Advances in Management & Applied Economics, Vol. 13, No. 6, 2023, 171-188
ISSN: 1792-7544 (print version), 1792-7552(online)
https://doi.org/10.47260/amae/1369
Scientific Press International Limited

Analyzing the Impact of the Labor Market on Company Location Selection Using Spatial Econometric Models

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Abstract

This study employed spatial econometric models to analyze the company registration site selection in various counties and cities of Taiwan from 2002 to 2021 and examined its correlation with the labor market. The results revealed that over the past two decades, the number of company registrations in Taiwan has consistently risen, with a growth rate of 60.61%. Metropolitan areas such as Taipei City, New Taipei City, Taichung City, Kaohsiung City, and Taoyuan City took the lead in terms of registration numbers. Furthermore, the study found that local labor market factors and spatial spillover effects significantly influence company location decisions. Specifically, using the spatial Durbin model, it was discovered that an increase in unemployment rates negatively impacts company registrations in neighboring counties and cities; growth in employment numbers has a positive overall effect on company registrations; a rise in the proportion of industrial workers may be detrimental to company startups; a higher proportion of employees with tertiary education positively affects company registrations; an increase in the proportion of employed individuals aged 45 to 64 negatively impacts company registrations. The research findings offer valuable insights for policymakers, assisting in the creation of a more conducive entrepreneurial environment.

JEL classification numbers: C31, J21.
Keywords: Spatial autocorrelation, Spatial Dubin model, Spillover effects, Labor market, Number of companies.

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Article Info: *Received:* August 8, 2023. *Revised*: September 4, 2023.
Published online: September 11, 2023.

1. Introduction

Previous studies have highlighted the indispensable role of a company's geographic location choice in corporate strategy (Kim, 2019; Li et al., 2022; Meng, Wei and Sun, 2020; Rico, Cantarero and Puig, 2021). In fact, the right location choice is considered a core element underpinning corporate success (Ferreira, Fernandes and Raposo, 2017) and has a decisive impact on a company's long-term survival and development direction (Yong, 2006).

While past literature has delved deeply into the significance of location factors, there remains a noticeable gap in the study of spatial effects on the number of company registrations in Taiwan. This research seeks to bridge this gap, focusing on the impact of the labor market on corporate location choices. A robust labor market has long been considered a key factor influencing business location choices because the supply and quality of labor directly relate to operational efficiency and market competitiveness, as shown by Akin and Seyfettinoglu (2022); Csiki, Horvath and Szasz (2019); Hecht, 2017; Mariotti, Mosconi and Piscitello (2019). Regrettably, past studies on Taiwanese company location decisions have predominantly centered on industrial or financial dimensions, largely overlooking the labor market perspective. Accordingly, we chose to study from the viewpoint of the labor market, aiming to reveal its specific impact on company registration numbers across Taiwanese counties and cities. We hope this research can provide a more comprehensive reference for related policies.

The choice of a company's business location exhibits clear spatial dependence, suggesting that business activities don't operate in isolation but are influenced by their geographically adjacent areas. In other words, company registration numbers and location strategies in an area can differ due to local and neighboring environmental factors and spillover effects. However, traditional econometric methods often assume the subjects under study are independent, typically overlooking the influence of spatial interdependencies, potentially leading to model errors and result instability (see Anselin, 1988, 1995; LeSage and Pace, 2009). Using spatial econometric methods to investigate factors influencing company location choices can address these issues and plug gaps in earlier research. Our research particularly focuses on the labor market, being a pivotal determinant in corporate location strategies. Unfortunately, studies on this theme, considering spatial econometric methods, remain sparse. Thus, our research aims to break this boundary, delving deeper into how spatial elements influence company registration distribution and changes.

Spatial econometrics, as a burgeoning branch of economics in recent years, can elucidate the relationship between physical space and economic behavior more holistically, taking into account spatial correlation and mutual influences (Elhorst, 2001, 2010). By analyzing through spatial econometric models, we can describe and predict company registration distribution changes and trends across counties more precisely, aiding businesses in making more informed location and operational decisions. Moreover, the outcomes of this research can be valuable for government agencies in crafting regional economic policies and businesses in formulating investment decisions.

