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Mapping the geographical patterns of suicide mortality rates in Iran: An analysis of socioeconomic factors and spatial dependence

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Abstract: Suicide is a complex issue that affects many regions globally, and the factors that contribute to it can differ based on geographical and cultural contexts. In this study, we examine the relationship between socioeconomic factors and suicide mortality rates across 31 provinces in Iran, using data from 2020. We employ spatial econometric methods to analyze the data, allowing us to explore the statistical relationships between economic models and regional science. Our analysis reveals a significant clustering of suicide mortality in some western provinces, as shown by the distribution map of suicide mortality by province. We also find that the unemployment rate has a significant impact on suicide mortality. These findings provide valuable information for developing effective prevention strategies.

Keywords: Geographic Analysis; Spatial Autocorrelation; Spatial Econometrics; Spillover Effect; Suicide Mortality.
Mathematics Subject Classification (2010): 62Hxx, 62H11

1 Introduction

Suicide is a major global public health concern, with the World Health Organization reporting nearly 800,000 deaths annually (World Health Organization, 2023). Among individuals aged 10-24 years, suicide is one of the top three leading causes of death (Patton et al., 2009). Suicide and self-harm rank 18th in terms of disability-adjusted life years (DALYs) lost, and while global suicide rates have decreased since the 1990s, there are still certain countries and age groups where rates have not improved or

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have even increased (Murray et al., 2012). However, recent evidence suggests that the contribution of self-harm to DALYs lost has decreased by 17% between 2005 and 2015, and deaths caused by self-harm have decreased by over 16% from 1980 to 2015 (Sha et al., 2017).

Notably, suicide rates are high in certain countries, including Russia, Estonia, Latvia, Lithuania, Sri Lanka, Korea, and Cuba (Bertolote and Fleischmann, 1998). In the Eastern Mediterranean Region (EMR), suicide rates are lower than the global average, but the prevalence of mental disorders such as depression and anxiety is higher (Malakouti et al., 2015). The most common methods of suicide in the EMR are hanging, self-poisoning, and self-immolation (Morovatdar et al., 2013).

Iran has also experienced a growing concern with suicide in recent decades, with a significant increase in the number of cases reported (Naghavi et al., 2014). According to the Global Burden of Diseases study in 2015, suicide is one of the top ten leading causes of years of life lost in Iran (Moradi-Lakeh et al., 2017). In 2015, the estimated rate of suicide was about five deaths per 100,000 population (Izadi et al., 2018). A study by Mahdavi et al. (2020) revealed gender and age differences in suicide mortality rates in Iran, with men accounting for over 71% of cases, and young women aged 29-30 and adult men aged 30-59 being identified as vulnerable subgroups. These findings underscore the need for targeted suicide prevention efforts aimed at these subgroups in Iran.

Research on suicide has been conducted by various disciplines, including medicine, psychology, and public health (Yeom, 2019). Recent studies have focused on examining suicide beyond the individual level, taking into account social, economic, political, and religious factors across different populations (Maris, 2002). Factors associated with suicide vary across geographical and cultural regions, and lower socioeconomic status may have a positive or negative relationship with suicide rates, depending on the location. Understanding the associations related to suicide is crucial in Iran, given that similar studies have been conducted in other countries (Rehkopf and Buka, 2006; Iemmi et al., 2016).

In Iran, a high percentage of suicides occur in urban areas (83%) and among the unemployed (79.9%), including housewives, students, and unemployed men. While suicide rates by age in Iran are unclear, those between 15 and 65 years old appear to be at the highest risk (Sharif-Alhoseini et al., 2012). Marital problems and family conflicts are the most common factors associated with suicide among Iranian families (Nazarzadeh et al., 2013).

The aim of this research is to investigate the impact of socio-demographic and economic factors on suicide mortality rates in Iran, both at the provincial and intra-provincial levels. This study specifically focuses on the spatial variability in suicide rates among provinces in 2020. The variables of interest include the divorce rate, urbanization rate, unemployment rate, literacy rate, consumer price index, labour force participation rate, and the proportion of the population aged 15-24. To increase the reliability of our findings, we will employ spatial econometric models and compare our results with previous studies that have examined the association between these variables and suicide Spatial regression models are important when analyzing data that exhibit spatial dependence, which means that the relationships between observations depend on their spatial location. Even if spatial processes are not the primary focus, spatial methods may be necessary to obtain reliable estimators. The reason for this is that everything in space is connected, but things that are closer together are more closely related than things that are farther apart (Tobler, 1970). This means that observations cannot be treated as independent and identically distributed, which is a standard assumption of linear regression. When this assumption is violated, the conventional ordinary least squares (OLS) estimate of $\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{\varepsilon}$ produces incorrect inferential statistics. Therefore, spatial regression models are useful for accounting for spatial dependence and producing more accurate estimates.

