 2009 to 2021. The observations mostly fall in the lower left (low in itself - low in its neighbours) and upper right (high in itself - high in its neighbours) regions of the diagram, suggesting the existence of potential spatial clusters related to IFE (Anselin et al., 2007).

Figure 2

Moran I Scatter Plot of the IFE



Source: Created by the authors in Stata 15.0

The Moran scatter plot only indicates clusters or outliers, lacking significance. Therefore, formal hypothesis testing must also be conducted (Anselin et al., 2007). The global Moran I index is calculated as follows:

$$I = \Sigma_{i=1}^{n} \Sigma_{j=1}^{n} W_{ij} \left(Y_i - \overline{Y}\right)\left(Y_j - \overline{Y}\right) / \Sigma_{i=1}^{n} \left(Y_i - \overline{Y}\right)^2 \quad (2)$$

where Y_i and Y_j describe the observations of the IFE in regions *i* and *j*, *n* represents the number of regions; $\overline{Y}$ is the average observation of the IFE, and W_{ij} is the spatial weight matrix. If the Z-score calculated from the Moran I index is positive, high and/or low values are spatially clustered (Yerdelen Tatoğlu, 2018).

$$Z = (I - E(I))/\sqrt{Var(I)} \quad (3)$$

In other words, the Moran I value being higher than the expected value $E(I) = -1/(n-1)$ confirms the presence of a positive spatial autocorrelation (Fisher & Wang, 2011).

Finally, in this section, Global Moran I statistics are examined to test the existence of spatial autocorrelation regarding IFE. The null hypothesis of the test statistic is "There is no spatial autocorrelation."

Table 2

Global Moran I Test Results for Spatial Autocorrelation

Years	I	E(I)	sd(I)	Z-score	p-value
2009	0.473***	-0.040	0.129	3.966	0.000
2010	0.533***	-0.040	0.130	4.420	0.000
2011	0.499***	-0.040	0.128	4.199	0.000
2012	0.492***	-0.040	0.129	4.141	0.000
2013	0.476***	-0.040	0.128	4.027	0.000
2014	0.550***	-0.040	0.129	4.572	0.000
2015	0.542***	-0.040	0.129	4.522	0.000
2016	0.411***	-0.040	0.129	3.511	0.000
2017	0.397***	-0.040	0.129	3.394	0.000
2018	0.339***	-0.040	0.128	2.955	0.002
2019	0.357***	-0.040	0.130	3.066	0.001
2020	0.491***	-0.040	0.130	4.097	0.000
2021	0.449***	-0.040	0.128	3.823	0.000
Avg.	0.493***	-0.040	0.129	4.134	0.000

Note: *** and ** denote statistical significance at the 1% and 5% level, respectively.

During the analysis period, a strong and positive spatial autocorrelation between the IFE rates of the regions in Türkiye was found, with a confidence level of 99%. This indicates that the rates tend to move together in neighbouring areas, and regions with similar rates are geographically clustered.

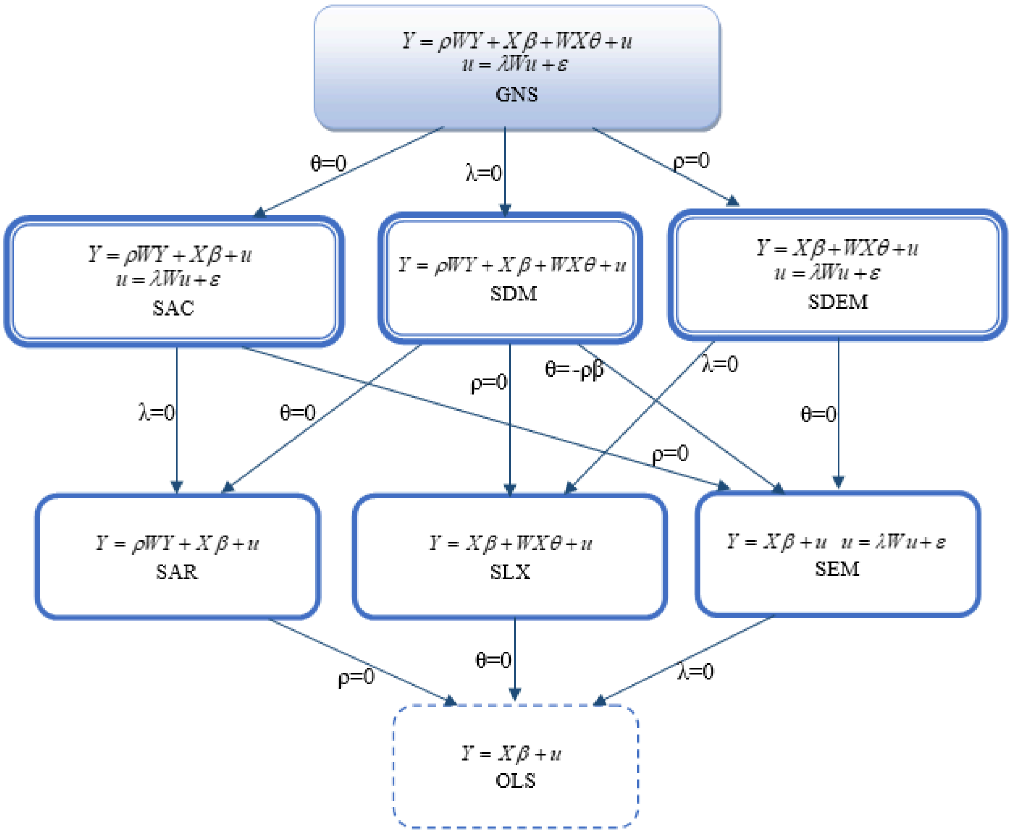
Spatial Panel Data Analysis

Spatial panel data models analyse time series data from various spatial units, such as districts, provinces, regions, and countries. Elhorst (2003) showed how spatial effects can be integrated into panel data models, leading to a rapid increase in studies in this field. An econometric model considering spatial effects may include a spatially lagged-dependent variable, a spatially lagged independent variable, or a spatial autoregressive process in the error terms. Figure 3 summarises eight linear spatial econometric models, among which are the nonspatial model at the bottom and the general nesting spatial model (GNS) at the top. Each model below the GNS model can be obtained by imposing restrictions on one or more of its parameters.

When deciding which model to use to estimate an equation with spatial effects, the standard approach in most empirical work is to start with a non-spatial linear regression model and then to test whether the model needs to be extended with spatial interaction effects. This approach is known as the specific-to-general approach (Elhorst, 2010b).

Figure 3

Spatial Econometric Models



Source: Yerdelen Tatoğlu, 2022.

