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Using the Spatial Econometric Approach to Study Impacts of FDI on Poverty in Vietnam

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Abstract

This paper examines the impact of foreign direct investment on provincial poverty in Vietnam. The provincial poverty severity index is calculated based on data from the Vietnam Household Living Standards Survey in 2022. Firm-level foreign direct investment measures are aggregated based on data from the Enterprise Survey in the same year. The Moran's I statistic and Lagrange multiplier test have shown that there exists a spatial correlation effect, and therefore this study employs the spatial econometric approach to examine the impacts of foreign direct investment on poverty to obtain reliable results. The study has shown a positive impact of foreign direct investment on poverty reduction in Vietnam, that is provinces with a higher share of foreign-owned enterprises' assets relative to provincial output tend to have lower poverty severity index, and vice versa. In addition, the estimation results also show that better governance quality at the provincial level has positive effects on poverty reduction. Another interesting finding is that provinces with higher levels of inequality tend to experience more severe poverty.

Keywords: Foreign direct investment, Poverty severity, Spatial econometric, Vietnam.

1. Introduction

Foreign direct investment (FDI) is frequently identified as exerting a positive influence on economic growth and contributing to productivity enhancement in host countries. However, its direct impact on the income of low-income labor groups—particularly as reflected in poverty indicators—and on the degree of income inequality within society has received comparatively less attention. At the cross-country level, many contend that globalization—of which the increase in bilateral FDI flows and, more importantly, capital inflows from developed to developing economies constitutes a central element—tends to exacerbate income disparities. This issue has been a persistent source of contention in numerous economic and political debates, especially in the context of negotiations concerning trade and investment liberalization (Tulus (2011), Ndagijimana & Wahyu (2025)).

The effects of FDI on the income of disadvantaged labor groups are observable not only across countries but also across regions within a given country (Deaton, 1997). When examining regional-level impacts, the spatial proximity of regions raises the possibility of interdependent or spillover effects with respect to poverty, inequality, and FDI—phenomena that are less likely to arise in cross-national analyses. Should such spatial correlations among provincial observations exist, the classical or traditional regression framework would prove inappropriate, given that the assumption of observational independence would be violated. Under such circumstances, it is widely argued that spatial econometric techniques should be employed as an alternative to ensure the robustness and reliability of estimated coefficients (Arogundade, 2021).

This paper examines the impact of foreign direct investment on the income of low-income labor groups, measured by the poverty severity, by using the spatial econometric approach.

2. Theoretical Framework

In this section, we will examine issues related to the measurement of variables, the selection of representative variables that reflect the target group under study, and the explanation of the mechanisms through which foreign direct investment affects poverty indicators.

2.1. Poverty Measures

In order to assess living standards, and thereby determine who is poor and who is not, it is necessary to employ a welfare measure for individuals. Welfare economics has introduced various forms of welfare functions for both individuals and society, and naturally, the classification of an individual or household as poor or non-poor will vary depending on the specific welfare function applied. Among the numerous welfare measures available, researchers commonly rely on indicators such as income, expenditure, wealth, or other observable and measurable indicators to reflect the level of welfare attained by each individual.

Once an appropriate measure has been selected to represent the welfare status of individuals or households, it is essential to establish a threshold to distinguish between poverty and non-poverty. Alternatively, multiple thresholds may be set if the objective is to categorize the population into more detailed groups—for instance, the extremely poor, the poor, the near-poor, and those above the near-poor threshold. The choice of such thresholds has long been a matter of considerable debate.

Once a welfare measure—most commonly income or expenditure—has been identified, along with one (or several) thresholds to define poverty status (or different levels of poverty), it becomes possible to determine which individuals or households are poor. However, in order to assess the overall poverty situation of a community, one may approach the issue from multiple perspectives, which has consequently led to the development of various poverty measures (World Bank, 2005)

[1] Headcount ratio

The most commonly used measure is the headcount ratio, which is simply calculated as the proportion of the population classified as poor. The formula for the headcount ratio is as follows:

$$P_0 = \frac{1}{N}\sum_{i=1}^{N} I\left(y_i < z\right)$$

In which P_0 is the headcount ratio, N is total population. Here, $I(\cdot)$ is an indicator function that takes the value of 1 if the condition inside the parentheses is satisfied, and 0 otherwise. This implies that if the expenditure level y_i is lower than the poverty line (z), then $I(\cdot)$ takes the value 1 and the household is classified as poor. For instance, if in a sample of 300 individuals there are 60 poor individuals, then the indicator function $I(\cdot)$ will take the value 1 for 60 cases and 0 for the remaining ones. Accordingly, the total number of poor individuals is 60, and the poverty rate is therefore 20%.

