To be Direct or Indirect Exporter: a Spatial Durbin Probit Approach

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Abstract

This paper studies how spatial interdependence matters for exporting mode (direct or indirectly via intermediaries). We study the export status transition matrix and adopt a spatial durbin probit model that allows the proper interpretation of changes in explanatory variables on dependent observations over space as well as the well-known nonlinear transformations. We find that a firm's decision to transit from an indirect exporter to be a direct exporter is affected by the exporting mode of other neighboring firms. Our results also indicate that firm's capital and the interaction of captial and skill labor ratio play an important role on its own and neighbor's choice of being direct or indirect exporter.

Keywords: Exporting mode, transition matrix, spatial durbin probit

JEL: F1

1 Introduction

Firms can choose to export directly or indirectly through trade intermediaries. What determines their exporting mode? Ahn, Khandelwal, and Wei (2011) develop a theoretical model and find that firms select their mode of export based on productivity. Wang and Gibson (2017) add heterogeneity in quality to the usual heterogeneity in productivity and find firms with the highest quality-adjusted productivity choose to export directly. Baltagi, Egger, and Kesina (2016) states that the total factor productivity is contagious and prone to spillovers which are geographicaly bounded. We consider if firms choose exporting mode affected by its neighboring firms. What kind of production factors have spatial spillover effect?

By answering the question, we first determine the direct and indirect exporter by merging Chinese customs data and Chinese enterprise survey data. Then we construct the export status transition matrix. Cem and Koch (2007) provide a theoretical model by taking account of technological interdependence among economies which should work through spatial externalities. Bai, Krishna, and Ma (2016) develop and estimate a dynamic discrete choice model that allows learning-by-exporting on the cost and demand side by export mode and find productivity evolve more favorably under direct exporting, but did not consider productivity spatial spillover effect.

In this paper, with the export status transition matrix, there is a higher rate of starting direct exporting as indirect exporters. It is possible that intermediaries help small firms learn about foreign markets, reducing the cost of market research, promoting matching with potential buyers, and facilitating their entry into foreign markets directly in later years at lower cost (Bai, Krishna, and Ma (2016)). With the location of direct and indirect exporters per region in China, there is high agglomeration in costal areas for both of them. Wallsten (2001) gave three reasons for industry localization: benefits of a pooled labor supply, access to specialized inputs, and information flows between people and firms. Petropoulou (2010) points out that the informations costs can affect the pattern of direct and intermediated trade. Therefore it is also possible that indirect exporters learn from their neighboring direct exporters, then transit to be direct exporter as well.

Then we adopt a spatial Durbin probit model set up by LeSage (2011). Elhorst, Heijnen, Samarina, and Jacobs (2017) also use a spatial probit model to explain interaction effects among geographical units when the dependent variable takes the form of a binary response variable and state transfers occur at different moments in time. In this paper, according to the export status transition matrix from year 2004 to 2005, the exporting mode indicator is considered to be 1, if a firm is either a direct or indirect exporter in year 2004, but will be direct exporter in 2005; is considered to be 0, if a firm is an indirect exporter in year 2004, and still be in 2005 as well. The unobservable profits are associated with the observed exporting mode choice outcomes.

The insights from estimation results are summarized here: capital plays a siginificant positive role in determineing firm's own and their neighbors' choice of being direct exporter. But its marginal direct and indirect effects are decreasing. The magnitude of indirect effects for capital is about ten times large as the direct effect. There should be about ten neighboring firms to each firm in the sample. The physical capital externalities shows that knowledge accumulation in the form of learning by doing also plays an important role in the firm's growth process as stated in Cem and Koch (2007). The marginal indirect effects of log of labor, capital, and material are all significantly negative. The capital interact with skill labor ratio have a negative spatial spillover effect. The increased capital will demand more skilled labor in its own firm, and vice versa.

The remainder of the paper is organized as follows. Secction 2 is the model specification. Section 3 is the data and merging results. Section 4 discusses the estimation results. Section 5 concludes.