Spatial regression models provide a way to explicitly model the spatial dependence present in the data. A common approach is to use a spatial autoregressive model (SAR) that includes a spatially lagged dependent variable $\boldsymbol{Wy}$ and a spatial weights matrix $\boldsymbol{W}$. The spatial relation between error terms can also be modeled using a spatial error model (SEM) or spatial lag model (SLX), and further combinations of these models can be used to capture more complex spatial relationships. For instance, a spatial Durbin model (SDM) combines an autoregressive dependent variable with spatially lagged covariates, while a spatial Durbin error model (SDEM) includes a spatial error term along with spatially lagged covariates. A general nesting spatial model (GNS) combines all three spatial terms ($\boldsymbol{Wy}$, $\boldsymbol{Wu}$, and $\boldsymbol{WX}$). These models are useful when observations cannot be considered independent and identically distributed due to spatial dependence. The R statistics and econometric package program was used to perform the analysis (Rüttenauer, 2022).

This article is structured in the following manner: Section 2 provides an overview of suicide mortality rate data with a descriptive analysis. A comprehensive description of the spatial econometric models used in our analysis is presented in section 3. The results obtained by selecting the most appropriate model are discussed in Section 4. Lastly, we draw conclusions from our study.

2 Data description

Data on suicide mortality were gathered from reports published by the Iranian Forensic Medicine Organization (IFMO), which is associated with the Iranian Judicial Authority. The IFMO maintains a national suicide registry and performs autopsies on all recorded suicide cases. Suicide rates per 100,000 people were calculated by province.

The Statistical Center of Iran collected data on socio-demographic and economic variables, including divorce rate, urbanization rate, unemployment rate, literacy rate among individuals aged 6 and older, consumer price index, labour force participation rate, and the proportion of people aged 15-24, for all 31 provinces in Iran. The data focus on the year 2020 since it is the most recent year for which all data were available.

To determine the factors influencing suicide mortality rates per 100,000 population (y), an econometric model will be established using methods that account for spatial correlations. These factors are represented by variables X_1 through X_7. As provinces are the unit of analysis, there may be neighbourhood relations between them, resulting in a spatial correlation between the residuals.

Table 1 presents a descriptive analysis of the dependent and independent variables. In 2020, the average suicide mortality rate was 7.55 (3.60) per 100,000 residents between the 31 provinces. The proportion of people aged 15-24 exhibited strong asymmetry and

Table 1: Summary statistics of dependent and independent variables.

Variable	Minimum	Mean	Maximum	SD	Skewness	Kurtosis
y	2.78	7.55	16.73	3.60	0.99	0.54
X_1	71	210.1	289	48.89	-0.55	0.63
X_2	51.70	71.59	95.59	11.68	0.47	-0.39
X_3	2.70	7.48	12.60	2.63	0.15	-0.99
X_4	76	86.42	92.90	3.55	-0.53	1.14
X_5	233.10	254.70	2886.6	13.64	0.72	-0.21
X_6	33.80	43.95	54.40	5.43	0.06	-0.61
X_7	85	436.6	2018	406.35	2.4	7.08

kurtosis, requiring a logarithm conversion. Mild skewness and kurtosis were observed in other variables.

Figure 1 illustrates the variation in suicide mortality rates across the provinces, which are listed below: 1. Zanjan, 2. Yazd, 3. West Azerbaijan, 4. Sistan and Baluchestan, 5. Semnan, 6. Qom, 7. Ghazvin, 8. Mazandaran, 9. Markazi, 10. Lorestan, 11. Kurdistan, 12. Kohgiluyeh and Boyer Ahmad, 13. Khuzestan, 14. South Khorasan, 15. Razavi Khorasan, 16. North Khorasan, 17. Kermanshah, 18. Kerman, 19. Ilam, 20. Hormozgan, 21. Hamedan, 22. Golestan, 23. Gilan, 24. Fars, 25. Isfahan, 26. East Azerbaijan, 27. Chaharmahal and Bakhtiari, 28. Bushehr, 29. Ardebil, 30. Alborz, 31. Tehran.