2. Literature Review

2.1 Factors influencing company location

In spatial econometric model analysis studying the influence of the labor market on the growth of company numbers, the geographical location's significance to company location is a key factor (Holl and Rama, 2016; Mariotti, Piscitello and Elia, 2010). Generally, geographic location factors include:

1. Labor Market Scale: Companies tend to select regions with larger labor markets to establish headquarters or branches to select suitable talent from a plethora of job-seekers. The geographical location significantly impacts a company's location choices as it directly affects the quality and quantity of labor they can recruit.
2. Transportation Accessibility: The importance of location to a company is manifested in transportation convenience. Companies typically favor areas with good transportation to reduce logistics costs, shorten transportation times, and increase efficiency. Furthermore, easily accessible areas are more attractive to consumers and clients, facilitating business expansion.
3. Industry Agglomeration Effect: The importance of location to companies is also evident in industry agglomeration. Companies tend to establish bases in clusters related to their industry, making it easier to access industry information, innovative technology, and specialized talent. Firms within industry clusters can also cooperate to share resources, lower production costs, and enhance market competitiveness.
4. Policy Support and Tax Incentives: Government policy support and tax incentives influence company location choices across regions. Firms often opt for regions with tax breaks and policy support to reduce operational costs and boost profitability.
5. Living Costs and Quality: The significance of location also entails living costs and quality. When choosing a location, companies consider the living costs and quality of life for their employees to attract and retain top talent. Areas with lower living costs and higher quality of life are more attractive for companies and employees, supporting long-term growth.
6. Market Demand and Consumption Level: Companies need to thoroughly consider local market demand and consumption levels when selecting a location. Companies should analyze consumer groups' characteristics, consumption habits, and purchasing power to ensure business success.
7. Environment and Infrastructure: Firms also take into account local environmental conditions and infrastructure when choosing a location. A favorable natural environment and robust infrastructure positively impact business operations, enhancing corporate image and fostering a conducive business environment.

8. Business Competition and Collaboration: Location importance is also reflected in terms of business competition and cooperation. Companies need to consider the competitive landscape in a region, choosing a market with balanced competition to avoid resource wastage due to excessive competition. Simultaneously, building collaborative relationships with other firms to share resources is crucial for mutual benefit.

In conclusion, the importance of geographical location for company siting is multifaceted, spanning factors like the scale of the labor market, transportation accessibility, industry agglomeration effects, policy support and tax incentives, living costs and quality, market demand and consumption level, environment and infrastructure, as well as business competition and collaboration. This study primarily focuses on the influence of labor market factors on company location decisions.

2.2 Research hypotheses

This study primarily focuses on the influence of the labor market, examining its direct and indirect effects on the growth of companies in both the local and adjacent regions. In this context, the exploration of spatial spillover effects or spatial competition effects is particularly crucial.

The development of businesses is intricately linked to their location, especially in the context of agglomeration economies. According to Akin and Seyfettinoglu (2022), the market size, labor quality, and geographical conditions of large cities or medium-sized regions make them prime locations for businesses. Moreover, Mariotti et al. (2019) emphasize that the specialized local labor market also serves as a driving force behind agglomeration economies. Csiki, Horvath and Szasz (2019) argue that while infrastructure is a primary location factor, regional innovation capacity and labor market efficiency are indispensable. Hecht (2017) explored more broadly how regional characteristics, including agglomeration economies, geographical distance, and labor market characteristics, impact the location choices of investors. Lo et al. (2010) found that China, with its vast and rapidly growing market, abundant low-cost labor, and extensive territory, has become one of the primary choices for investments and factory establishments for advanced Asian economies. Walcott (2001) delved into the role of location in business location strategies, illustrating how local attributes alter the strategies of high-tech companies. Chatzoglou et al. (2018) contend that choosing an appropriate factory location is among the most vital decisions a company makes. Their findings suggest that cost concerns (land, production process, raw materials, and labor), market characteristics (size and future growth prospects), and infrastructure are primary factors influencing investors' decisions.

Given the literature, the significance of the labor market in business location decisions is evident (see Akin & Seyfettinoglu, 2022; Csiki et al., 2019; Hecht, 2017; Mariotti et al., 2019). Against this backdrop, this study has formed the following hypotheses:

Hypothesis 1: The local county's labor market (including unemployment rate, employed population, proportion of employees in the industrial sector, proportion of employees with tertiary education or above, proportion of employees aged 45-64, and total working hours) has a significant impact on the growth of companies in that county.
Hypothesis 2: The labor market of adjacent counties (including unemployment rate, employed population, proportion of employees in the industrial sector, proportion of employees with tertiary education or above, proportion of employees aged 45-64, and total working hours) significantly affects the growth of companies in the local county.

The influence of the labor market on business location decisions is undeniable. The objective of these hypotheses is to further understand the impact of the regional labor market on company registrations, especially differentiating and comparing local effects with those from nearby regions. This aims to provide empirical evidence to assist policymakers, entrepreneurs, and investors in making better company location decisions.