2 The Spatial Durbin Probit Model

Wet let the $n \times 1$ vector y be a 0,1 binary vector reflecting the direct or indirect choice outcomes for n firms in our sample. A conventional probit model would attempt to explain variation in the binary vector y using an $n \times k$ matrix of firm-specific explanatory variables X and associated $k \times 1$ vector of parameters β, under the assumption that each observed outcome is independent from all others.

Lesage and Pace (2009) set forth a spatial autoregressive variant of the conventional probit model, called the spatial Durbin probit model (SDM), that unobservable profits associated with the observed exporting mode choice outcomes.

$$y^* = \rho W y^* + X\beta + WX\theta + \varepsilon,\ \varepsilon \sim N(0, I_n) \tag{1}$$

The spatial lag of the latent dependent variable Wy^* involves the $n \times n$ spatial weight matrix W that contains elements consisting of either $1/d_{ij}$ or 0, where d_{ij} is the distance between firms. All elements in the i^{th} row of the matrix W that are not associated with neighboring observations take values of 0. The scalar parameter ρ measures the strength of dependence, with a value of zero indicating independence.

The Bayesian approach to modeling binary limited dependent variables treats the binary 0, 1 observations in y as indicators of latent, unobserved y^* profits associated with two choices, with the unobservable profits underlying the observed choice outcomes.

More formally, the firm choice of exporting mode depends on the difference in profits: $(\pi_{1i} - \pi_{0i})\,, i = 1, ..., n$ associated with observed 0, 1 firm choice indicators, where π_{1i} represents profits (of firm i) associated with direct exporter 1 and π_{0i}, that from indirect exporter 0. The probit model assumes this difference, $y_i^* = \pi_{1i} - \pi_{0i}$, follows a normal distribution. We do not observe y_i^*, only the exporting mode choices made, which are reflected in:

$$
\begin{aligned}
y_i &= 1, \text{ if } y^* \geq \overline{y^*} \\
y_i &= 0, \text{ if } y^* \leq \overline{y^*}
\end{aligned}
$$

where $\overline{y^*}$ is the profits cutoff of exporting directly.

Since the point estimates of the parameter vector β in the probit $y = X\beta + \mu$ or spatial model with continuous dependent variable $y^* = \rho W y^* + X\beta + \mu$ are not equal to their marginal effects, see respectively Cameron and Trivedi (2005) and LeSage and Pace (2009). LeSage et al. (2011) construct a matrix version of partial derivatives, and provide a computational approach to calculating the marginal effects of spatial probit model. The matrix of partial derivatives of the expected value of Y with respect to the k^{th} explanatory variable of X of model (1) takes the form

$$
\begin{pmatrix}
\frac{\partial E(y_1)}{\partial x_{1k}} & \cdots & \frac{\partial E(y_1)}{\partial x_{nk}} \\
\vdots & \ddots & \vdots \\
\frac{\partial E(y_n)}{\partial x_{1k}} & & \frac{\partial E(y_n)}{\partial x_{nk}}
\end{pmatrix}
= diag(\phi(\eta))(I - \rho W)^{-1}(I_n \beta_k + W\theta_k) \tag{2}
$$

where $\eta = (I - \rho W)^{-1}(X\beta + WX\theta)$ denotes the vector of predicted values of y^*, $E(y^*)$. $diag(\phi(\eta))$ indicates the diagonal matrix of order n whole elements ϕ_i represent the probability that the dependent variable takes its observed value, dependent on the observed values of the other units in the sample. $(I-\rho W)^{-1}(I_n\beta_k+W\theta_k)$ is an $n\times n$ matrix whose diagonal elements represent the impact on the depdent variable of unit 1 up to n if the k^{th} explanatory variable in the own unit changes, while its off-diagonal elements represent the impact on the dependent variable if the k^{th} explanatory variable in another unit changes. The first is called a direct effect and the second an indirect or spatial spillover effect. LeSage and Pace (2009) propose to report direct effect measured by the average of the diagonal elements of the matrix on the right-hand side of Equation 2, and indirect effect measured by the average of the row or column sums of the off-diagonal elements of that matrix.