[2] Poverty gap index

Another poverty measure that is also widely used is the poverty gap index, which aggregates the shortfall of the poor relative to the poverty line and computes the average value. Specifically, let the poverty gap be denoted by G_i, the poverty line by z, and actual income by y_i . In that case, the poverty gap of an individual is calculated as follows:

$$G_i = \left(z - y_i\right) \cdot I\left(y_i < z\right)$$

And the poverty gap (P_1) can be calculated as follow:

$$P_1 = \frac{1}{N}\sum_{i=1}^{N} \frac{G_i}{z}$$

Here, individuals who are not classified as poor will have a poverty gap of zero. This measure can be interpreted as reflecting the minimum cost required to eliminate poverty (relative to the poverty line). By examining this measure, we can determine the amount of expenditure that must be subsidized for the poor (relative to the poverty line) in order to lift them above the poverty threshold.

If $\sum G_i$ represents the minimum amount of subsidy required to eliminate poverty, then nZ denotes the maximum amount of subsidy necessary to guarantee the eradication of poverty, that is, the government would provide each individual with an expenditure level exactly equal to the poverty threshold. Accordingly, the poverty gap index is defined as the ratio between the minimum expenditure required to eliminate poverty and the maximum expenditure. In other words, it serves as an indicator of the potential budgetary savings in poverty reduction that can be achieved through accurate targeting of subsidies. The smaller this measure, the greater the economic efficiency of poverty alleviation expenditures through precise targeting. In such cases, conducting surveys to collect more detailed information in order to better identify eligible recipients becomes increasingly meaningful, as it helps reduce the government's overall poverty reduction budget.

Although this measure provides an additional source of important information on the poverty at the aggregate level compared to the headcount ratio, it still has a limitation in which it does not capture the severity of poverty arising from differences in the distribution of the poverty gap.

[3] Poverty severeity index

To construct a poverty measure that accounts for inequality among the poor, some researchers employ the poverty severeity index. This measure is the weighted average of individual poverty gaps, where the weight assigned to each observation is its own poverty gap. For instance, a poverty gap of 10% relative to the poverty line is assigned a weight of 10%, while a poverty gap of 50% relative to the poverty line is assigned a weight of 50%. This differs from the poverty gap index, which assigns equal weights to all observations. By squaring the poverty gaps, this measure places greater weight on individuals who are further below the poverty line.

The formula for the poverty severeity index is as follows:

$$P_2 = \frac{1}{N}\sum_{i=1}^{N} \left(\frac{G_i}{z}\right)^2$$

On the basis of the poverty index mentioned above, , Foster, Greer and Thorbecke (1984) has generalized a family of poverty measures as follows:

$$P_\alpha = \frac{1}{N}\sum_{i=1}^{N} \left(\frac{G_i}{z}\right)^\alpha$$

In which, α is a parameter that measures the sensitivity of the index to poverty status and the poverty line z. The per capita expenditure of household i is denoted as z_i, and the poverty gap for this individual is $G_i = z - x_i$. When $\alpha = 0$, the measure becomes the headcount poverty ratio. When $\alpha = 1$, the index turns into the poverty gap index P_1, and when $\alpha = 2$, it becomes the poverty severity index. For any value of $\alpha > 0$, the measure decreases with the expenditure; that is, if an individual/household is poor and their expenditure falls further, their degree of poverty increases.

However, the FGT measure does not specify which value of α is optimal. According to the authors, these measures are complementary to one another. Of course, in some cases, certain groups may have a high poverty rate but a lower poverty gap (when most people fall just slightly below the poverty line), and vice versa. Similarly, some groups may exhibit a lower poverty gap but a higher squared poverty gap (due to large disparities within the distribution of those below the poverty line).

2.2. Measurement of FDI

Provincial-level FDI statistics published by the National Statistics Office only include registered capital and the number of projects, which are not very useful when assessing their impact on socio-economic indicators in the corresponding year. Moreover, even data on actual foreign direct investment disbursements do not reveal the multidimensional effects of this capital on the economy. Instead, we will compile data from wholly foreign-owned enterprises in the localities, thereby identifying the scale of assets, equity, employment, revenue, and so on of these enterprises based on the Enterprise Survey dataset. This approach will allow us to evaluate the impact of foreign direct investment in a more accurate and multidimensional way.

2.3. Spatial Econometrics Model

In spatial econometrics, it is assumed that geographically proximate observations may exert mutual influences on one another, leading to the phenomenon of spatial autocorrelation (LeSage, 1999). Here, spatial autocorrelation is categorized into two types: (i) spatial autocorrelation of the dependent variable itself, and (ii) spatial autocorrelation of the error term. Consequently, traditional estimation methods are no longer appropriate because the assumptions are violated. Two corresponding spatial econometric models have been introduced to address this issue: the Spatial Autoregressive Model (SAR) and the Spatial Error Model (SEM).

The spatial autoregressive model is expressed as follows:

$$(I - \rho W)y = x\beta + e$$

The spatial error model is expressed as follows:

$$(I - \lambda W)y = (I - \lambda W)x\beta + u$$

in which, y is the dependent variable, x represents the independent variables, W is the spatial weight matrix, and the coefficients λ and ρ are the spatial autoregressive parameters, reflecting the effects of spatial autocorrelation. The error term ε follows a normal distribution with constant variance and no autocorrelation, while the error term u in the spatial error model follows a distribution with spatial autocorrelation, that is $u = \lambda W + \varepsilon$.