3. Methodology

3.1 Data and sample

The data scope of this study covers a lengthy span of 20 years, from 2002 to 2021, and encompasses comprehensive information for Taiwan's 22 counties and cities. The primary data source comes from the Important Statistical Indicator Query System of the Statistical Information Network of the Republic of China, which is a public and credible official statistical resource. Its accuracy and credibility are widely acknowledged.
In our analysis of the company registration numbers across various counties and cities in Taiwan from 2002 to 2021, it is evident that the municipalities lead in terms of company registrations. This includes cities like Taipei, New Taipei, Taichung, Kaohsiung, and Taoyuan. These municipalities have maintained a leading position in the number of company registrations over these two decades. From 2002 to 2021, there's been a significant upward trend in the number of registered companies in Taiwan. In 2002, there were approximately 588,493 companies in Taiwan. This number continuously grew from 2002 to 2006, witnessed a decline between 2007 and 2008, but then resumed its growth. By 2021, the number of registered companies in Taiwan had risen to 736,889. These data suggest that Taiwan's economic development didn't stagnate due to short-term economic challenges but rather demonstrated strong resilience and vitality.
In 2020, the global pandemic of COVID-19 had a massive impact on the world's economy. However, even under such circumstances, the number of registered companies in Taiwan continued to grow, reaching a new peak of 720,293 in 2020. This underscores the robustness and vitality of Taiwan's economy. By 2021, even as the pandemic persisted, the number of company registrations in Taiwan

continued to rise, further highlighting the resilience and dynamism of Taiwan's economy.

3.2 Research variables

The definitions and explanations for the dependent and independent variables in this study's empirical model are described as follows:
Dependent Variable:
Number of Company Registrations (NC_{it}): Refers to the number of new companies registered in the ith county/city of Taiwan in the tth year, in accordance with the company law.
Labor Market-Related Independent Variables:

1. Unemployment Rate (%) (UR_{it}): Refers to the percentage of unemployed population relative to the labor force in the ith county/city of Taiwan in the tth year. The unemployed are defined as those aged 15 and above who, during the reference week: (1) are without work, (2) are available for work, and (3) are seeking employment or waiting for results. Additionally, it includes those waiting to return to work and those who have found jobs but have not yet started and are not getting paid. The formula is: (Number of Unemployed / Total Labor Force) × 100.
2. Employment Population (in thousands) (EP_{it}): Refers to the population aged 15 and above in the ith county/city of Taiwan in the tth year who are engaged in paid work or unpaid family labor for 15 hours or more.
3. Proportion of Employees in Industrial Sector (%) ($PEIS_{it}$): Refers to the percentage of employees working in industries including mining, manufacturing, electricity, water, and construction out of the total employed in the ith county/city of Taiwan in the tth year. The formula is: (Number of Industrial Employees / Total Employed Population) × 100.
4. Proportion of Employees with College or Higher Education (%) ($PECE_{it}$): Refers to the percentage of employees with a college degree or higher education out of the total employed in the ith county/city of Taiwan in the tth year. The formula is: (Number of Employees with College or Higher Education / Total Employed Population) × 100.
5. Proportion of Employees Aged 45-64 (%) ($PEAA_{it}$): Refers to the percentage of employees aged 45 to 64 out of the total employed in the ith county/city of Taiwan in the tth year. The formula is: (Number of Employees Aged 45-64 / Total Employed Population) × 100.
6. Total Working Hours ($\ln TWH_{it}$): Refers to the sum of actual working hours of workers employed by units designated by the competent central authority under the Occupational Safety and Health Act, and workers directed or supervised by the person in charge at the workplace in the ith county/city of Taiwan in the tth year. For salespersons or other business travelers, whose hours are difficult to determine, they are typically estimated at an average of 8 hours per day; standby workers, with the employer's consent, may have their hours calculated as regular

workers. For this study, the natural logarithm of total working hours is taken for subsequent model analysis.