3 Data

3.1 Firm-Level Production Manufacturing Data

China's National Bureau of Statistics conducts an annual survey of manufacturing enterprises. The data include all State-Owned Enterprises (SOEs) and non-SOEs with sales over 5 million RMB (about 600,000 US dollars). The data contain information on the firm's ownership type, age, employment, capital stocks, and revenues. The data also contain information on the total export value of the firm. Thus we know if the firm receives international sales, though this data neither provide sales value by destination market nor whether the firm exported itself or used an intermediary as the exporter of record.

The production data is composed of those firms that do not receive any sales from international markets (non-exporters), firms that directly sell abroad (exporter), and firms that receive international sales though they themselves are not the exporter of record (indirect exporters).

3.2 Product-Level Transaction Trade Data

The trade transaction data are customs-level data obtained from China's General Administration of Customs. These data contain information on the exported product at the HS 8-digit level, the sales prices, the quantity shipped, and the export destination country. Each entry also contains a firm ID, the name of the firm, the postal code of the firm's location, the firm's phone number, and the date of the transaction.

Because these are customs data, every observation is either a production (manufacturing) firm that fills out its own customs form or a firm that is not a production firm but exports the output produced by other firms. We define the former as a **Direct exporter** and the latter as an **Intermediary**. Because Intermediary firms are not production manufacturers, they will not be in the the production data described above. However, we cannot know that any firm that is in the trade data that is not in the production data is an intermediary because the trade data also includes manufacturing firms with fewer than 5 million RMB in sales as well as firms that export non-manufactured goods.

3.3 Merged Data

Though we know in principle that the production data firm count total must be the sum of direct exporters, indirect exporters, and nonexporters, we can only identify the nonexporters from the exporters using that data. We cannot identify direct exporters separately from indirect exporters. To do that we need to merge the production data to the transaction trade data. In a perfect world, any firm that is in *both* the production data set and the trade transaction data set is a direct exporter whereas a firm that has positive export value in the production data but is not in the trade transaction data set must be an indirect exporter.

First, the firm identifier in the production data is *not* the same as the firm identifier in the trade data. So we cannot match by a firm ID. Instead we match useing two sets of identifying criteria. Our ultimate match is the unique firms that are matched by one set of criteria together with the unique firms matched by the other set of criteria.

The first set of criteria used for the match are firm name and year. The year variable is a necessary auxiliary identifier, since some firms could have different names across years and newcomers could possibly take their original names.

The second set of criteria used for the match are the postal code and the last seven digits of a firm's phone number. The rationale is that firms should have different and unique phone numbers within a postal district. We use only the last seven digits of the phone number because of inconsistencies on how hyphens are coded in the phone number data as well as the fact that some parts of China (Shantou, Guangdong for example) increased their phone number length to eight digits.

The set of firms from the production data that are also in the transaction trade data are the direct exporters in the production data. The set of firms in the production data with positive exports but that we do not match in the trade transaction data are the indirect exporters.

Because of mistakes in the trade transaction data, we do not necessarily believe that any firm that appears in that data that does NOT appear in the production data is a trade intermediary. For example, it could be a manufacturing firm with sales of less than 5 million RMB. Therefore we narrow the list of intermediaries to those firms in the trade transaction data whose name indicates they are an intermediary. That is we use the method of Ahn et al. (2011) and search for firms whose names contain the Chinese characters meaning *trading*, *export*, or *import*. In pinyin (Romanized Chinese), these phrases are *jinchukou*, *jingmao*, *waijing*, *kemao*, *shangmao*, *maoyi*, and *waimao*.