If λ=θ=0, and ρ≠0, it is Spatial Autoregressive Model (SAR) accounts for the spatial dependence in the dependent variable and is shown as follows (Elhorst, 2010a; Fisher & Wang, 2011):

$$y_{it} = \rho \Sigma_{j=1}^{N} W_{ij} y_{it} + X_{it}\beta + \mu_i + \varepsilon_{it} \tag{4}$$

where i is an index for the cross-sectional dimension (spatial units), with i = 1,...,N, and t is an index for the time dimension, with t = 1,...,T. y_{it} is an observation on the dependent variable at i and t, X_{it} a 1-by-K row vector of observations on the independent variables, and β a matching K-by-1 vector of fixed but unknown parameters. ε_{it} is an independently and identically distributed error term for i and t with zero mean and variance σ^2, while μ_i denotes a spatial specific effect. ρ is called the spatial autoregressive coefficient, and W_{ij} is an element of the spatial weights matrix.

If ρ=θ=0 and λ≠0, it is Spatial Error Model (SEM) suggests that the dependent variable depends on a set of observed local characteristics and that the error terms are correlated across space. The spatially autocorrelated error term φ_{it} in the SEM model is:

$$\varphi_{it} = \lambda \Sigma_{j=1}^{N} W_{ij} \varphi_{it} + \varepsilon_{it} \tag{5}$$

where λ is called the spatial autocorrelation coefficient. In this case, the representation of the SEM model takes the form:

$$y_{it} = X_{it}\beta + \mu_i + \varphi_{it} \tag{6}$$

If the spatially lagged dependent variable and the spatial autoregressive error term are present together in the spatial model, $\rho \neq \lambda \neq 0$ and θ=0, it is called a Spatial Autoregressive Combined (SAC) model. In this case, the form of the SAC is as follows:

$$y_{it} = \rho \Sigma_{j=1}^{N} W_{ij} y_{it} + X_{it}\beta + \mu_i + \varphi_{it} \tag{7}$$

If a spatially lagged dependent variable and a spatially lagged independent variable are included in the spatial model, $\rho \neq \theta \neq 0$ and λ=0 it is called a Spatial Durbin Model (SDM) and takes the following form:

$$y_{it} = \rho \Sigma_{j=1}^{N} W_{ij} y_{it} + X_{it}\beta + \theta \Sigma_{j=1}^{N} W_{ij} X_{it} + \mu_i + \varepsilon_{it} \tag{8}$$

If $\lambda \neq \theta \neq 0$ and ρ=0, it is called a Spatial Durbin Error Model (SDEM) and takes the form:

$$y_{it} = X_{it}\beta + \theta \Sigma_{j=1}^{N} W_{ij} X_{it} + \mu_i + \varphi_{it} \tag{9}$$

Diagnostic Tests and Model Selection

Before selecting the appropriate spatial model, it should be examined whether the model has spatial effects (Yerdelen Tatoğlu, 2018). Since the test results show the presence of spatial effects (see Table 9 in the Appendix), the Hausman test was applied to choose between spatial fixed effects and spatial random effects (Elhorst, 2010a). The Hausman test statistic was obtained as 36.139 (p = 0.000). Therefore, the fixed-effects model is preferred, which will deal with omitted variable bias and control for cross-region heterogeneity.

For the selection of the appropriate spatial model, the Lagrange Multiplier (LM) and Likelihood Ratio (LR) tests are examined and given below in Table 3. The null hypothesis of the LM_λ test developed by Burridge (1880) is H_0: λ=0 and tests the spatial error dependence. LM_λ statistic is:

$$LM_\lambda = \left(\frac{e'We}{e'en^{-1}}\right)^2 \frac{1}{tr[W'W + W^2]} \tag{10}$$

where *tr* stands for the trace operator (the sum of the diagonal elements of a matrix), and $(e'en^{-1})$ represents the error variance.

The null hypothesis of the LM_ρ test developed by Anselin (1988b) is H_0: ρ=0 and tests spatial lag. LM_ρ statistic is:

$$LM_\rho = \left(\frac{e'Wy}{e'en^{-1}}\right)^2 \frac{1}{\left(WX\hat{\beta}\right)' M \left(WX\hat{\beta}\right) \hat{\sigma}^{-2} + tr[W'W + W^2]} \tag{11}$$

where $\hat{\beta}$ and $\hat{\sigma}^2$ denote OLS estimates, Wy is the spatial lag, $WX\hat{\beta}$ is a spatial lag for the predicted values $X\hat{\beta}$, and $M = \left[I - X(X'X)^{-1}X'\right]$ is a familiar projection matrix (Fisher & Wang, 2011). Robust LM test statistics developed by Anselin et al. (1996) are also reported.

The LR test is used to assess the spatial error and spatial lag together and separately. It is also used to test the significance of the spatially lagged independent variables. The following equations give the test statistic:

$$LR_{\rho\lambda} = -2\left[\hat{L} - \tilde{L}\right] \tag{12}$$

$$LR_\lambda = -2\left[\hat{L} - \tilde{L}\right] \tag{13}$$

$$LR_\rho = -2\left[\hat{L} - \tilde{L}\right] \tag{14}$$

$$LR_\theta = -2\,[\hat{L} - \tilde{L}] \tag{15}$$

$\hat{L}$ is the likelihood function of the model without the spatial effect. $\tilde{L}$ (12) represents the log-likelihood function of the unconstrained SAC model, $\tilde{L}$ (13) represents the log-likelihood function of the SEM model, $\tilde{L}$

(14) represents the log-likelihood function of SAR model and $\tilde{L}$ (15) represents the log-likelihood function of the SDM model (Burridge, 1980; Yerdelen Tatoğlu, 2022).

Table 3

Diagnostic Test Results

	Hypothesis	Test statistic	p-value
Global Moran I		0.1353***	0.0004
Moran I (Error)		3.4947***	0.0005
$LM_{\rho\lambda}$	H_0: ρ=λ=0	11.4952***	0.0032
LM_{λ}	H_0: λ=0	11.4932***	0.0007
Robust LM_{λ}	H_0: λ=0	11.4952***	0.0007
LM_{ρ}	H_0: ρ=0	0.0000	0.9949
Robust LM_{ρ}	H_0: ρ=0	0.0020	0.9642
$LR_{\rho\lambda}$	H_0: ρ=λ=0	21.6189***	0.0000
LR_{ρ}	H_0: ρ=0	0.1253	0.7233
LR_{λ}	H_0: λ=0	21.5191***	0.0000
LR_{θ}	H_0: θ=0	25.0899***	0.0001

Note: *** and ** denote statistical significance at the 1% and 5% level, respectively.