3.3 Empirical model

In spatial econometrics, LeSage and Pace (2009) proposed the Spatial Durbin Model (SDM) that incorporates both lagged dependent variables and lagged independent variables. The Spatial Durbin Model integrates the characteristics of the spatial lag model and the spatial error model, thereby reflecting spatial effects more accurately for spatial panel data. Based on this, our study establishes the following empirical model:

$$
\begin{aligned}
NC_{it} = \rho \sum_{j=1}^{N} W_{ij} NC_{jt} + \alpha + \beta_1 UR_{it} + \beta_2 EP_{it} + \beta_3 PEIS_{it} + \beta_4 PECE_{it} + \beta_5 PEAA_{it} \\
+ \beta_6 \ln TWH_{it} + \theta_1 \sum_{j=1}^{N} W_{ij} UR_{jt} + \theta_2 \sum_{j=1}^{N} W_{ij} EP_{jt} + \theta_3 \sum_{j=1}^{N} W_{ij} PEIS_{jt} \\
+ \theta_4 \sum_{j=1}^{N} W_{ij} PECE_{jt} + \theta_5 \sum_{j=1}^{N} W_{ij} PEAA_{jt} + \theta_6 \sum_{j=1}^{N} W_{ij} \ln TWH_{jt} + \mu_i \\
+ \varepsilon_{it}
\end{aligned}
$$

$$i \neq j$$

Here:

NC_{it} denotes the dependent variable - number of company registrations.

i, *j* are cities and counties in Taiwan.

t refers to the year (t=2002~2021).

W_{ij} represents the spatial weight matrix, a symmetrical matrix where rows and columns are equal to the number of regions (there are 22 cities/counties in this study). A "contiguity matrix" is used to define neighboring relations; if two regions are "adjacent", its value is 1, otherwise 0, with diagonal values also being 0 (indicating no neighboring relationship with itself). This study adopts the "queen contiguity" method to define spatial adjacency, meaning that as long as city borders or corners touch, they are considered adjacent (Sawada, 2004).

ρ, also known as the spatial lag coefficient, measures the correlation of the dependent variable (in this case, number of company registrations) across neighboring geographical areas. It illustrates how company registrations in one area influence those in another. A significant ρ value, different from zero, indicates explicit spatial dependency among the dependent variables. If ρ is positive, it implies a positive spatial spillover effect, suggesting an increase in company registrations in one region can promote the same in adjacent regions. The magnitude of ρ reflects the strength of inter-regional spatial interaction or spillover.

The term $W_{ij}NC_{jt}$ represents the spatial autocorrelation matrix for the dependent variable (number of company registrations). It indicates the influence of the number

of company registrations in neighboring area j (represented as NC_{jt})on the number of company registrations in area i (represented as NC_{it}).
α is the constant term.
β and θ are coefficients to be estimated, representing the original effect coefficient and spatial correlation coefficient for independent variables, respectively. A positive θ denotes a positive spatial effect from neighboring regions, implying improvements in a region's economic or social conditions may positively influence its surroundings. Conversely, a negative θ suggests competitive effects among neighboring areas.
$W_{ij}UR_{jt}$, $W_{ij}EP_{jt}$, $W_{ij}PEIS_{jt}$, $W_{ij}PECE_{jt}$, $W_{ij}PEAA_{jt}$, and $W_{ij}\ln TWH_{jt}$ are spatial autocorrelation terms for both dependent and independent variables, showing the spatial effects of all variables from neighboring regions on the dependent variable in region i.
μ_i is the spatial (individual) effect, representing the unique effect of city/county i.
ε_{it} is an independent and identically distributed random error term, representing the spatial autocorrelation error term.

4. Results

4.1 Descriptive statistics

Table 1 presents the variables used in this study's model. Table 2 displays the results of the correlation analysis. The variables used in the table are based on raw data.

Table 1: Descriptive statistics

Variables	Obs.	Mean	Std. Dev.	Min.	Max.
NC	440	28898.34	44883.41	54.00	180033.00
UR	440	3.98	1.05	0.10	6.00
EP	440	486.63	500.69	3.00	2002.00
PEIS	440	32.87	9.81	14.55	52.78
PECE	440	39.17	12.92	10.57	83.58
PEAA	440	35.58	5.29	23.21	54.04
TWH	440	260299733.19	403208574.00	3744.00	2224554104.00

Table 2: Pearson correlation analysis

Variables	NC	UR	EP	PEIS	PECE	PEAA	TWH
NC	1						
UR	.144**	1					
EP	.888**	.231**	1				
PEIS	.039	.291**	.296**	1			
PECE	.557**	-.102*	.363**	-.016	1		
PEAA	-.098*	-.694**	-.193**	-.471**	.256**	1	
TWH	.883**	.097*	.791**	.112*	.606**	-.025	1

Note: ** p<0.01

4.2 Results of the spatial lag model estimation

Table 3 displays the analytical results conducted for SAR with spatial fixed-effects (Model 1), SAR with time fixed-effects (Model 2), and SAR with random-effects (Model 3). In this model, the spatial lag coefficients ρ of Model 1, Model 2, and Model 3 are significant at a crucial level ($p<0.001$). This indicates that the number of company registrations in neighboring counties significantly affects the number of company registrations in the local county.