A second issue is that there are firms that whose entry in the production data indicate they have zero exports, but we find a transaction in the trade data indicating they had positive trade. This could be due to a discrepancy between the year the data on exports in recorded in the trade transaction data and the production data.

A third issue is that in principle a firm could directly export to one destination but not another. Or directly export to one buyer in the same country but indirectly export to a different buyer in the same country. We define firms that report exports larger than their exports in the trade data are exporting both directly and indirectly and are tagged as direct exporters (Bai, Krishna, and Ma (2016)).

Here, we only consider data in year 2004, and 2005, in which the education background of labor is available. The merging results are reported in Table 1. By examining the merging technique, first, the sum of number of direct (column (5)) and indirect exporters (column (7)) after merging should be equal to the number of exporters in production data (column (3)) minus zero exporters (merged with trade data, but not report positive exports in production data. 4,264 in year 2004, 8,354 in year 2005); second, the sum of direct (column (6)) and indirect exports (column (8)) should be equal to exports in production data (column (4)).

Why are there so many unmatched firms in the trade transaction data? Only 40,855 out of 120,590 firms matched in the trade customs data, the reasons there are so many firms in the trade data unmatched is because first there are 19,372 in 2004, 12,513 in 2005 are intermediary firms. Second, the production data only contains firms over 5 million RMB. Third, in the trade data, there are many firm name missing or telephone, zipcode missing, which also cause many firms unmatched. Fourth, the trade data includes agricultural exporters, but not service exporters, since they are not in HS codes, while trade data only records transactions with HS code. Also there is no low-codes in the customs data. That means there are extremely small packages from all kinds of firms too small to really be counted.

By looking at the composition of firms in Table 2, there are 276,474 unique firms IDs in the production data. Of those, 76,990 indicate they had positive export sales, and are thus either a direct or an indirect exporter. We are able to match 40,855 to an observation in the trade data using either firm name and year or postal code, and phone number and also have positive exports. These are the direct exporters. We find 40,399 are indirect exporters meaning the production data says they export but we find no record in the transaction data. And 4,264 are firms with a customs record that exported zero value. There are 40,855 unique firm matches between the trade and production data, but of those 4,264 indicate they had zero exports in the production data, leaving 36,591 direct exporters with a positive transaction that is recorded in the production data.

Table 1: Merged Results

Year	Trade Data		Prodcution Data		Merged Data			
	Expter	Value bil. yuan	Expter	Value bil. yuan	DExpter	Value bil. yuan	INDExpter	Value bil. yuan
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2004	120,590	5,937	76,990	4,048	40,855	2,198	40,399	1,850
2005	144,030	7,567	75,624	4,774	43,610	2,658	40,368	2,116

Notes: Expter, DEpter, INDExpter are short for exporter, direct exporter, and indirect exporter respectively.

Table 2: Composition of Firms

Year	Non-Exporter	Indirect Exporter	Direct Exporter	Zero Exporters	Production Firms
2004	195,220	40,399	40,855(36,591)	4,264	276,474
2005	187,857	40,368	43,610(35,256)	8,354	271,835

Notes: A non-exporter is a unique firm in the production data that is not found in the trade transaction data. A Direct exporter is a unique firm in the production data that has been matched to a unique firm in the trade transaction data. An indirect exporter is a firm that has positive export value in the production data but is not in the trade transaction data set.

Table 3: Export Status Evolution

Export Status	Year 2005		
Year 2004	Non Exporter	Indirect Exporter	Direct Exporter
Non Exporter	0.954	0.025	0.021
Indirect Exporter	0.108	0.750	0.142
Direct Exporter	0.056	0.107	0.837

4 Estimation

4.1 Export Status Transition

In Roberts and Tybout (1997), they state that in the presence of sunk costs, current market participation is affected by prior experience. Table 3 reports the dynamic transition of export status and export modes over the sample period among all the manufacturing firms. The high persistence of non-exporting suggests the existence of significant sunk export costs that prevent firms from starting to export. The fact that more non-exporting firms start exporting indirectly than directly suggests that starting to export directly requires a higher sunk entry cost that less productive firms may not wish to cover. The high entryinto and exit from indirect exporting suggesting that the sunk cost of entry may not be quite as high as that of direct exporting. The much higher rate of starting direct exporting as indirect exporters is consistent with firms self-selecting into different export modes based on their productivity levels.