The Global Moran I test shows spatial autocorrelation in the model, but it does not provide information about the structure of spatial dependence (Anselin, 1988a). LM_{ρ} and LR_{ρ} test results show that there is no spatial lag in the model, while the LM_{λ} and LR_{λ} tests show that there is spatial error dependence. LR_{θ} test results show that the spatially lagged independent variables are significant. Therefore, the appropriate models to use in the analysis are the fixed effects SEM model with a spatially autocorrelated error term or the fixed effects SDEM model with a spatially autocorrelated error term and spatially lagged independent variables. To decide which model was appropriate, we performed two models and compared the information criteria and log-likelihood values.

Table 4

Model Selection Results

Criteria	SEM	SDEM
R^2	0,6999	0,7232
AIC	1750,725	1731,771
BIC	1785,132	1781,471
Log-likelihood	-866,3625	-852,8855

According to the model selection criteria, the model with the highest R^2 and log-likelihood and the lowest information criteria is the appropriate model. The results show that the fixed effects SDEM model offers a better fit to the data.

Results

Table 5 presents the estimation results obtained from the fixed effects SDEM model to determine the effects of macroeconomic variables on IFE. Model estimation was performed using the Stata 15 programme and the *xsmle* code suggested by Belotti et al. (2017). The determination coefficient for the model was found to be 0.72. Accordingly, the relevant independent variables explain 72% of the IFE in 2009-2021. The lambda coefficient (λ=0.19), which is the indicator of the spatial error dependence, is statistically significant and positive. The results indicate that the error terms are correlated, showing that the IFE rate in a specific region is influenced by the shocks that occur in neighbouring regions.

Table 5

Model Results

Variables	Coef.	Std. Err.	z	P>|z|
GDP	-16.264***	4.1156	-3.95	0.000
UNP	-0.2884***	0.0747	-3.86	0.000
INF	-0.3374	0.2419	-1.39	0.163
EXP	-0.4545**	0.1954	-2.33	0.020
TXB	-0.0355	0.1171	-0.30	0.762
C20	-3.2302***	0.9898	-3.26	0.001
C21	-4.7258***	1.2966	-3.64	0.000
wGDP	-14.2026***	4.6523	-3.05	0.002
wUNP	0.2284*	0.1255	1.82	0.069
wINF	0.5197**	0.2543	2.04	0.041
wEXP	-0.9357***	0.3384	-2.76	0.006
λ	0.1919***	0..0724	2.65	0.008
R^2	0.7232			

Note: *** and ** denote statistical significance at the 1% and 5% level, respectively.

The results indicate a negative and statistically significant correlation between the real GDP per capita, unemployment, public expenses, and IFE. In particular, an increase of 1% in the real GDP per capita leads to a decline of 0.16% in IFE. Likewise, a rise of 1% in the unemployment rate causes IFE to decrease by 0.29%, while an increase of 1% in the ratio of public spending to GDP results in a 0.45% drop in IFE. On the other hand, the tax burden and inflation were found to have no significant impact on IFE in this study. Besides, the results indicate that the IFE rates underwent a dramatic fall during the COVID-19 pandemic.

The investigation of the significant spatially lagged independent variables shows that the spatially lagged GDP per capita and public expenditures have a negative influence on IFE. Specifically, a 1% increase in the GDP per capita of neighbouring regions leads to a 0.14% decrease in IFE, while a 1% increase in the public expenditures of neighbouring regions results in a 0.93% decrease. Conversely, spatially lagged unemployment and inflation exhibit positive and statistically significant effects on IFE. While a 1% increase in the unemployment rate of neighbouring regions is associated with a 0.22% increase in IFE, a 1% increase in inflation of neighbouring regions corresponds to a 0.51% increase.

To check the robustness of the model estimation, we re-estimated it using an inverse distance matrix instead of a contiguity matrix. The results remained consistent, confirming the reliability of our findings (see Table 10 in the Appendix).

Discussion and policy recommendations

In countries at a lower economic level such as Türkiye, the issue of informality emerges as the main one that along with the negative effects on economic growth, income distribution, and public finance, becomes the major problem that countries have to face. This research brings together the main findings that are very important from the macroeconomic and geographical points of view while dealing with informal employment in Türkiye. The above-presented results indicate that the phenomenon of informality has its roots in the geographical effects and the movements of the regions. Consequently, the situation necessitates broader regionally specific policies aimed at reducing IFE.

The regional variations are of utmost importance in the comprehension of the IFE and its connection to the spatial dependency. Among the 26 regions of Türkiye, there are significant differences in economic development levels, labour market dynamics, and social policy practices. The Eastern and Southeastern Anatolia regions, where informality rates are particularly high, point to a strong connection between low economic development and limited social security access in these areas. According to the spatial error dependence coefficient retrieved from the analysis (λ = 0.19), the informality in one area is influenced by the economic and social circumstances of the adjacent areas. Therefore, it implies that not only national policies but also region-specific and local strategies are essential in the battle against informality.

The fact that real GDP per capita had a negative effect on IFE is an indication that development has been recognised as an effective method to reduce informality. A similar conclusion can be drawn from a number of studies in the literature (Munir & Pollin, 2009; Volchik et al., 2020; Caro & Nicotra, 2016; Hazans, 2011; Adekoya & Biala, 2023; Herwartz et al., 2015; Williams, 2014; Elgin & Uras, 2013; Vidović & Ritan, 2022; Bolukbas, 2018; Eralp, 2024; Celik et al., 2021; Dalgıc, 2023; Uslu, 2021). The presence of an adverse as well as a significant coefficient for spatially lagged GDP per capita points to the conclusion that economic development is the major factor contributing to the decline of informal labour, both directly and through spatial spillovers. It is necessary to mention that the effects noticed are not the same all over the country. The growth rates in the western (higher income) areas of Türkiye are much quicker than in the eastern (lower income) areas under informal economy reduction, although the latter may be much slower. This reality implies that regional disparities should be the target of economic growth policies. The differences among the regions also signify that the effect of economic growth on informality should be considered in conjunction with geographical, sectoral, and socio-economic factors.