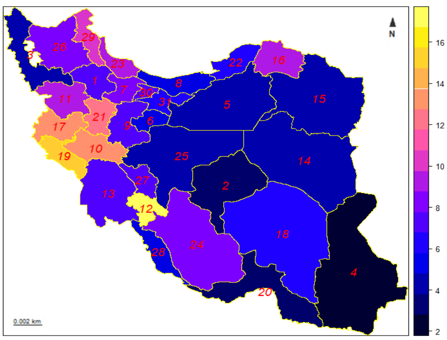


Figure 1: Geographic distribution of suicide mortality rates across provinces in Iran in 2020.

In the data set presented in Figure 1, there are a large number of low-valued data points and only a few high-valued data points. Kohgiluyeh and Boyer Ahmad provinces had the highest average accused subject input ratio at 16.73, while Sistan and Baluchestan had the lowest at 2.78 accused subjects per 100,000 population, making them the provinces with the highest and lowest ratios in the country, respectively

Based on these data, it can be inferred that the distribution of suicide mortality in Iran in 2020 was not even. In Table 2, Moran's I is independently calculated for each of the 7 variables, assessing the spatial clustering of suicide mortality rates based on each variable individually. It indicates the spatial dependence coefficient of inter-province, ranging from -1 to 1 (Lottmann, 2012). In this study, we examined the 31 provinces that affect suicide mortality rates and their factors based on spatial dependencies.

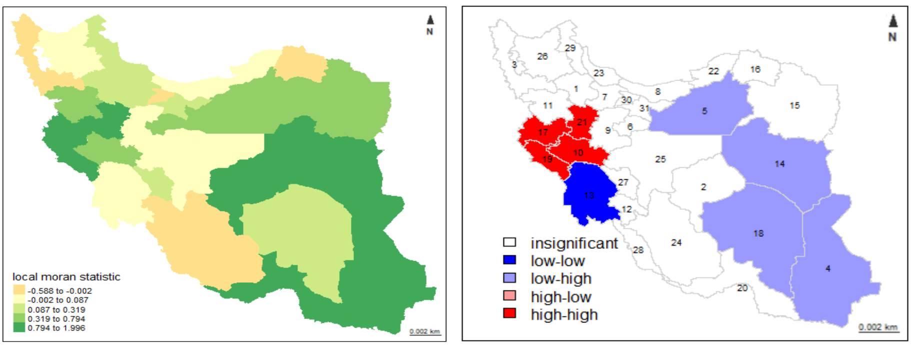
According to Table 2, the global Moran's I index is positive and significant for suicide mortality rates, divorce rates, urbanization rates, unemployment rates, literacy rates, consumer prices, and labour force participation rates in the general population aged 6 and older. Therefore, it can be concluded that suicide mortality in Iran has a spatial autocorrelation.

Table 2: Global Moran's I.

Variable	Moran's I statistic	p-value
y	0.342	0.000***
X_1	0.401	0.000***
X_2	0.258	0.004***
X_3	0.115	0.091*
X_4	0.302	0.001***
X_5	0.172	0.030**
X_6	0.276	0.002***
X_7	-0.185	0.943

*Significance code: $p < 0.1$. ** Significance code: $p < 0.05$. *** Significance code: $p < 0.01$

The analysis of local statistical indicators reveals that Lorestan, Kermanshah, Ilam, and Hamedan are the provinces with the highest suicide rates, making them the nation's suicide mortality hotspots. The high-high relationship (in red) demonstrates a positive and statistically significant correlation between suicide mortality rates in neighbouring provinces, while the high-low and low-high relationships indicate the opposite. This finding is consistent with the strong spatial autocorrelation of suicide mortality rates in Iran, as indicated by the positive and significant global Moran's I index for suicide mortality rates and other related factors (Table 2). Moreover, Khuzestan is the coldest province based on the data displayed in Figure 2.



(a) Local Moran Map (b) Hotspot Analysis

Figure 2: Assessment of local spatial autocorrelation in suicide mortality rates for 2020.

3 Analytical strategy

Spatial data analysis is a complex field that requires consideration of two main issues: spatial dependence and spatial heterogeneity (Anselin et al., 1998). Spatial dependence refers to the idea that observations in spatial data are not independent and can influence one another based on their proximity. Spatial heterogeneity, on the other hand, refers to the idea that the relationships between variables can vary across different spatial locations.