4.2 Direct and Indirect Exporters per Region

The dataset contains information about the postcodes of firms which identify the geographical location of all entities in terms of the longitude and latitude of a firm's residence. We define counties as regional using the first four digits of the postcode.

Figure 1: Distribution of Direct Exporters

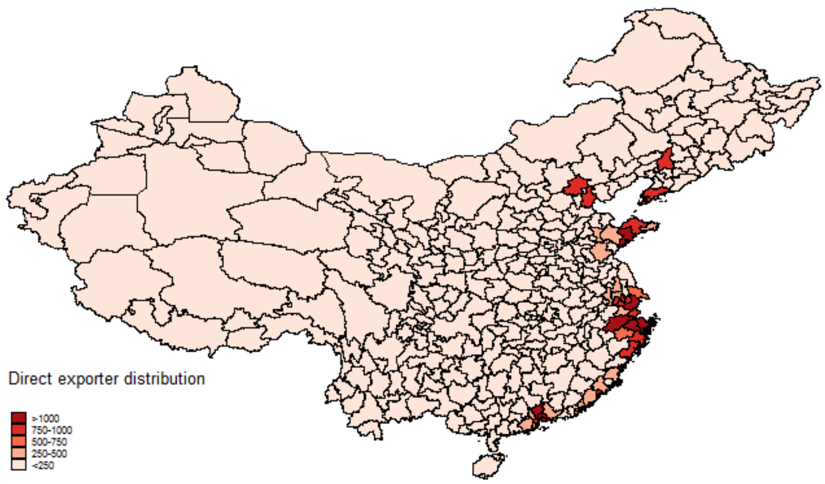

Figure 1 colors counties according to the number of direct exporters, while Figure 2 colors counties according to the number of indirect exporters.

According to Figure 1 and 2, most of direct and indirect exporters locate around coastal regions. By looking at the exporting mode transition from year 2004 to 2005, we found that the top five provinces with transitors from indirect to direct exporters are Guangdong (24.16%), Zhejiang (20.46%), Jiangsu (17.72%), Shanghai (8.70%), and Fujian (5.98%). It is reported in Table 4. Therefore, we only consider Guangdong province for our spatial analysis.

The descriptive statistics of variables regarding to Guangdong province are reported in Table 5. The exporting mode indicator is considered to be 1, if a firm is a direct exporter in year 2004, and keep its exporting status in 2005, and if a firm is an indirect exporter in year 2004, but transit to be direct exporter in 2005; is considered to be 0, if a firm is an indirect exporter in year 2004, and keep its exporting status in 2005 as well.