The surprising adverse impact of the unemployment rate on IFE might be a consequence of the peculiar nature of the Turkish labour market. The current research contradicts the prevailing view of a positive correlation between the unemployment rate and the IFE trend. For instance, studies in Mexico (Ortiz & Torres, 2024) and EU countries (Herwartz et al., 2015) have evidenced that, conversely, higher unemployment brought about higher IFE. In the same manner, the national data by Çelik et al. (2021) and Dam et al. (2018) revealed that increased IFE is a byproduct of unemployment in Türkiye. On the contrary, Vidović and Ritan (2022) argue that in developing nations, the unemployment rate lowers IFE. In agreement with this hypothesis, Eralp (2022b) has shown a negative link between female/youth unemployment and IFE in Türkiye based on regional data. All these findings along with ours infer that in the areas where unemployment is high, certain demographic divisions tend to leave the labour market instead of taking up casual labour probably because they are discouraged or rely on social assistance. Or vice versa, the reverse relationship could mean that with unemployment going down, IFE is on the rise, thus reinforcing the argument that the informal sector in Türkiye alongside the formal sector functions is a common scenario in the case of developing countries. Moreover, lagged unemployment rates in the areas around have an amplifying effect on IFE, which agrees with the prevailing literature. Assuming complementarity between the formal and informal sectors, rising unemployment in neighbouring regions may shrink their formal sectors, thus reducing informal employment opportunities in those regions. As a result, informal workers may shift geographically, increasing the IFE in adjacent areas. Overall, particularly in Türkiye, where social security mechanisms show regional and sectoral differences, the complex dynamics underscore the importance of spatially disaggregated analysis to fully understand the multifaceted relationship between unemployment and informality.

The literature already had studies showing that there is no significant relationship between public expenditures and informal employment (Williams, 2014; Vidović & Ritan, 2022); however, our study found that the relationship was negative and significant. This means that government expenditures, especially those in social services and infrastructure, offer economic security to the individuals and therefore encourage them to join the formal labour market. In this case, for example, the government may invest in health, education, or infrastructure, which will lead the people to switch from informal to formal jobs as they will have access to sustainable and regulated employment. When the public expenditures are lagged spatially, they continue to experience a powerful effect of the IFE being reduced. Consequently, this indicates the possibility for government policies to revitalise the formal employment sector through the inter-regional positive spill-over effects. This conclusion requires the fiscal policies to be coordinated and evenly distributed among the regions to be effective in achieving the goal of formal employment and reduction of labour market informality.

The small impact of the tax burden on the informal sector and hence the need to study its relationship with the informal sector in the wider context of Türkiye was highlighted. Some authors have shown that the tax burden was an important factor for IFE (Ortiz & Torres, 2024; Caro & Nicotra, 2016), whereas others supported the opposite view (Nikulin, 2023; Williams, 2014). Inflation has been discussed as a factor in informal employment dynamics, with studies reporting different impacts: Çelik et al. (2021), Eralp (2022b), and Eralp (2024) presented a negative relationship, indicating that inflationary pressures might disturb informal sector activities. On the other hand, Dam et al. (2018) found no significant link between inflation and IFE, a finding that resonates with ours.

The analysis shows a negative relationship between inflation and IFE, which is, however, non-significant. The negligible local effect could be attributed to the nationwide and demand-driven character of inflation in Türkiye during the analysis period. If inflation affects the economy uniformly, it would reduce real wages and might even cause the entire economy to lose its stability. In such cases, there will be no relative movement of cost/benefit that could lead to a significant alteration in the formalisation incentives of a region. Nevertheless, the inflation variable is both positive and significant when examined through the spatial lag, meaning that macroeconomic instability in the neighbouring regions could lead to increased informal employment through spillover effects. This geographic result reveals a different mechanism whereby high inflation in a bordering area could act as a localised negative shock that might demoralise its formal sector and cause the workers to exit. This, in turn, can lead to a labour supply push into informality that crosses regional borders and thus increases IFE in nearby areas. This observation highlights that regional inflation shocks, even if not locally felt, can affect informality by causing economic instability and reducing formal job opportunities in nearby locations.

The findings imply that informal employment in both 2020 and 2021 was negatively and statistically significantly related to the COVID-19 dummy variables. Initially, this co-relates with the study by Eralp (2022b). The reason behind this could be that the pandemic led to the informal sector being temporarily suppressed mainly due to the public support that was exclusively meant for registered workers. In addition, the lockdowns and restrictions imposed on movements during the pandemic hit the informal sectors that were low in productivity and were contact-intensive the hardest, leading to a temporary shrinkage of informal activities. Thus, one could argue that this decline is not really a healthy formalisation of the informal sector but rather a distress-driven contraction of the same. The type of shock that occurred in the economy had the same fate on high-informality service sectors where the demand for such services was greatly reduced, while the policy support that was given to the formal sector was asymmetric and thus it was able to survive. In this case, the drop in IFE that was apparent can therefore be seen as a reflection of the harsh conditions under which the informal sector was living rather than the informal sector's transition to the formal sector being sustainable. Although some researchers have stated that the impact of COVID-19 on informal employment was limited or insignificant (Munir & Pollin, 2009; Adekoya & Biala, 2023), our research supports a larger effect. Particularly, the stronger negative impact seen in the year 2021 could be a sign of divergence in the recovery patterns: the formal sector actors, who were supported by the continuous public support, were quicker to recover, whereas the informal sector, due to the continued limitations on movement and lack of access to financial and institutional support, was experiencing the adverse impacts of the pandemic even more deeply.

Table 6

Hypothesis Results

Hypothesis	Variable	Direction	Prob.	Status
1: As GDP per capita increases, the IFE ratio decreases	GDP	(-)	0.000	Accepted
2: As the unemployment rate increases, the IFE rate increases	UNP	(-)	0.000	Rejected
3: As inflation increases, the IFE rate increases	INF	(-)	0.163	Rejected
4: As the tax burden increases, the IFE rate increases	TXB	(-)	0.261	Rejected
5: As public expenditures increase, the IFE rate decreases	EXP	(-)	0.024	Accepted
6: During the COVID-19 pandemic, the IFE rate decreased	C20 C21	(-) (-)	0.001 0.000	Accepted
7: The regional dynamics affected IFE in Türkiye	λ	(+)	0.000	Accepted

Source: Own work.

The findings on the macroeconomic determinants of IFE reveal that several factors, including economic growth, public expenditures, unemployment, and inflation, should be considered in policy design. Consequently, developing actionable and effective policy recommendations to reduce informality is crucial, particularly in developing countries such as Türkiye. Below are the policy recommendations derived from the insights of this study.

Economic Policies to Reduce Regional Disparities: Türkiye's economic growth strategies should prioritise reducing regional development disparities. Because of the contribution of economic development to reducing IFE, institutions that promote investment, especially in low-income regions, must be instituted. Development agencies must consider ways to create economic opportunities through top-priority investment in infrastructure that responds to the respective needs of the regions.

Enhancing Regional Data Collection and Analysis Capacity: The esoteric-driven and sometimes overlapped anti-informality being the crux of the data capacity in the regions, regional data collection and analysis capacity will have to be re-enforced in order to transform the labour market dynamics knowledge, and even more so, the understanding of informality's determinants. The establishment of regional-based data collection systems for capturing more precise and recent data, thus, will not only enable government decision-makers to draw "more accurate and efficient" policy interventions but also to come up with the "ones" fitted for the need of the situation.