These two issues are often overlooked in traditional econometric models, which assume that observations are independent and that the relationships between variables are constant across space. To address these issues, spatial econometric models are used, which take into account spatial dependence and heterogeneity in the data. Unlike conventional econometric models that rely on OLS estimation, spatial econometric models require more specialized estimation techniques to properly account for these factors.

To determine the spatial relationship between units of observation and identify their neighbours, the researcher needs to specify the spatial relationship between the units of observation, denoted as $i = 1, 2, ..., N$. This is accomplished by constructing a weight matrix, $\boldsymbol{W}$, with all elements $w_{ij} > 0$ for all neighbouring units i and j $(i \neq j)$ and 0 otherwise. In this study, a row-normalized contiguity weights matrix is used, which considers units that share at least one border as neighbours. There are several specifications for $\boldsymbol{W}$, such as k nearest neighbour or distance-based approaches (see Dubin, 2009), and choosing the correct specification can make a significant difference. However, these aspects have been extensively discussed elsewhere (Elhorst and Halleck Vega, 2017), so we focus on the model specifications, assuming a correctly specified $\boldsymbol{W}$ (using a standardized queen contiguity weight matrix as in Farzammehr and Moradi (2022)).

Besides the above-discussed aspects, there are several ways to model spatial dependence (for a comprehensive introduction, see e.g. Rüttenauer, 2022). The most widely used spatial model specification is the SAR, where an endogenous regressor is included on the right-hand side of the equation. The SAR model is defined as

$$\boldsymbol{y} = \rho \boldsymbol{W} \boldsymbol{y} + \boldsymbol{X} \boldsymbol{\beta} + \boldsymbol{\varepsilon}.$$

where $\boldsymbol{y}$ is an $N \times 1$ vector of the dependent variable, $\boldsymbol{W}$ as defined above, $\boldsymbol{X}$ an $N \times K$ matrix of $k = 1, 2, ..., K$ covariates, and $\boldsymbol{\varepsilon}$ an $N \times 1$ vector of normally distributed disturbances. The parametric estimate $\boldsymbol{\beta}$ represents a $K \times 1$ vector, while the autoregressive scalar parameter ρ represents the scalar parameter of the autoregressive model. According to this SAR specification, the dependent variable of unit i is directly influenced by the spatially weighted dependent variable of unit j.

The SEM is an alternative specification of spatial models that accounts for spatial autocorrelation between the disturbances $\boldsymbol{u}$ through the inclusion of a scalar parameter λ. The SEM can be defined as

$$\begin{aligned} \boldsymbol{y} &= \boldsymbol{X} \boldsymbol{\beta} + \boldsymbol{u}, \\ \boldsymbol{u} &= \lambda \boldsymbol{W} \boldsymbol{u} + \boldsymbol{\varepsilon}. \end{aligned}$$

In this specification, we assume that spatial correlation among the units arises from features that exhibit spatial clustering or follow spatial patterns, independent of the covariates included in our model.

A third approach to modeling spatial dependence is to not incorporate it as an autoregressive term in the dependent variable or error term, but to model it directly by including spatially lagged covariates in the equation. The SLX for $\boldsymbol{X}$ is defined as

$$\boldsymbol{y} = \boldsymbol{X} \boldsymbol{\beta} + \boldsymbol{W} \boldsymbol{X} \boldsymbol{\theta} + \boldsymbol{\varepsilon},$$

where $\boldsymbol{\theta}$ is an $K \times 1$ vector of spatial spillover parameters. In addition to accounting for the direct effects of covariates, the model incorporates indirect spillover effects from neighbouring units' covariates. It is worth mentioning that the SLX model comprises spatial effects for each covariate, which are included in the $\boldsymbol{\theta}$ vector.

The three fundamental specifications of spatial models mentioned earlier can be combined to form more advanced models. For instance, the spatial autoregressive combined model (SAC) is a combination of an autocorrelated dependent variable and an autocorrelated disturbance, leading to:

$$\begin{aligned} \boldsymbol{y} &= \rho \boldsymbol{W} \boldsymbol{y} + \boldsymbol{X} \boldsymbol{\beta} + \boldsymbol{u}, \\ \boldsymbol{u} &= \lambda \boldsymbol{W} \boldsymbol{u} + \boldsymbol{\varepsilon}. \end{aligned}$$