3. Data and Empirical Results

We use the Enterprise Survey dataset conducted and published by the National Statistics Office to calculate indicators on revenue, assets, equity, and employment of wholly foreign-owned enterprises aggregated at the provincial level.

We use the industrial output value as a measure reflecting provincial production activity. To indicate the relative scale of foreign direct investment, we compute the ratios of revenue, assets, and so forth of foreign-owned enterprises in each province to the scale of industrial output value. In addition, we may also compute the ratios of these indicators to provincial population size. Data on industrial output and population size are obtained from the Statistical Yearbook published by the National Statistics Office.

Data on poverty measures are calculated based on the Vietnam Living Standards Survey (VLSS) dataset, which is conducted by the National Statistics Office every two years. Here, the poverty measure we use is the poverty severity index.

Data reflecting the capacity and quality of provincial governance are taken from the Provincial Competitiveness Index (PCI), surveyed and published by the Vietnam Chamber of Commerce and Industry (VCCI).

In this model, the independent explanatory variables include: (i) the ratio of total assets of wholly foreign-owned enterprises to the province's industrial output, (ii) the Provincial Competitiveness Index (PCI), and (iii) the Atkinson inequality index. The first variable illustrates the impact of foreign direct investment on poverty reduction. If its coefficient is negative, it indicates that provinces with a larger relative scale of foreign enterprises (measured by the size of their assets compared to the province's industrial output) experience a reduction in the poverty severity index—in other words, foreign direct investment has a positive effect on poverty alleviation.

Furthermore, the Provincial Competitiveness Index captures differences among provinces in terms of the quality of local governance. If its coefficient is negative, it implies that provinces with better governance, in addition to the general effect of boosting provincial production, also benefit from other policies that help reduce the incidence of poor households. The third variable, the Atkinson inequality index, if positively signed, suggests that provinces with higher levels of inequality face more severe poverty conditions.

The descriptive statistics of the variables used in the model are summarized in the following table.

Table 1. The descriptive statistics of the variables used in the model.

Variable	Observations	Mean	Std. Error	Min.	Max.
Poverty severity index	63	0.007371	0.007579	0	0.03881
Atkinson inequality index	63	0.211525	0.037496	0.14678	0.32697
pci	63	57.01764	4.145726	45.11707	63.79096
asset_output	63	0.203826	0.225472	0.000786	1.366224

Source: National Statistics Office and và Chamber of Commerce and Industry (2024).

The estimation results of the model using the spatial econometric approach are presented in the table below.

Table 2. The estimation results.

Dependent variable: Poverty severity index	OLS	SAR	SEM
Atkinson	.1311801* (2.14)	.1154969* (.0521949)	.1143195* (.0554369)
pci	-.0024411** (.005615)	-.0018665** (.0004867)	-.0016892** (.0005556)
asset_output	-.0334829** (0.0104459)	-.0298406* (.0088948)	-.0295825** (.0096477)
_cons	.1219312 (.0388796)	.0756014 (.0339375)	.0888529 (.0379555)
λ			0.7933359** (.1750113)
ρ		.8294253** (.1397497)	
SEM	p-value		
Moran's I	0.000		
SAR			
Lagrange multiplier	0.000		

In the first model, we find that all variables included are statistically significant, at least at the 5% level. The Atkinson inequality index carries a positive sign, implying that provinces with higher inequality tend to have a larger poverty severity index. The PCI variable has a negative sign, indicating that provinces with better governance quality have a lower poverty severity index, and vice versa. The variable of greatest interest here is the one representing foreign direct investment (FDI)—specifically, the ratio of total assets of wholly foreign-owned enterprises in the province to the value of the province's industrial output. This variable has a negative sign, suggesting that as this ratio increases—that is, as FDI becomes relatively larger—the poverty severity index decreases. This finding indicates that FDI has a positive effect on poverty reduction in Vietnamese provinces.

Moreover, the test for spatial correlation shows that spatial dependence does exist. Both the Moran's I statistic and the Lagrange multiplier tests in the spatial error model and the spatial lag model are statistically significant at the 1% level. This demonstrates that applying the OLS model would yield biased results. In this case, we must adopt a spatial econometric approach to estimate the impact of FDI on the poverty severity index.

4. Conclusion

This paper examines the impact of foreign direct investment (FDI) on the poverty severity index. After calculating indicators such as the poverty severity index and inequality across Vietnamese provinces based on the Household Living Standards Survey, the author investigates the effect of FDI on the poverty severity. Instead of relying on realized investment capital or committed investment capital published by the National Statistics Office, the author employs the Enterprise Survey to measure the total scale of assets, equity, and employment generated by foreign enterprises in each province. The estimation results lead to the following conclusions.

First, FDI has a positive impact on poverty reduction at the provincial level. Provinces with larger foreign enterprise assets per unit of output tend to have lower poverty severity index, and vice versa.

Second, in the model assessing the impact on the poverty severity index, spatial autocorrelation is present. Therefore, spatial econometric estimation methods must be employed instead of OLS in order to obtain reliable results.

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