Policies to Prevent Engagement in Informal Sectors: In the overall context of the unemployment fight, it is an already existing and practice-supported view that one of the more efficient measures would be the reduction of the recourse to informal sectors through the introduction of supportive policies. As a case in point, increasing the intensity with which the mechanisms of registered employment and tax and insurance premium cuts favour small- and medium-sized enterprises should be one of the first options. Also, the granting of benefits such as social security or job security to scare the registered sectors could be an approach to making them attractive. Furthermore, an in-depth study into the ways through which increasing unemployment rates reduce informality might well lead to the creation of such policies.

Macroeconomic Stability and Combating Informality: There is no doubt that macroeconomic stability is one of the most important factors that can really help in the process of the informal economy`s gradual disappearance. The anti-inflation strategies must be directed towards not only achieving price stability but also making the migration of the people to the formal sector lifecycle easier. Government spending should be restricted to such an extent that its impact on basic health and education service provision is not negative but rather increases their financial viability.

Effectiveness of Public Expenditures and Regional Differences: Given that public expenditures have a positive effect on the war against informality, a mix of policies should be adopted that will predominantly focus on social services and employment-creating projects in the low-income areas. In this aspect, the local government's empowerment through the provision of better resources to implement economic and social policies is deemed a positive move.

Revising Tax Policies to Encourage Formal Employment: In view of the limited impact of the current tax system on the fight against informality, it might be a good choice to review tax policies. The direction should be towards increasing the incentives for the businesses that are registered and coming up with the micro-level strategies to have the unregistered and non-insured workers enrolled and registered officially.

Sectoral and Regional Policies to Address Informality in the Aftermath of the Pandemic: A thorough assessment of the COVID-19 impact on IFE would be very beneficial to improving the protection of people in distress. We suggest that informal workers be made less vulnerable to economic shocks by providing support primarily for temporary income and initiatives for the transition to the formal sector as the main point.

Education and Skills Development Programmes: Workers in the formal sectors should be trained better so that they are more likely to get formal jobs. The organised skills training and vocational courses for the informal workers will open up the option of transferring to formal employment for the persons who have lost their jobs in that sector.

Digitalisation and the use of Technology: In the battle against informality, digitalisation and new technologies should be the primary methods used. The adoption of an e-government application can ensure the regular and transparent maintenance of the records of both employers and employees.

Enhancing Audit and Implementation Capacity: The labour inspections should be made more stringent to unearth the hidden workforce. The inspections should be carried out in such a way that they not only act as a deterrent but also help the employers to be incorporated into the formal system.

Strengthening Social Dialogue and Participation: A stronger social dialogue with employer and worker organisations in the policy-making process can accrue a common vision against informality. The local communities involved in this sphere can assist in making more inclusive policies.

The recommendations indicate the need for adopting a policy framework that is multi-faceted, spatially oriented, and inclusive to tackle the IFE issue. It is hoped that these policies will keep in line with the economic, social, and regional aspects of Türkiye and thus turn out to be an effective weapon against informality.

Conclusion

Through the use of a spatial panel method and a dataset consisting of 26 regions in Türkiye covering the period from 2009 to 2021, the study investigates the macroeconomic factors that influence IFE. The main objective of this study is to determine the effects of GDP per capita, unemployment, inflation, public expenditure, tax burden, and the COVID-19 pandemic on IFE and to explore their geographical dependence. A spatial weight matrix that considers neighbourhood relations was incorporated into the model to account for spatial dependency in the study, with the spatial Durbin error model (SDEM) being applied in the analysis.

The methodology and scope of the study are significant because they portray the applicability of spatial econometric methods in IFE analysis. The employed method indicated that informality is associated not only with socioeconomic variables but also with regional and spatial influences. Consequently, the research presents an original contribution to the literature by highlighting the role of spatial dependency.

The paper adds to the body of literature by conducting a spatial econometric analysis of informal employment in Türkiye, which is, though, a rather unexamined area, and the country has a significant difference in its various regions. The authors employed spatial panel data techniques to disclose the effects of interregional spillovers and the geographic dependency's impact on informality, which is contrary to previous studies that mostly depend on national-level or non-spatial models. Data at the NUTS-2 level has been used, which makes the analysis more detailed and gives an understanding of how macroeconomic factors are affecting IFE in different regional contexts more deeply. By considering spatial interactions within the modelling framework, this study provides new cutting-edge insights that connect national policy and local labour market situations.

The outcomes show the respective impact of real GDP, unemployment rate, public spending, and COVID-19 on the decrease in informality. No statistically significant impact was detected for the tax burden and inflation variables on IFE. With respect to the tax burden, it seems like the present tax system has inadequacies in dealing with informality. Nonetheless, the tax burden applied in this study is a general indicator and does not specifically show the tax pressure imposed on workers. When drawing the policy implications from the results, this difference should be considered. The analysis of spatial dependency indicates that the IFE rate in a certain area is influenced by the disturbances that take place in adjacent areas; thus, regional policies should be developed and implemented in a coordinated manner. There are also indications that the economic and social conditions of the neighbouring regions are influencing the IFE through the spillover effects of GDP per capita, unemployment, public expenditure, and inflation.

In the end, it can be concluded that the support given to the fight against the informal economy should come from economic growth and macroeconomic stability policies together with measures that aim to lower the differences between the regions. Policies that can be termed as multidimensional, such as giving bigger incentives for registered employment, channelling public expenditures to the areas of low-income, and fortifying the social protection mechanisms should be considered for the reduction of informality. Furthermore, it is believed that future research, which will be conducted on these relationships in a more comprehensive manner with wider datasets and different spatial techniques, will be a great contribution to the success of the fight against informality.

Limitations and directions for future research

This study provides important insights into the regional determinants of IFE in Türkiye; however, several limitations should be acknowledged. First, the analysis is constrained by data availability. The dependent variable (IFE) is officially published by SSI at the NUTS-2 level only for 2009–2021, which constrains both temporal coverage and spatial granularity. Türkiye currently lacks an alternative, consistent regional IFE series; as a result, extending the period with substitute proxies is not feasible without introducing substantial measurement error. Future work could explore microdata-based constructions or administrative records to refine the series. Public expenditures and the tax burden are modelled as aggregate measures to capture the macro-level footprint of fiscal policy. While appropriate for identifying the broad fiscal stance associated with informality, this choice necessarily abstracts from instrument-specific channels and may mask heterogeneous effects across functional (e.g., education, health, social protection, active labour market policies) and economic (consumption vs. investment) classifications on the expenditure side, and across tax instruments (e.g., PIT progressivity, CIT, SSCs, VAT, enforcement intensity) on the revenue side. Future work can disaggregate these components to pinpoint policy-relevant margins.