Figure 2: Distribution of Indirect Exporters

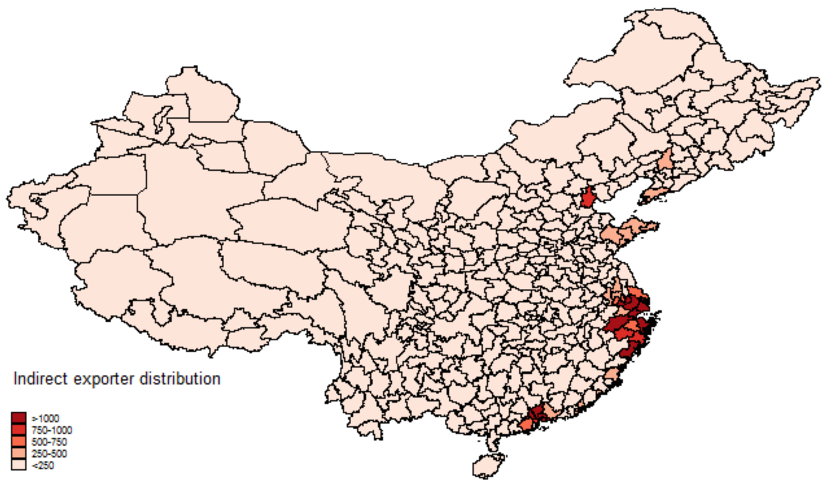

Table 4: Top Five Provinces with Export Transitors

Province	Number	Percent
Guangdong	1155	24.16
Zhejiang	978	20.46
Jiangsu	847	17.72
Shanghai	416	8.70
Fujiang	286	5.98

Table 5: Descriptive Statistics

	Descriptive Statistics			
Variables	Mean	Std	Min	Max
Deindicator	0.6102	0.4877	0	1
Sale(in logs)	10.3649	1.2955	3.9120	18.0863
Labor(in logs)	5.3744	1.1334	.6931	11.1832
Capital(in logs)	8.9105	1.5709	1.3863	15.2768
Material(in logs)	9.8152	1.4812	0.6931	18.0136
Stated-owned	0.0279	0.1648	0	1
Foreign captial ratio	0.2089	0.4138	0	1.8806
Intangile assets intensity	0.0219	0.0546	0	0.8303
Number of firms	11,550			

Table 6: SDM Probit estimates

	SDM Probit estimates		
	Posterior mean	Std	p-level
Constant	-5.926^{***}	1.083	0.000
labor(in logs)	0.277	0.237	0.120
labor×labor	-0.036^{*}	0.024	0.060
capital (in logs)	0.695^{***}	0.159	0.000
capital×capital	-0.018^{*}	0.012	0.063
material (in logs)	0.287^{*}	0.175	0.054
material×material	-0.024^{**}	0.008	0.003
labor×skill labor ratio	0.719^{*}	0.492	0.067
labor×capital	-0.019	0.023	0.200
labor×material	0.038^{*}	0.026	0.063
capital×material	-0.007	0.018	0.348
capital×skill labor ratio	-0.948^{***}	0.415	0.005
material×skill labor ratio	0.254	0.416	0.292
rho	0.915^{***}	0.0139	0.000

4.3 Estimation Results

The coefficient estimates (posterior means, standard deviations, and Bayesian p-levels) for the model parameters β, ρ, and θ are shown in Table 6. As already noted, the coefficient estimates β and θ from the spatial Durbin probit model can not be interpreted as representing how changes in the explanatory variables affect the probability of firm-level choice outcomes in favor of being a direct or indirect exporter. One point to note is that the coefficient ρ associated with the spatial lag of the dependent variable pos is positively significant with a value of 0.915, which indicates there is a positive spatial dependence in firm-level decisions of being direct or indirect exporter.

The posterior median marginal effects estimates are shown in Table 7. These are scalar summary measures calcuated using the methods described in Section 2.

These scalar summary estimates from the basis for proper inference regarding the impact of changes in the various explanatory variables on the probability of a firm choice of being direct exporter. In addition to the posterior means, Bayesian 95% credible intervals for these estimates were constructed using the set of 1000 draws from the MCMC estimation.

By looking at the results in Table 7, we found that five of them have 95% credible intervals that do not span zero for the direct, indirect, and total effect estimates. These variables are: *labor×labor, lncapital, capital×capital, material×material, capital×skill labor ratio.* This indicates that these variables play an important role in firm-levl choice of being direct or indirect exporter.

As mentioned earlier, the direct effect measures how a change in an explanatory variable in firm i affects the dependent variable in firm i, plus any feedback effects. In terms of the direct effects that have an important influence on choice being direct exporter, we find signs that are in accordance with a priori expectations.

The only variable with a positive direct effect estimates is the log of capital. log of capital increased the probability of a firm choose to be a direct exporter. At the same time, the marginal effect of log of labor, capital, and material is decreasing. The interaction term of log capital and skill labor ratio has negative impact on the probability as well.