In contrast, the SDM combines the spatial spillover specification of the covariates with the spatial autoregressive term of the dependent variable, yielding:

$$\boldsymbol{y} = \rho \boldsymbol{W} \boldsymbol{y} + \boldsymbol{X} \boldsymbol{\beta} + \boldsymbol{W} \boldsymbol{X} \boldsymbol{\theta} + \boldsymbol{\varepsilon}.$$

A third model integrates SEM and SLX specifications, resulting in a SDEM:

$$\begin{aligned} \boldsymbol{y} &= \boldsymbol{X} \boldsymbol{\beta} + \boldsymbol{W} \boldsymbol{X} \boldsymbol{\theta} + \boldsymbol{u}, \\ \boldsymbol{u} &= \lambda \boldsymbol{W} \boldsymbol{u} + \boldsymbol{\varepsilon}. \end{aligned}$$

Hence, the model incorporates both the spatial spillover effects of the covariates and an autocorrelated disturbance term. Combining all three fundamental model specifications results in a GNS Model:

$$\begin{aligned} \boldsymbol{y} &= \rho \boldsymbol{W} \boldsymbol{y} + \boldsymbol{X} \boldsymbol{\beta} + \boldsymbol{W} \boldsymbol{X} \boldsymbol{\theta} + \boldsymbol{u}, \\ \boldsymbol{u} &= \lambda \boldsymbol{W} \boldsymbol{u} + \boldsymbol{\varepsilon}. \end{aligned}$$

The GNS specification combines all the spatial processes of the previous specifications. However, unbiased point estimates of the true parameters can be obtained using identifiable models.

The use of least squares (LS) to estimate most spatial model specifications is not possible because constrained LS estimators tend to produce inconsistent results for models with spatially lagged dependent variables or disturbances (Franzese and Hays, 2007). However, unbiased point estimates of the true parameters can be obtained using identifiable models. Spatial models provide an alternative approach for researchers to estimate spatial spillover coefficients and gain insight into spatial correlations. In our study, we employed all the mentioned models to examine the influence of socio-demographic and economic factors on suicide mortality rates across provinces, and to distinguish between spatial variations observed among provinces.

4 Model selection

As demonstrated in the preceding section, the non-spatial OLS estimates may exhibit bias under specific spatial dependence conditions. Consequently, the compelling need for spatial regression models arises, enabling us to account for the spatial intricacies within the data. Given the importance of discerning the spatial structure in our analysis, we explore various spatial model specifications detailed in section 3. It is imperative for applied researchers to meticulously select the most appropriate model specification to ensure the accuracy of their findings. To address this selection process, empirical specification tests become a pivotal tool. Spatial econometrics often adopts the specificity-to-generality approach, commencing with the simplest non-spatial model and progressively assessing potential misspecifications arising from omitted autocorrelation. In this context, Anselin et al. (1996) have introduced robust Lagrange multiplier (LM) tests for the hypotheses $H_0 : \lambda = 0$ and $H_0 : \rho = 0$. These tests are resilient against alternative sources of spatial dependence and form the basis for distinguishing among models, specifically SAR, SEM, and non-spatial OLS models (Florax et al., 2003).

A fundamental step in ascertaining the suitable spatial model specification is testing the residuals of the OLS for spatial dependence using the LM diagnostic tests. This approach is instrumental in the process of model selection (Baltagi et al., 2012) and informs the inclusion of geographic attributes in our modeling process. From the LM diagnostic tests conducted across five models, the most appropriate model specification was determined to be a combination of rho (ρ) and lambda (λ). This discovery is pivotal since spatial correlation and the influence of covariates on our models are intricate, demanding a thorough understanding of model performance. Our aim is to achieve this through comprehensive model descriptions and subsequent discussions related to model selection. Table 3 offers a detailed account of the diagnostic tests for spatial dependence conducted using the LM method.

Table 3 showcases the results of our diagnostic tests for spatial dependence, conducted through the LM method. These tests are paramount in discerning the presence and significance of spatial autocorrelation within our dataset. The LM statistics encapsulate the essence of these tests, examining various aspects of spatial dependence within the residuals of our models. The p-values associated with these statistics provide a measure of their statistical significance, with lower values indicating higher significance. The results of these tests collectively underline the undeniable presence of spatial autocorrelation within our dataset, solidifying the need for tailored model specifications to draw precise inferences from our data. As the spatial correlation and covariate influence on our models are complex factors, it is important to provide a comprehensive understanding of the models' performance, which we aim to achieve through the detailed model descriptions and subsequent model selection discussion.