However, research by LeSage and Pace (2009) as well as Elhorst (2010, 2001) suggests that the spatial Durbin model can be simplified to a spatial lag model. In this context, this study can conduct a hypothesis test to determine whether to choose the spatial Durbin model or the spatial lag model. If this study assumes $\theta=0$ and rejects this assumption, then the spatial Durbin model cannot be reduced to the spatial lag model, making the choice of the spatial Durbin model more reasonable. Thus, this study carried out both the Wald test and the Likelihood-ratio test to compare these two models. According to the findings of this study, the Wald test statistic for Model 1 is x^2=71.06, $p<0.001$, while the Likelihood-ratio test statistic is x^2=79.03, $p<0.001$. Both test p-values are less than 0.001, clearly rejecting the null hypothesis ($\theta=0$) of this study.

The analytical results of Model 2 and Model 3 are consistent with this. Therefore, the results of this study suggest that the spatial Durbin model is more appropriate for the data in this study. The rationale for choosing the spatial Durbin model can further be understood as this model not only considers the impact of neighboring regions on the target region but also incorporates the spatial effects of the independent variables. Such comprehensive consideration enables this study to delve deeper into the mutual influences between spaces and understand how these impacts affect the target variable of this study-the number of company registrations.

Table 3: Estimation results of the spatial lag model

Variables	Model 1 SAR with spatial fixed-effects		Model 2 SAR with time fixed-effects		Model 3 SAR with random-effects	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
UR	-842.809**	253.698	-5108.965***	1324.237	-793.780**	257.358
EP	57.159***	3.221	60.102***	1.744	59.160***	3.114
PEIS	-64.795	85.881	-856.612***	105.652	-64.519	85.097
PECE	75.690	50.855	930.483***	57.722	76.779	51.248
PEAA	-222.305*	88.673	-221.438	294.438	-251.191**	90.223
lnTWH	-1192.933**	454.087	4117.312***	812.239	-1120.777*	457.388
Constant					23777.340**	8976.485
ρ	0.268***	0.047	0.329***	0.024	0.291***	0.046
Log-likelihood	-4070.0938		-4659.7743		-4157.5707	
Wald test	H_0: θ=0 x^2=79.03 p-value=0.0000		H_0: θ=0 x^2=26.38 p-value=0.0002		H_0: θ=0 x^2=58.39 p-value=0.0000	
Likelihood-ratio test	LR x^2=71.06 p-value=0.0000		LR x^2=1250.42 p-value=0.0000		LR x^2=246.02 p-value=0.0000	

Note: * p<0.05; ** p<0.01; *** p<0.001; n=440.
The spatial lag model is also known as the Spatial Autoregressive Model (SAR).

4.3 Results of the spatial error model estimation

Table 4 presents the results for SEM with spatial fixed-effects (Model 4), SEM with time fixed-effects (Model 5), and SEM with random-effects (Model 6). In this model, the spatial error coefficients λ for Model 4, Model 5, and Model 6 all reached a significant level (p<0.001). This suggests that there is a certain degree of spatial autocorrelation in the error term of this study's model, meaning that the error term of the number of company registrations in the target county is influenced by the error term of the number of company registrations in neighboring counties.

According to LeSage and Pace (2009) and Elhorst (2010, 2001), the spatial Durbin model might be simplifiable to the spatial error model (SEM). However, this study tested the hypothesis H_0: θ+ρβ=0. Rejecting the null hypothesis implies that the spatial Durbin model cannot be simplified to the spatial error model, making the spatial Durbin model a potentially more suitable choice. When deciding between the spatial error model and the spatial Durbin model, this study conducted both Wald and Likelihood-ratio tests. In the Wald test for Model 4, the study obtained results of x^2 =21.97, p<0.01. In the Likelihood-ratio test, the results were x^2=22.37, p<0.01. Both outcomes reject the null hypothesis of this study (θ+ρβ=0), thereby supporting the choice of the spatial Durbin model for this study.

The analytical results for Model 5 and Model 6 are consistent with this. Hence, integrating the above analytical outcomes, the spatial Durbin model might be the more fitting choice for this study, as it more comprehensively captures spatial effects and other factors' influences, providing a more accurate depiction of the number of company registrations in the target counties.