In summary, we find that the direct effect estimates have sign in accordance with theoretical expectations and that a majority of the explanatory variables play an important role in explaining firm's choice of being direct exporter.

In terms of the indirect effects, we find a similar pattern for the 95% credible intervals as for the direct effects, leading to the same five explanatory variables having posterior distributions do not span from zero for us to conclude that important spatial spillover effects existed for these variables. As noted, the indirect effects measure how changes in the explanatory variables associated with firm i cumulatively impact the dependent variable in all other $n-1$ observations/firms. These effects are commonly referred to as spatial spillovers, and the numerical values of the indirect effects provide quantitative measures of these.

The indirect effects for *labor*$\times$*labor, lncapital, captial*$\times$*capital, material*$\times$*material, capital*$\times$*skill labor ratio* are all larger in magnitude than their associated direct effects. This is because the indirect effect proposed by LeSage et al. (2011) measures the cumulative spatial spillovers falling on all other observations to produce a single numerical value for the indirect effect estimate.

By looking at the indirect effects estimates, the changes in log of capital have a positive indirect effect of 1.065, which is about ten times as large as the direct effect of 0.100 of this variable. There should be about ten neighboring firms to each firm in the sample. The positive effect for *lncapital* indicates that higher log of capital in firm i lead to an increase in the probability of neighboring firm choose to be direct exporter. This is because the physical capital externalities shows that knowledge accumulation in the form of learning by doing also plays an important role in the firm's growth process as stated in Cem and Koch (2007). The marginal indirect effects of log of labor, capital, and material are all significantly negative. The indirect effect of capital interact with skill labor ratio is significantly negative, which means if there are more capital, the effect of skill labor ratio from firm i on its neghbor's choice being direct exporter decrease. This is because, firm i's skill labor might be able to provide technology support for its neighboring firms, but now they have to spend more time on its own firm's increased capital.

Table 7: SDM Probit Effect estimates

	SDM probit effects estimates		
	Lower 0.05	Median	Upper 0.95
Part I: Direct effects			
labor×labor	−0.011	−0.005	0.000
lncapital	0.060	0.100	0.152
capital×capital	−0.005	−0.002	0.000
material×material	−0.006	−0.003	-0.001
capital×skill labor ratio	−0.262	−0.137	−0.046
Part II: Indirect effects			
labor×labor	−0.115	−0.054	0.003
lncapital	0.661	1.065	1.518
capital×capital	−0.060	−0.027	0.002
material×material	−0.060	−0.036	−0.15
capital×skill labor ratio	−2.647	−1.456	−0.492
Part III: Total effects			
labor×labor	−0.126	−0.059	0.003
lncapital	0.736	1.165	1.655
capital×capital	−0.066	−0.030	0.002
material×material	−0.065	−0.040	−0.016
capital×skill labor ratio	−2.919	−1.594	−0.545

5 Conclusion

This paper conducts analysis of the determinants of direct and indirect exports in Guangdong province over the years 2004-2005. Using spatial Durbin probit model, we show that there is a spatial interdependence for firms' choice of exporting mode (direct or indirectly via intermediaries). We find that a firm's decision to transit from an indirect exporter to be a direct exporter is affected by the exporting mode of other neighboring firms.

Our results also find that capital plays a siginificant positive role in determineing firm's own and their neighbors' choice of being direct exporter. But its marginal direct and indirect effects are decreasing. The magnitude of indirect effects for capital is about ten times large as the direct effect. There should be about ten neighboring firms to each firm in the sample. The physical capital externalities shows that knowledge accumulation in the form of learning by doing also plays an important role in the firm's growth process. The capital together with skill labor ratio will have a negative spatial spillover effect. The increased capital will demand more skilled labor in its own firm, and vice versa.

Moreover, future work might consider state transfers occur at different moments in time with a duration.

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