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ABSTRACT

Various public programs have been implemented in the Philippines to foster growth in the MSME sector in recognition of the sector's contribution to economic development. However, growth in the sector has remained stunted due in part to the inability of firms to maximize the benefit from positive externalities arising from agglomeration. This paper seeks to explain the role of locational externalities on the agglomeration of MSMEs in the Philippines. More specifically, it aims to identify the factors that influence location choice among firms, and gauge the spillover impacts of these factors on the decision of firms to locate in distant regions. Our results show that agglomeration economies, labor supply quality, fiscal policies and infrastructure support are important factors considered by MSMEs when choosing where to locate. Significant spatial spillovers are present, which pose both opportunities and challenges to administrators.

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INTRODUCTION

The Micro-, Small- and Medium-scale Enterprises (MSMEs) sector is widely recognized as an important driver of economic growth in the Philippines. In 2008, for instance, MSMEs employed about 61.2 percent of the total number of persons employed by firms. In 2006, the Gross Value-Added by the sector amounted to about USD15 billion, representing more than a tenth of the country's Gross Domestic Product for that year. In addition, recent studies propose much larger roles of MSMEs in the economy including regional development promotion, income redistribution and export industry support. These benefits has prompted the government to foster MSME growth as a development strategy in the Philippines through various government interventions outlined in its economy-wide and sector-specific development plans.[1]

In recent years, various programs have been implemented to support the MSME sector. However growth in the sector remains stunted. Several studies (Nangia and Vaillancourt, 2006; Aldaba, Medalla, del Prado and Yasay, 2010; Aldaba, 2010, 2011) attributed the weak performance of MSMEs to a number of barriers, particularly access to finance, technology and skills, as well as information gaps and difficulties with product quality and marketing. Despite efforts in explaining the slow growth of the MSME sector, little attention have been given to the role of agglomeration economies and the extent of spatial externalities, which may be vital in understanding the dynamics at play when dealing with MSMEs. Literature on the dynamics and the role of location choice in MSME development has also been limited, thus hindering effective policy response from the government.

This study explores the effect of agglomeration and the role of location heterogeneity and spatial externalities on the location choice of MSMEs. More specifically, it aims to (a) identify factors that influence location choice among firms, and (b) gauge the spillover impacts of these factors on the decision of firms to locate in distant regions, by relating traditional discrete choice theory with recent developments in the empirical specification of spatial models of count data.

This paper's contribution is important in a number of ways. First, it bridges the gap on the empirical measure of the degree of industrial agglomeration among MSMEs in the Philippines. While various studies have observed and posited weak agglomeration among firms in the Philippines, measures of the degree of agglomeration remain descriptive and graphical.

[1] See for instance Department of Trade and Industry (2011). *Micro- Small and Medium Enterprise Development Plan 2011-2016*. Makati City, Philippines: DTI, and National Economic Development Administration (2011). *Philippine Development Plan 2011-2016*. Pasig City, Philippines: NEDA.

Second, the study provides a better measure of spatial externality arising from agglomeration. Studies on agglomeration economies may have underestimated the impact of agglomeration by assuming independence among firms in the estimation despite theoretical studies and empirical observations pointing otherwise. A better understanding of agglomeration dynamics and the factors affecting the location choice of MSMEs in the Philippines shall elicit better responses at the policy front.

Identification of the factors that affect the location choice of MSMEs is important for both local and national administrators to be able to provide adequate support for MSME growth. If location externalities among MSMEs are found to be present, then initial support in key regions or locations may be enough to generate the desired outcomes through a spillover effect to distant locations. Targeted interventions shall allow stakeholders to concentrate resources for better results, rather than spreading resources thinly across all regions. Agglomeration shall mean easier access to the MSME network and lower cost of targeted interventions.

The next section presents the theoretical and empirical framework of the paper. We linked the seminal work on discrete choice theory by McFadden (1974) with the more recent spatial count data econometric model by Lambert, Brown and Florax (2010) to account for spatial externalities in location choice. We depart from the modelling approach employed in Alama-sabater, Artal-tur and Navarro-azorin (2011) using Spanish data, and in Autant-Bernard (2007) using French data by specifying location choice as a spatial autoregressive process instead of a variable-specific low-order neighborhood spatial process. In Section 3, we describe the data sources and variables used. Section 4 provides a discussion of the results. Similar to previous studies, our results show that agglomeration economies, labor supply quality, fiscal policies and infrastructure support are important factors considered by MSMEs when choosing where to locate. However, we argue that previous models may have under-estimated the impact of different factors on the location choice of firms by failing to account for spatial externalities in the decision process. Finally, the last section summarizes the main conclusions of the research.