In terms of methodology, although a fixed-effects SDEM addresses spatial dependence and unobserved time-invariant heterogeneity, the results can be sensitive to outliers in IFE (see Eralp, 2024). However, spatial panel quantile methods are not widely implemented in standard software. For partial robustness, we re-estimated the model using an inverse-distance spatial weights matrix; the core results remain qualitatively similar. Future research could: (i) implement non-spatial panel quantile regressions as a complementary robustness check or (ii) develop novel approaches to extend quantile analysis into the spatial panel framework.

Furthermore, future studies could gain a lot by integrating differentiated labour market indicators such as part-time/full-time or sectoral employment dynamics, youth/elder unemployment patterns, and gender-specific unemployment rates that might display subtler relationships with informality. Besides, the analysis could be longitudinally conducted to identify the medium- and long-term structural effects of the COVID-19 pandemic, which could even contribute to the understanding of regional labour market dynamics.

Peer Review	Externally peer-reviewed.
Author Contributions	Conception/Design of study: G.N.E, B.K.; Data Acquisition: G.N.E, B.K; Data Analysis/Interpretation: G.N.E, B.K.; Drafting Manuscript: G.N.E, B.K.; Critical Revision of Manuscript: G.N.E, B.K.; Final Approval and Accountability: G.N.E, B.K; Technical or Material Support: G.N.E, B.K; Supervision: G.N.E, B.K
Conflict of Interest	The authors have no conflict of interest to declare.
Grant Support	The authors declared that this study has received no financial support.

Author Details

Gözde Nalbant Efe (Asst. Prof.)

[1] İstanbul Medeniyet University, Department of Public Finance, İstanbul, Türkiye

0000-0002-4651-2007 gozde.nalbant@medeniyet.edu.tr

Berat Kara (Asst. Prof.)

[1] İstanbul Medeniyet University, Department of Public Finance, İstanbul, Türkiye

0000-0002-6948-2197 berat.kara@medeniyet.edu.tr

References

Acar, S., Bilen Kazancık, L., Meydan, M. C. & Işık, M. (2019). *İllerin ve bölgelerin sosyo-ekonomik gelişmişlik sıralaması araştırması SEGE-2017.* Ankara: T.C. Sanayi ve Teknoloji Bakanlığı Kalkınma Ajansları Genel Müdürlüğü Yayını, Sayı: 3.

Adekoya, O. I., & Biala, M. I. (2023). Impact of governance and economic factors on informal employment in West Africa. *Malete Journal of Accounting and Finance, 3*(1), 265-287. https://majaf.com.ng/index.php/majaf/article/view/77

Aikaeli, J. and Mkenda, B. (2013). Determinants of informal employment: A case of Tanzania construction industry. http://dx.doi.org/10.2139/ssrn.2706021

Anselin, L. (1988a). *Spatial econometrics. Methods and models*. Kluwer Academic Publishers. doi:10.1007/978-94-015-7799-1

Anselin, L. (1988b). Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity. *Geographical Analysis, 20*(1), 1-17. https://doi.org/10.1111/j.1538-4632.1988.tb00159.x

Anselin, L., Bera, A. K., Florax, R. and Yoon, M. J. (1996). Simple diagnostic tests for spatial dependence. *Regional Science and Urban Economics, 26*(1), 77-104. doi:10.1016/0166-0462(95)02111-6

Anselin, L., Le Gallo, J. and Jayet, H. (2008). Spatial panel econometrics In L. Mátyás & P. Sevestre (Eds.), *The econometrics of panel data: Fundamentals and recent developments in theory and practice* (3rd ed., pp. 625-660). Springer. https://doi.org/10.1007/978-3-540-75892-1_19

Anselin, L., Sridharan, S. and Gholston, S. (2007). Using exploratory spatial data analysis to leverage social indicator databases: The discovery of interesting patterns. *Social Indicators Research, 82*(2), 287-309. doi:10.1007/s11205-006-9034-x

Basol, O., & Yalcin, E. C. (2020). İstanbul'da kayıt dışı istihdamın sosyo-demografik belirleyicileri. *Anadolu Üniversitesi Sosyal Bilimler Dergisi, 20*(4), 173-190. doi:10.18037/ausbd.845773

Belotti, F., Hughes, G., Mortari, A.P. (2017). Spatial panel-data models using Stata. *The Stata Journal, 17*(1), 139-180. doi: 10.1177/1536867X1701700109

Benavides, F. G., & Silva-Peñaherrera, M. (2022). Informal employment, precariousness, and decent work: From research to preventive action. *Scand J Work Environ Health, 48*(3), 169-172. doi:10.5271/sjweh.4024

Bolukbas, M. (2018). Kayıt dışı istihdam ve genç işsizlik ekonomik büyüme ile ilişkili olabilir mi? Türkiye için ekonometrik bir analiz. *Sosyal Güvenlik Dergisi (Journal of Social Security), 8*(2), 75-90. https://doi.org/10.32331/sgd.492902

Bosch, M., Goñi-Pacchioni, E. and Maloney, W. (2012). Trade liberalization, labor reforms and formal-informal employment dynamics. *Labour Economics, 19*(5), 653–667. doi:10.1016/j.labeco.2012.03.001

Burridge, P. (1980). On the cliff-ord test for spatial correlation. *Journal of the Royal Statistical Society: Series B (Methodological), 42*, 107-108. doi: 10.1111/j.2517-6161.1980.tb01108.x

Caro, P. D., & Nicotra, G. (2016). Short, long and spatial dynamics of informal employment. *Regional Studies, 50*(11), 1804-1818. doi:10.1080/00343404.2015.1072274

Celik, R., Keskin, A., & Keskin, A. (2021). Türkiye'de ekonomik büyüme, işsizlik ve enflasyonun kayıt dışı istihdam üzerindeki etkisi: ARDL sınır testi yaklaşımı. *Journal of Social Policy Conferences, 80*, 451-474. https://doi.org/10.26650/jspc.2021.80.000053

Charmes, J. (2016). The informal economy: Definitions, size, contribution and main characteristics. In E. Kraemer-Mbula & S. Wunsch-Vincent (Eds.), *The informal economy in developing nations: Hidden engine of innovation?* (pp. 13-52). Cambridge University Press. doi:10.1017/CBO9781316662076.006

Dalgic, Y. (2023). *Türkiye'de istihdamın kayıt dışılığını etkileyen faktörler: Sektörel ve bölgesel etkilere yönelik ampirik bir analiz.* [Unpublished doctoral dissertation]. Bursa Uludağ University

Dam, M. M., Ertekin, S., & Kizilca, N. (2018). Türkiye'de kayıt dışı istihdamin boyutu: Ekonometrik bir analiz. *Dokuz Eylül Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 33*(1), 293-318. doi:10.24988/deuiibf.2018331725