Table 4: Estimation results of the spatial error model

Variables	Model 4 SEM with spatial fixed-effects		Model 5 SEM with time fixed-effects		Model 6 SEM with random-effects	
	Coef.	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
UR	-663.877	357.893	-9006.916***	1533.092	-625.291	367.196
EP	64.444***	3.025	64.602***	2.589	65.906***	2.961
PEIS	-61.606	77.167	-1244.124***	119.858	-79.736	77.985
PECE	131.189**	46.753	1138.006***	65.691	143.253**	47.850
PEAA	-283.369**	85.182	-704.662*	347.772	-308.602***	86.804
lnTWH	-685.261	441.436	6124.959***	1040.753	-622.369	445.520
Constant					18575.710	9151.500
λ	0.482***	0.048	-0.422***	0.103	0.485***	0.049
Log-likelihood	-4045.7451		-4736.9991		-4137.1147	
Wald test	$H_0: \theta + \rho\beta = 0$ x^2=21.97 *p*-value=0.0012		$H_0: \theta + \rho\beta = 0$ x^2=351.61 *p*-value=0.0000		$H_0: \theta + \rho\beta = 0$ x^2=25.17 *p*-value=0.0002	
Likelihood-ratio test	LR x^2=22.37 p-value=0.001		LR x^2=1404.87 p-value=0.0000		LR x^2=205.10 p-value=0.0000	

Note: * p<0.05; ** p<0.01; *** p<0.001; n=440.

4.4 Results of the spatial Durbin model estimation

Table 5 displays the results from three distinct Spatial Durbin Models: Model 7 (SDM with spatial fixed-effects), Model 8 (SDM with time fixed-effects), and Model 9 (SDM with random-effects). In Model 7, the spatial lag coefficient ρ has a value of 0.406, underscoring the significance of spatial influence in the model, with this coefficient being statistically significant at the p<0.001 level. Conversely, in Model 8, the spatial lag coefficient ρ stands at -0.002 and does not achieve statistical significance (p>0.05). Finally, in Model 9, the spatial lag coefficient ρ equals 0.453, indicating that even when taking random effects into account, the spatial influence remains significant (p<0.001).

When assessing the overall fit of the model, spatial econometric models typically employ the Maximum Likelihood Estimation (MLE) method. This approach seeks to maximize the likelihood function within the model, ensuring that the estimated parameters align as closely as possible with the observed data. Under the MLE framework, this study can leverage crucial statistical metrics to evaluate model fit, which include the Log Likelihood (LIK), Akaike Information Criterion (AIC, introduced by Akaike in 1973), and the Schwartz Bayesian Information Criterion (SBC or BIC, presented by Schwarz in 1978). These indicators, based on non-linear principles, effectively measure the model fit. A higher Log Likelihood value indicates that the model aptly explains the observed data. On the other hand, AIC and BIC, grounded in information theory, consider the model's complexity and fit to assess its superiority. Generally, lower AIC and BIC values denote higher model fit and, from a complexity standpoint, a superior model. Thus, when selecting the optimal model, this study typically searches for the one with the highest Log Likelihood or the lowest AIC/BIC values.

The study found that the Log-likelihood, AIC, and BIC values for Model 7 are superior to those of Model 8 and Model 9. Hence, this study opted for Model 7. The significant spatial lag coefficient ρ in Model 1 suggests a pronounced spatial autocorrelation in the distribution of company registrations across counties. This further corroborates the rationality of incorporating spatial effects into econometric models. Subsequent decisions were made to decompose direct and indirect effects (spatial spillover effects) using the spatial Durbin model with spatial fixed effects.

Table 5: Estimation results of the spatial Durbin model

Variables	Model 7 SDM with spatial fixed-effects		Model 8 SDM with time fixed-effects		Model 9 SDM with random-effects	
	Coef.	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
UR	51.788	465.331	-4615.129***	1203.048	-68.442	474.516
EP	62.435***	3.153	63.961***	2.740	64.072***	3.118
PEIS	-133.600	79.365	-947.734***	97.947	-128.024	80.503
PECE	195.632***	53.978	818.705***	60.666	191.914***	54.921
PEAA	-299.762**	90.985	-193.192	260.885	-295.107**	92.604
lnTWH	-501.997	452.193	3973.265***	909.988	-640.800	462.588
W×UR	-1333.868*	529.271	1766.630	1960.009	-861.153	518.789
W×EP	-40.985***	5.725	27.562	20.054	-38.155***	5.732
W×PEIS	-378.205**	138.519	482.633	281.134	-227.017	141.168
W×PECE	132.275	113.769	243.909	148.740	11.949	104.792
W×PEAA	-160.023	196.206	-221.142	653.679	-92.741	192.024
W×lnTWH	-1285.152	1115.007	-2062.948	1615.408	356.113	764.040
Constant					30124.510*	12582.750
ρ	0.406***	0.052	-0.002	0.307	0.453***	0.050
Log-likelihood	-4034.5625		-4647.7696		-4130.8597	
AIC	8097.125		9321.539		8293.719	
BIC	8154.34		9374.667		8359.108	

Note: * p<0.05; ** p<0.01; *** p<0.001; n=440.