EMPIRICAL SPECIFICATION

Following McFadden (1974), consider a firm i from a collection of firms N faced with the choice to locate in a region r against other locations s in the continuum of space S. Suppose the profit function of the firm if it locates in region r is given by

$$\pi_{ir} = \overline{\pi_{ir}(.)} + e_{ir} \tag{1}$$

The profit function is composed of a deterministic term $\pi_{ir}(.)$ that reflects systemic production technology, and a stochastic term e_{ir} that captures the idiosyncrasies of the firm. Region r is preferred to other locations by firm i if the profit to be had from that region is highest. More formally,

$$\pi_{ir} > \pi_{is} \text{ for all } s \in S, s \neq r \tag{2}$$

Suppose the stochastic terms in the profit functions are independently distributed following an Extreme Value Type I distribution, then it can be shown that the probability of locating in region r is

$$P_{ir} = \frac{\exp\left(\overline{\pi_{ir}(.)}\right)}{\sum_{s\in S} \exp\left(\overline{\pi_{is}(.)}\right)} \tag{3}$$

The above expression is the conditional logit formulation proposed by McFadden (1974). Figueiredo, Guimaraes, and Woodward (2003) show that the parameters in Equation (3) may be consistently estimated by maximizing the log-likelihood of a Poisson distribution, rather than that of a multinomial logistic distribution above. The deterministic expression $\overline{\pi_{.r}(.)}$ is related to the expected number of firms in a region r in a Poisson model as follows

$$E(n_r) = \lambda_r = exp(m + \overline{\pi_{.r}(.)}) \tag{4}$$

We assume that the deterministic component of the profit function may be modeled as a linear combination of explanatory variables. Consider a functional form for $\pi_{.r}(.)$ that depends not just on the values of location-specific attributes in region r, but also on values of the attributes in neighboring regions. This may be viewed as a strategic response of firms to locate centrally, taking into consideration backward and forward linkages in the input and consumption goods markets (Fujita and Krugman, 1995, Hefner and Guimaraes, 1994). Alternatively, spatial dependence may arise from the presence of external economies and spillover effects (Acs, Braunerhjelm, Audretsch and Carlsson, 2009; Fujita and Thisse, 2002; Laakso and Kostiainen, 2009; Qian and Acs, 2013).

We specify the deterministic function as

$$\overline{\pi_{,r}(.)} = \sum_{v=0}^{V} \rho^{v} W_r^{v} X\beta \tag{5}$$

where X is an S by k matrix of location-specific regressors and β is a conformable column-vector of parameters to be estimated. The row-vector W_r^v is the r^{th} row of the v^{th} spatial lag based on the spatial weight matrix W. The spatial weight matrix W, with non-zero elements w_{rs} if r and s are spatial neighbors, summarizes the spatial relationship among regions in the space A. For exposition, suppose element w_{rs} is an indicator function with value equal to 1 if regions r and s share a common boundary, and equal to 0 if otherwise. The spatial lag W^v represents the neighborhood order of locations, where $W^0 = I$ represents own location, $W^1 = W$ represents first-degree neighbors, $W^2 = WW$ represents neighbors of neighbors, etc. The matrix I is a conformable identity matrix. With a row-standardized weight matrix, WX is a matrix of spatially weighted average of attributes of neighboring locations as defined in W. The spatial parameter ρ, assumed to be bounded[2] by $(-1,1)$, measures the degree of spatial relatedness among locations ranging from spatial diffusion, where $\rho \to -1$, to clustering, where $\rho \to 1$. When the spatial autoregressive parameter is equal to zero, the model $\pi_{,r}(.)$ collapses into the usual non-spatial linear-in-parameters function. A similar model is used by Alama-sabater, Artal-tur and Navarro-azorin (2011), where they specify the upper bound of the spatial lag order to one, and by Autant-Bernard (2007), where first-order spatial lags of a subset of the explanatory variables are used, in a spatial conditional logit framework to account for spatial spillovers from neighboring regions.
For sufficiently large number of spatial lags V, the term $\pi_{,r}(.)$ in Equation (5) may be approximated by a more parsimonious representation