Dereli, T. (2011). Informal employment in Turkey. *Journal of Social Policy Conferences, 53*, 65-82. https://dergipark.org.tr/en/download/article-file/9280

Elgin, C., Erturk, F. (2019). Informal economies around the world: Measures, determinants and consequences. *Eurasian Economic Review, 9,* 221-237. https://doi.org/10.1007/s40822-018-0105-5

Elgin, C., Uras, B. R. (2013). Public debt, sovereign default risk and shadow economy. *Journal of Financial Stability*, 9, 628-640. http://dx.doi.org/10.1016/j.jfs.2012.09.002

Elhorst, J. P. (2003). Specification and estimation of spatial panel data models. *International Regional Science Review, 26*(3), 244-268. doi: 10.1177/0160017603253791

Elhorst, J. P. (2010a). Spatial panel data models. In M. M. Fischer & A. Getis (Eds.), *Handbook of applied spatial analysis. Software tools, methods and applications* (pp. 377-408). Springer. https://doi.org/10.1007/978-3-642-03647-7_19

Elhorst, J.P. (2010b). Applied spatial econometrics: raising the bar. *Spatial Economic Analysis, 5*(1), 9-28. https://doi.org/10.1080/17421770903541772

Eralp, A. (2022a). Türkiye'de kayıtlı ekonomi ile kayıt dışı istihdam oranı arasındaki ilişkinin sektörler itibarıyla incelenmesi. *Üçüncü Sektör Sosyal Ekonomi Dergisi, 57*(2), 1027-1039. https://doi.org/10.15659/3.sektor-sosyal-ekonomi.22.05.1801

Eralp, A. (2022b). Türkiye'de kayıt dışı istihdamın belirleyicileri: Panel veri analizi yaklaşımı. In E. A. Kaplan (Ed.), *İktisatta güncel gelişmeler: panel veri uygulamaları* (pp. 19-39). Gazi Kitabevi.

Eralp, A. (2024). Türkiye'de kayıt dışı istihdam üzerinde ekonomik büyüme, işsizlik ve enflasyonun etkisi: panel kantil regresyon yaklaşımı. *Ankara Hacı Bayram Veli Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 26*(1), 79-102. https://doi.org/10.26745/ahbvuibfd.1399901

Fischer, M. M., & Wang, J. (2011). *Spatial data analysis. Models, methods, and techniques*. Springer. https://doi.org/10.1007/978-3-642-21720-3

Gumprecht, D. (2005). *Spatial methods in econometrics: An application to R&D spillovers*. Department of Statistics and Mathematics, WU Vienna University of Economics and Business, Research Report Series No. 26. https://doi.org/10.57938/39f720e6-61c9-40fd-a88b-ec1a3a83fe12

Hazans, M. (2011). *What explains the prevalence of informal employment in European countries: The role of labour institutions, governance, immigrants, and growth.* The World Bank Europe and Central Asia Region Human Development Economics Unit, Policy Research Working Paper, WPS5917. Retrieved February 15, 2024, from http://documents.worldbank.org/curated/en/186571468023

366551/What-explains-prevalence-of-informal-employment-in-European-countries-the-role-of-labor-institutions-governance-immigrants-and-growth

Herwartz, H., Tafenau, E., Schneider, F. (2015). One share fits all? Regional variations in the extent of the shadow economy in Europe. *Regional Studies, 49*(9), 1575-1587. https://doi.org/10.1080/00343404.2013.848034

Ihrig, J., & Moe, K. S. (2001). Tax policies and informal employment: The Asian experience. *Asian Economic Journal, 15*(4), 369-383. https://doi.org/10.1111/1467-8381.00150

International Labour Organisation (ILO). (2015). *Recommendation 204. Recommendation concerning the transition from the informal to formal economy*. Retrieved November 5, 2024, from https://www.ilo.org/sites/default/files/wcmsp5/groups/public/%40ed_norm/%40relconf/documents/meetingdocument/wcms_377774.pdf

International Labour Organisation (ILO). (2018). *Women and men in the informal economy: A statistical picture (Third Edition)*. Retrieved November 8, 2024, from https://www.ilo.org/sites/default/files/2024-04/Women_men_informal_economy_statistical_picture.pdf

International Labour Organisation (ILO). (2023). *Women and men in the informal economy: A statistical update*. Retrieved November 8, 2024, from https://www.ilo.org/sites/default/files/wcmsp5/groups/public/@ed_protect/@protrav/@travail/documents/publication/wcms_869188.pdf

Jonasson, E. (2011). Informal employment and the role of regional governance. *Review of Development Economics, 15*(3), 429–441. doi:10.1111/j.1467-9361.2011.00618.x

Joshi, A., Prichard, W. and Heady, C. (2014). Taxing the informal economy: The current state of knowledge and agendas for future research. *The Journal of Development Studies, 50*(10), 1325-1347. https://doi.org/10.1080/00220388.2014.940910

Karaarslan, E. (2010). *Kayıt dışı istihdam ve neden olduğu mali kayıpların bütçe üzerindeki etkileri: Türkiye örneği.* [Unpublished master's thesis]. Gazi University.

Kutbay, H. (2018). Kayıt dışı istihdamın vergi gelirleri üzerindeki etkisi. *Social Sciences Research Journal, 7*(2), 172-189. https://socialsciencesresearchjournal.blogspot.com/p/2018-0702.html

Lehmann, H. and Pignatti, N. (2007). *Informal employment relationships and labour market segmentation in transition economies: evidence from Ukraine.* IZA Discussion Paper Series, No. 3269. https://www.econstor.eu/handle/10419/34879

LeSage, J. P. and Pace, R. K. (2010). Spatial econometrics models. In M. M. Fisher & A. Getis (Eds.), *Handbook of applied spatial analysis. Software tools, methods and applications* (pp. 355-374). Springer. https://doi.org/10.1007/978-3-642-03647-7_18

Ministry of Treasury and Finance. (2023). *Government finance statistics*. Retrieved December 12, 2023 from https://en.hmb.gov.tr/government-finance-statistics

Moran, P. A. P. (1950). A test for the serial independence of residuals. *Biometrika, 37*(1/2), 178-181. https://doi.org/10.2307/2332162

Munir, J. and Pollin, M. (2009). Informal sector, inflation level and economic growth rate for the period 1970-2005 in the economy of Malaysia. *Journal of the Informal Sector, 24*, 19-25.