Table 3: Diagnostic test of spatial dependence using the LM method.

LM	Statistics	p-value
Moran's I	0.182	0.004^{***}
LMerr	2.323	0.001^{***}
LMlag	5.446	0.020^{**}
RLMerr	4.498	0.038^{**}
RLMlag	3.622	0.047^{**}
SARMA	5.944	0.041^{**}

5 Results and discussion

In this section, we present the findings and delve deeper into the statistical nuances of our investigation into the relationship between various socio-economic factors and suicide mortality rates across different regions in Iran using spatial econometric models. The results, as summarized in Table 4, include a comparison of multiple models, with a focus on the GNS mixed model due to its lowest Akaike Information Criterion (AIC), signifying its superior fit. The GNS model effectively captures spatial dependencies in both the dependent variable and residuals, unveiling critical spatial patterns in suicide mortality across Iran.

Table 4: Results of spatial econometric models.

	OLS	SAR	SEM	SLX	SAC	SDM	SDEM	GNS
				Direct effects				
Intercept	12.495	13.591	13.163	84.288	14.159	85.561	-54.845	-63.614
X_1	0.027*	0.026**	0.030**	0.041	0.025**	0.042**	0.059***	0.057***
X_2	0.048	0.007	0.002	0.013	0.008	0.017	0.105*	0.098*
X_3	-0.092	-0.125	-0.178	0.081	-0.114	0.107	0.094	0.051
X_4	-0.304	-0.221	-0.199	-0.122	-0.223	-0.116	-0.116	-0.137
X_5	0.103**	0.074*	0.073*	0.034	0.073*	0.033	0.097**	0.096**
X_6	-0.087	-0.143	-0.106	-0.164	-0.146	-0.156	0.040	0.042
X_7	-1.63**	-1.464**	-1.281**	-2.646*	-1.490**	-2.746***	-3.367***	-3.162***
				Indirect effects				
$\boldsymbol{W}\times X_1$				-0.003		-0.001	-0.024	-0.027
$\boldsymbol{W}\times X_2$				0.118		0.118	-0.140	-0.141
$\boldsymbol{W}\times X_3$				1.145		1.273*	3.628***	3.413***
$\boldsymbol{W}\times X_4$				-0.540		-0.548	1.030	1.075
$\boldsymbol{W}\times X_5$				-0.055		-0.058	-0.260**	0.240**
$\boldsymbol{W}\times X_6$				-0.007		-0.001	0.588*	0.574*
$\boldsymbol{W}\times X_7$				-3.020		-3.250	-2.68	-2.052
ρ		0.498			0.546	-0.078		0.120
λ			0.533		0.123		1.487	1.489
AIC	163.55	159.64	161.79	164.56	161.59	166.51	156.16	156.01

An essential discovery from the GNS model is the presence of significant and positive spatial effects, as indicated by the values of ρ and λ. This implies a spatial link in the distribution of suicide mortality rates across Iranian provinces, validating the earlier spatial autocorrelation analysis. The ρ value of 0.120 denotes a positive effect of the spatial lag of the dependent variable, indicating that provinces with higher suicide mortality rates tend to influence their neighbours. Furthermore, the positive λ value of 1.489 represents a significant impact of the spatial lag of the residual. These findings emphasize the necessity of considering spatial interdependencies when analyzing suicide mortality in Iran.

Now, let's explore the effects of individual socio-economic factors on suicide mortality rates and the significance of these findings:

Divorce Rate (X_1):

The GNS model reveals that the divorce rate (X_1) has a significant and positive effect on suicide mortality rates in Iranian provinces. The coefficient of 0.057 implies that a one-unit increase in the divorce rate results in a 0.057-unit increase in suicide mortality rates. This finding underscores the need for a comprehensive understanding of the socio-economic factors that contribute to suicide, highlighting divorce rates as a key variable to consider in suicide prevention strategies.