[2] See LeSage and Pace (2004) for a mathematical exposition on the theoretical bounds of the autoregressive parameter under different assumptions.

$$\overline{\pi_{.r}(.)} = (I - \rho W)_r^{-1} X\beta \qquad (6)$$

where $(I - \rho W)_r^{-1}$ is the r^{th} row of the spatial multiplier $A^{-1} = (I - \rho W)^{-1}$. The same specification is applied in Vichiensan, Tokunaga and Miyamoto (2005), wherein they consider spatial dependencies in both the deterministic and stochastic components of the conditional logit model. Combining expressions (4) and (6) yields the expected value of the spatial-autoregressive (SAR) Poisson model proposed by Lambert, Brown and Florax (2010).

$$\lambda_r^{SAR} = \exp\left(\tilde{m} + \rho \sum_{r \neq s} w_{rs} \lambda_s^{SAR} + X\beta\right) \qquad (7)$$

Unlike in non-spatial autoregressive Poisson models where β may be interpreted as the proportional change in the expected number of firms in region r induced by a unit change in a variable in X holding others constant, the SAR-Poisson model by construction takes into account the effect of the variable to and from other locations as well. Interpreting β as the relative effects in SAR-Poisson model understates the marginal impact of variables. From (7), the marginal impact from a unit change in covariate x_k in location i can be decomposed as the sum of direct and indirect effects:

$$\frac{\partial \lambda_r^{SAR}}{\partial x_{rk}} = \left(a_{rr}^{-1} \lambda_r^{SAR} + \sum_{r \neq s} a_{rs}^{-1} \lambda_s^{SAR}\right) \beta_k \qquad (8)$$

The first and second term of the multiplier refers to direct and indirect impact multipliers, respectively, where a_{ii}^{-1}, and a_{ij}^{-1} of the spatial multiplier weights are diagonal and off-diagonal elements of the spatial multiplier matrix A^{-1}, respectively. These location-specific marginal effects may be averaged over the sample locations R as an estimate of the population marginal effect as follows:

$$\left(\frac{\partial \lambda_r^{SAR}}{\partial x_{rk}}\right)_{direct} = \frac{\beta_k}{R} \sum_{r \in S} a_{rr}^{-1} \lambda_r^{SAR} \qquad (9)$$

$$\left(\frac{\partial \lambda_r^{SAR}}{\partial x_{rk}}\right)_{indirect} = \frac{\beta_k}{R}\sum_{s\in S}\sum_{s\neq r} a_{rs}^{-1}\lambda_s^{SAR} \tag{10}$$

Direct effect refers to the marginal impact of a change in the variable x_{ik} that emanated in location i to the expected firm count in the same location, including feedback effects from other locations. Indirect effect, on the other hand, refers to the marginal impact on neighboring locations brought about by a unit change in a variable x_{rk}. Indirect effect captures the spatial spillover impacts of a marginal change of a policy variable in a location i to other regions in the space S. The sum of the direct and indirect marginal effects is the total marginal effect presented in (8).

Following the framework proposed by Lambert, et. al. (2010) for the SAR Poisson model, and by Anselin (1988) and Kelejian and Prucha (1999) for the linear SAR lag models, we treat the spatial lag of firm counts as an endogenous variable, and estimate the reduced form equation in (7) based on a generalized method of moments (GMM) approach. We use moment conditions by Windmeijer and Santos-Silva (1997) on count data models with endogenous regressors.[3] Monte Carlo simulation based on the distribution of parameters estimated by the GMM-SAR Poisson model were used to approximate the distribution of the partitioned coefficients used in Equations (9) and (10).