4.5 Decomposition of direct and spillover effects

Table 6 presents the decomposition results based on the spatial Durbin model with spatial fixed effects. Significant influencing factors in the model include: Unemployment Rate (%)(UR_{it}), Employment Population (thousands)(EP_{it}), Proportion of Employees in Industrial Sector (%)($PEIS_{it}$), Proportion of Employees with an Educational Level of College and Above (%)($PECE_{it}$), and Proportion of Employees aged 45-64 years (%)($PEAA_{it}$).

Spatial effects of Unemployment Rate (%)(UR_{it}):

1. Direct Effect: An increase in the unemployment rate does not have any significant impact on the number of company registrations in the respective county/city.
2. Indirect Effect: An increase in the unemployment rate continually spreads to neighboring counties/cities, resulting in a negative spatial spillover effect on their number of company registrations. For every unit increase in the unemployment rate of neighboring counties/cities, the number of company registrations in the respective county/city decreases by 1771.161 units.
3. Total Effect: The cumulative effect of the direct and indirect impacts of the unemployment rate on the average number of company registrations across all counties/cities in Taiwan is significantly negative, resulting in a total effect decrease of 1842.078 units.

Spatial effects of Employment Population (thousands)(EP_{it}):

1. Direct Effect: An increase in the employment population leads to a rise in the number of company registrations in the respective county/city. For every unit increase in the employment population, the number of company registrations in the respective county/city increases by 60.644 units.
2. Indirect Effect: An increase in the employment population spreads to neighboring counties/cities, leading to a negative spatial spillover effect on their number of company registrations. For every unit increase in the employment population of neighboring counties/cities, the number of company registrations in the respective county/city decreases by 21.274 units.
3. Total Effect: The cumulative direct and indirect effects of the employment population result in a positive significant impact on the average number of company registrations across all counties/cities in Taiwan, with a total effect increase of 39.370 units.

Spatial effects of Proportion of Employees in Industrial Sector (%) ($PEIS_{it}$):

1. Direct Effect: An increase in the proportion of employees in the industrial sector suppresses the growth of company registrations in the respective county/city. For every 1% increase in this proportion, the number of company registrations decreases by 170.852 units.
2. Indirect Effect: An increase in this proportion spreads to neighboring counties/cities, causing a negative spillover effect on their company registrations. For every 1% increase in the proportion of neighboring counties/cities, the number of company registrations in the respective

county/city decreases by 567.557 units.

3. Total Effect: The cumulative direct and indirect effects of the proportion of employees in the industrial sector have a significant negative impact on the average number of company registrations across all counties/cities in Taiwan, with a total decrease of 738.409 units.

Spatial effects of Proportion of Employees with Tertiary Education or Above (%) ($PECE_{it}$):

1. Direct Effect: An increase in this proportion drives the growth of company registrations in the respective county/city. For every 1% increase, the number of company registrations increases by 217.463 units.
2. Indirect Effect: An increase in this proportion spreads to neighboring counties/cities, causing a positive spillover effect on their company registrations. For every 1% increase in the proportion of neighboring counties/cities, the number of company registrations in the respective county/city increases by 289.011 units.
3. Total Effect: The cumulative direct and indirect effects of the proportion of employees with tertiary education or above have a significant positive impact on the average number of company registrations across all counties/cities in Taiwan, with a total increase of 506.474 units.

Spatial effects of Proportion of Employees aged 45-64 years (%)($PEAA_{it}$):

1. Direct Effect: An increase in this proportion suppresses the growth of company registrations in the respective county/city. For every 1% increase, the number of company registrations decreases by 329.072 units.
2. Indirect Effect: An increase in this proportion does not spread to neighboring counties/cities.
3. Total Effect: The cumulative direct (and lack of indirect effects) of the proportion of employees aged 45-64 years results in a significant negative impact on the average number of company registrations across all counties/cities in Taiwan, with a total decrease of 718.824 units.