Nikulin, D. (2023). Driving forces of informal employment: An empirical study based on Polish enterprise data. *Entrepreneurial Business and Economics Review, 11*(3), 93-106. doi:10.15678/EBER.2023.110306

Organisation of Economic Co-operation and Development (OECD) & International Labour Organisation (ILO). (2019). *Tackling vulnerability in the informal economy*. Development Centre Studies, OECD Publishing. doi:10.1787/939b7bcd-en

Organisation of Economic Co-operation and Development (OECD). (2023). *Informality and globalisation: In search of a new social contract*. OECD Publishing. doi:10.1787/c945c24f-en

Organisation of Economic Co-operation and Development (OECD). (2024). *Breaking the vicious circles of informal employment and low-paying work*. OECD Publishing. doi:10.1787/f95c5a74-en

Ortiz, D. R., & Torres, R. A. A. (2024). Informal employment, the tertiary sector, and the gross domestic product: A structural equations model for the Mexican economy. *Economies, 12*(11), 301. doi:10.3390/economies12110301

Ozturk, S., & Basar, D. (2018). Türkiye'de kadınların işgücü piyasasına yönelik tercihleri: Kayıt dışı sektör özelinde bir analiz. *Sosyal Güvenlik Dergisi (Journal of Social* Security), *8*(2), 41-58. doi:10.32331/sgd.492887

Rogan, M. (2019). *Tax justice and the informal economy: A review of the debates*. Women in Informal Employment: Globalising and Organising (WIEGO) Working Paper, No 41. https://www.wiego.org/sites/default/files/publications/file/Rogan_Taxation_Debates_WIEGO_WorkingPaperNo41_2020.pdf

Social Security Institution (SSI). (2022). *Kayıt dışı istihdam oranları*. Retrieved April 23, 2022, from http://eski.sgk.gov.tr/

Social Security Institution (SSI). (2024). *Kayıt dışı istihdam nedir?* Retrieved October 29, 2024, from https://www.sgk.gov.tr/Content/Post/e3f8021f-6c7e-49a7-a51a-51d79a187ada/Genel-Bilgi-2024-01-15-11-17-08

Sultana, N., Rahman, M. M., & Khanam, R. (2022). Informal sector employment and economic growth: Evidence from developing countries in SDG perspective. *Sustainability, 14,* 11989. doi:10.3390/su141911989https://doi.org/10.3390/su141911989

Tansel, A. and Acar, E. O. (2016). *The formal/informal employment earnings gap: Evidence from Turkey*. *Research on Economic Inequality, 24,* 121-154. http://dx.doi.org/10.1108/S1049-258520160000024006

Tansel, A., Keskin, H. I., & Ozdemir, Z. A. (2020). Is there an informal employment wage penalty in Egypt? Evidence from the quantile regression on panel data. *Empirical Economics, 58,* 2949-2979. doi:10.1007/s00181-019-01651-2

Tobler, W. R. (1970). A computer movie simulating urban growth in the detroit Region. *Economic Geography, 46,* 234-240. doi:10.2307/143141

Torgler, B. and Schneider, F. (2007). *Shadow economy, tax morale, governance and institutional quality: A panel analysis*. Centre for Research in Economics, Management and the Arts (CREMA) Working Paper, No. 2007-02, Basel. https://hdl.handle.net/10419/214376

Turkish Statistical Institute. (2023). *Regional statistics*. Retrieved September 28, 2023 from https://biruni.tuik.gov.tr/bolgeselistatistik/sorguGiris.do

Uslu, H. (2021). Türkiye'de kayıt dışı istihdamın vergi geliri ve ekonomik büyüme üzerindeki etkileri: ampirik bir analiz. *Ömer Halisdemir Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 14*(4), 1222-1250. https://doi.org/10.25287/ohuiibf.845770

Vidović, N., & Ritan, V. (2022). New Approach to Estimating Macroeconomic Determinants of Informal Employment. *Economics, 10*(2), 95-108. https://doi.org/10.2478/eoik-2022-0012

Volchik, V., Maslyukova, E., & Strielkowski, W. (2020). Spatial effects of informal employment and precarization in urban centres and regions. *Theoretical and Empirical Researches in Urban Management, 15*(4), 21-37. https://www.jstor.org/stable/26955972 [accessed on 23.11.2024]

Williams, C. C. (2014). Explaining crossnational variations in the prevalence and character of undeclared employment in the European Union. *European Spatial Research and Policy, 21*(2), 115-131. doi:10.1515/esrp-2015-0008

Williams, C. C., & Kayaoglu, A. (2020). COVID-19 and undeclared work: Impacts and policy responses in Europe. *The Service Industries Journal, 40*(13–14), 914–931. doi:10.1080/02642069.2020.1757073

Yerdelen Tatoglu, F. (2018). *İleri panel veri analizi* (3rd ed.). Beta Yayınları.

Yerdelen Tatoglu, F. (2022). *Mekansal ekonometri*. Beta Yayınları.

Appendix

See Table 7, Table 8, Table 9, and Table 10

Table 7

Descriptive Statistics on the Explanatory Variables

Variables	Number of obs.	Mean	S.d.	Min.	Max.
IFE	338	42.71	13.87	13.96	78.62
GDP	338	9.57	0.40	8.55	10.59
UNP	338	10.69	4.74	3.4	33.5
INF	338	10.76	4.27	4.18	23.2
EXP	338	14.59	7.35	3.03	37.17
TXB	338	9.83	8.84	2.23	44.46

Source: Own work

Table 8

Variance inflation factor test results

Variables	VIF	1/VIF
GDP	3.14	0.318120
UNP	1.26	0.792151
INF	2.10	0.476234
EXP	2.11	0.474177
TXB	1.94	0.516680
C20	1.10	0.908909
C21	1.81	0.551684
Avg.	**1.92**	

Source: Own work

Table 9

Spatial Effects Test Results

	Test statistics	p-value
Breusch-Pagan LM Test	443.7873	0.0000
Breusch-Pagan ALM Test	278.0729	0.0000
Sosa-Escudero-Yoon LM Test	21.0663	0.0000
Sosa-Escudero-Yoon ALM Test	16.6755	0.0000

Source: Own work

Table 10

Model results with inverse distance matrix

Variables	Coef.	Std. Err.	z	P>|z|
GDP	−15.531***	4.3289	−3.59	0.000
UNP	−0.2767***	0.0764	−3.62	0.000
INF	−0.3691	0.2489	−1.48	0.138
EXP	−0.4451**	0.1968	−2.26	0.024
TXB	−0.0475	0.1184	−0.40	0.689
C20	−3.362***	0.9887	−3.40	0.001

Variables	Coef.	Std. Err.	z	P>|z|
C21	−4.8408***	1.2922	−3.75	0.000
wGDP	−14.5599***	4.8195	−3.02	0.003
wUNP	0.2360*	0.1294	1.82	0.068
wINF	0.5350**	0.2628	2.04	0.042
wEXP	−0.9765***	0.3418	−2.86	0.004
λ	0.1891***	0.1008	1.87	0.061
R^2	0.7232			