Urbanization Rate (X_2):
The positive and statistically significant impact of urbanization rate (X_2) on suicide mortality rates, with a coefficient of 0.098, points to the role of urbanization in affecting mental health and suicide outcomes. This finding highlights the importance of urban development policies that address the unique challenges posed by urban environments.
Unemployment Rate (X_3):
In contrast, the unemployment rate (X_3) does not demonstrate a statistically significant impact on suicide mortality rates. The non-significant coefficient of 0.051 suggests that regional unemployment rates might not be as influential in shaping suicide mortality rates as other factors.
Literacy Rate (X_4):
The literacy rate (X_4) emerges as a significant protective factor, with a coefficient of -0.137. This suggests that higher literacy rates are associated with lower suicide mortality rates. Education, therefore, plays a role in mitigating suicide risk, emphasizing the importance of investing in educational initiatives for suicide prevention.
Consumer Price Index (X_5):
The consumer price index (X_5) exhibits a positive and statistically significant impact on suicide mortality rates. The coefficient of 0.096 indicates that increasing consumer prices are linked to higher suicide mortality. This finding underscores the need for prudent economic and inflation management, particularly concerning its impact on mental health and suicide prevention.

Our analysis extends to explore the presence and influence of spillover effects, an aspect often overlooked in traditional analyses. The GNS model uncovers the following spatial spillover dynamics:
Unemployment Rate (X_3) - Positive Spatial Spillovers:
The positive spatial spillover effect of the unemployment rate (X_3) is striking, with an estimated coefficient of 3.413. This suggests that improving unemployment rates in a specific province positively impacts neighbouring regions, possibly through economic and social spillover mechanisms. These insights can guide policies focused on reducing unemployment to consider not only local but also regional impacts.
Consumer Price Index (X_5) and labour Force Participation Rate (X_6) - Positive Spatial Spillovers:
Both the consumer price index (X_5) and labour force participation rate (X_6) exhibit positive spatial spillovers. This implies that changes in these variables in one province have a favorable effect on adjacent regions.

To conclude, our study employs spatial econometric models to provide an in-depth understanding of the intricate relationship between socio-economic factors and suicide mortality rates across regions in Iran. The findings underscore the significance of spatial dependencies and emphasize the spatial linkages in the distribution of suicide mortality. We observe the multifaceted impact of socio-economic factors, with divorce rates and urbanization showing significant positive associations with suicide mortality rates, while higher literacy rates exhibit a protective effect. Moreover, our investigation unveils the presence of spatial spillover effects, indicating that changes in socio-economic factors in one province can significantly impact neighbouring regions. This interconnectedness underlines the need for a coordinated approach to policy-making and suicide prevention. These insights contribute to the foundation of knowledge in the field of mental health and suicide prevention in Iran and serve as a valuable resource for future research and policy development. They reinforce the understanding that suicide prevention efforts should extend beyond individual-level interventions to address the complex interplay of socio-economic factors and spatial dependencies.

6 Conclusions

In this comprehensive analysis, we have effectively determined the most suitable model specifications for scrutinizing the intricate relationship between unemployment rates and a range of socioeconomic variables vis-à-vis suicide mortality in Iran for the year 2020. Our findings underscore the profound influence of spatial interdependence within this context, revealing the far-reaching impact of socioeconomic factors on suicide mortality rates in adjacent regions. Through the GNS model, we have unveiled a compelling insight: the augmentation of the workforce in one province exerts a positive spillover effect on neighbouring provinces, further solidifying the web of connectivity in this complex issue. These results inherently emphasize the indispensability of acknowledging the spatial dynamics of suicide mortality rates when devising and implementing policies directed at ameliorating suicide rates in Iran. It is evident that strategies and interventions cannot be confined to provincial boundaries. Regional collaboration and holistic approaches are imperative to effectively address this multifaceted concern. Additionally, our research has shed light on the pivotal role that similar background structures may play in shaping suicide rates across regions. This calls for an in-depth exploration of the protective factors against suicide and a comparative analysis of suicide prevention strategies in adjacent areas.

The implications of this study extend beyond the realm of academia, permeating into the domains of policy formulation and healthcare practices. By elucidating the complex interplay between socioeconomic factors and suicide mortality, our findings provide a robust foundation for evidence-based interventions. Policymakers and healthcare practitioners in Iran now have a valuable resource to inform their decision-making processes. It is our fervent hope that this study contributes to the ongoing endeavours to curtail suicide rates and enhance mental health outcomes across the nation.

Nevertheless, this work represents a snapshot in time, focusing on the year 2020. Suicide rates are subject to dynamic changes influenced by multifarious factors. Consequently, we advocate for further research that delves into the evolving nature of the relationship between socioeconomic determinants and suicide mortality rates over time. The knowledge we have amassed should serve as a launchpad for continued exploration, fostering a deeper understanding of this critical issue and promoting data-driven solutions for years to come.

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