Table 6: Direct, indirect, and total effects of the spatial Durbin model with spatial fixed-effects

Variables	**Direct Effects**		**Indirect Effects**		**Total Effects**	
	Coef.	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
UR	-70.916	449.958	-1771.161**	515.077	-1842.078***	429.420
EP	60.644***	3.168	-21.274**	7.187	39.370***	8.806
PEIS	-170.852*	80.129	-567.557**	184.997	-738.409**	228.048
PECE	217.463***	52.631	289.011*	141.624	506.474**	159.752
PEAA	-329.072***	90.893	-389.752	248.088	-718.824*	281.315
lnTWH	-634.072	470.774	-1942.663	1433.728	-2576.735	1610.724

Note: * p<0.05; ** p<0.01; *** p<0.001; n=440.

5. Conclusion and Recommendations

5.1 Research conclusion

Based on the spatial Durbin model with spatial fixed effects, this study examined the influence of labor market factors in various counties and cities in Taiwan on company location choices. The main findings from this research are as follows: An increase in the unemployment rate does not directly have a significant impact on the number of company registrations in a county/city. However, its indirect effect is pronounced in neighboring counties/cities, suggesting that an increase in unemployment might lead to a decrease in company registrations in adjacent areas. The growth in the employed population positively affects the number of company registrations in a county/city. Although there is a negative indirect effect on neighboring counties/cities, the overall impact on company registrations across various counties and cities in Taiwan remains positive. An increase in the proportion of employees engaged in the industrial sector has negative effects in both a county/city and its neighboring areas, implying that this growth may not be conducive to entrepreneurial activities. An increase in the proportion of employees with tertiary education and above positively influences the number of company registrations in both a county/city and its neighboring areas. This might indicate that higher education plays a crucial role in entrepreneurship and company development. An increase in the proportion of employees aged 45-64 has a negative impact on the number of company registrations in a county/city, but no apparent indirect effects on neighboring areas.

In conclusion, this research offers in-depth insights into how labor market factors in various counties and cities in Taiwan affect the number of company registrations. Future policymakers should consider these factors, especially the unemployment rate and changes in the structure of the employed population, to cultivate an environment more conducive to company startups and growth.

5.2 Policy recommendations

Based on the aforementioned research findings, we put forth the following policy recommendations to enhance Taiwan's business registration and entrepreneurial environment:

1. Enhance Vocational Training and Continuing Education: Given the negative impact of the unemployment rate on company registrations in neighboring counties, the government should offer more opportunities for vocational training and continuing education. This would assist the unemployed in upgrading their skills and re-entering the labor market.
2. Promote the Importance of Higher Education: In light of the positive effect that higher-educated workers have on company registrations, policies should emphasize the value of higher education and encourage more individuals to pursue advanced studies or further professional training.
3. Optimize the Middle-aged and Elderly Labor Market: Considering that the increasing proportion of workers aged 45 to 64 may adversely affect company

registrations, the government should consider launching entrepreneurship guidance or employment support policies specifically tailored for this age group.
4. Support Emerging Industries: Since an increase in the industrial workforce's proportion might be unfavorable for entrepreneurial activities, the government should enhance support and funding for emerging industries, such as technology, green energy, and creative sectors.
5. Strengthen Regional Collaboration: Recognizing the key role spatial spillover effects play in company registrations, there should be heightened collaboration between counties to jointly provide a better business environment and support.

By implementing these recommendations, cities and counties across Taiwan can further optimize their entrepreneurial settings, attract more business registrations, and boost overall economic development.

5.3 Suggestions for future research

Considering the findings and scope of this study, we propose the following recommendations for future research to offer a more comprehensive and deeper understanding:

1. Time Series Analysis: Although this research has covered data from 2002 to 2021, future work could consider employing time series analysis to explore long-term trends and the dynamic relationship between the labor market and company registrations.
2. Differences across Industries: This study mentions that an increase in the industrial workforce's proportion might be unfavorable for entrepreneurship. Future research could delve into different industries to investigate their specific impacts on company registration and entrepreneurship.
3. Influence of Other Socio-economic Factors: Beyond labor market factors, subsequent research can contemplate other socio-economic variables, such as regional economic development, educational resources, infrastructure, etc., and analyze their effects on company registrations.
4. Advanced Application of Spatial Models: Consider utilizing other spatial econometric models or integrating different statistical methods to more intricately capture inter-regional interactions and spatial effects.
5. Assessment of Policy Impact: In response to the policy recommendations made in this research, future studies could be designed to evaluate the actual effectiveness and benefits of these policies.
6. International Comparisons: It might be valuable to compare Taiwan's situation with that of other countries or regions, exploring the unique characteristics and differences in terms of company registrations and labor market factors.

By undertaking these suggested future research directions, we can gain a more holistic understanding of the relationship between company registrations and labor market factors, providing more robust guidance for policy-making.

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