DATA

We are interested in identifying factors that influence firms' locational decision, and estimating the spatial spillover impacts of changes in these factors on the expected number of firms across space. Based on the discussion of the theoretical and empirical specification of the model, the dependent variable in our analysis is the number of micro-, small- and medium-sized enterprises (MSMEs) operating at the municipality level in the Philippines in 2000, which is available from the National Statistics Office (NSO) (2002) Data Kit on Philippine Official Statistics (DATOS). We follow Alama-sabater, et. al. (2011) in specifying municipality as our spatial unit of study to capture the spatial spillover impacts on locational choice. As noted in Arauzo (2008) and Holl (2004a), spatial externalities decline rapidly in space, thus using higher level of spatial

[3] Linear-in-parameters SAR models based on the log-linearization of Equation (6) were also specified. However, the model performs poorly compared with the SAR Poisson model. Furthermore, for some specifications of the linear model, the estimated spatial autoregressive parameter is outside the theoretical bounds, i.e. $\rho > 1$.

aggregation may not be able to capture such features. Furthermore, the use of municipality more closely resembles the decision maker's locational problem (Alama-sabater, et. al., 2011), thereby reducing possible omitted variables bias and improving estimation of spatial effects (Arauzo, 2008; Arauzo and Manjon, 2004).

We control for various factors that may affect expected firm profit, thus firm location choice. Following the typology by Lambert, McNamara and Garrett (2006), we use variables to capture the effects of agglomeration economy, labor supply quality, infrastructure availability, and fiscal policy. We likewise control for geophysical attributes and possible historical determinism in the distribution of MSMEs. Table 1 provides descriptive statistics of the variables used in our analysis.

Agglomeration economies play a decisive role on the location choice of firms (Guimaraes, Figueiredo and Woodward, 2000). In general, agglomeration economies comprise those positive externalities that arise from the higher geographic concentration of economic activity. The literature usually distinguishes between urbanization and localization economies, wherein urbanization economies refer to benefits derived from agglomeration of population, while localization economies are external benefits derived from the agglomeration of industrial activities. To measure urbanization economies, we use population data available from NSO DATOS. Data on industry-specific characteristics by firm size commonly used in the construction of location quotients, which used to measure agglomeration effects (see for instance Gabe, 2005), are not available at the municipality level. As proxy, we use the presence of a large firm in the municipality. Empirical evidence show positive correlation between industrial agglomeration and firm size (Kim, 1995; and Holmes and Steven, 2002) as smaller firms are likely to benefit from locating near large firms (Li, Lu and Wu, 2012). For instance, knowledge spillovers from large firms may attract smaller firms who are receptive to innovations (Feldman, 1994; Kelley and Helper, 2006). Large and smaller firms may likewise take advantage of complementarity in production while avoiding direct competition among each other, especially smaller firms (Noteboom, 1994).

Firm productivity is highly dependent on the availability and quality of labor (McNamara, Kriesel and Deaton, 1988). High quality workers help increase the productivity of firms, thus increasing their profitability. Based on our model of location choice, it is hypothesized that MSMEs locate in areas where high-quality workforce is available. To capture the effect of labor quality on the locational decision of firms, we use the percentage of working age population with high school diploma for each municipality calculated from 2000 NSO Census of Population and Housing.

Local infrastructures, including physical and governance infrastructures, are important in fostering the growth of MSMEs as firm performance is affected by investment climate (Dollar, Hallward-Dreimeier and Mengistae, 2005). Firms locate where there is better public infrastructure (Martin and Rogers, 1995; Egger and Falkinger, 2006; Holl, 2004b; and McCann and Sheffer, 2004). Likewise, institutional quality is also positively correlated with investment flows (Benassy-Quere, Coupet and Mayer, 2007; Buchanan, Le and Rishi, 2012), and new firm survival (Shane and Foo, 1999). Areas with better local infrastructures attract MSMEs due to reduced costs of operation.

The proportion of barangays (villages) in a municipality with available infrastructure is used to capture the effect of physical infrastructures on MSME location choice. Because of the high dimensionality of infrastructure types and correlation among them, we develop an infrastructure index based on factor analysis of the correlation matrix using principal axis factoring method. This is similar to Francois and Manchin (2013), who used principal component analysis to develop an international infrastructure index. The construction of the infrastructure index deals with the difficulty dealing with the analysis of large number of variables and explaining them based on their common underlying factors. We use the first principal factor, which is able to capture 66 percent of variations in the data, to predict a municipality infrastructure index using a regression scoring method. The factor scores are rescaled to be defined between the interval $(0,1)$, wherein higher values indicate better local physical infrastructure. A list of infrastructure types used and their factor loadings are available as an Appendix. Availability of public infrastructure at the barangay level is sourced from NSO DATOS.

We likewise develop an index for local government inclusiveness. We abstract from the definition of Acemoglu and Robinson (2012), which focused on the creation of incentives for investment and innovation and a level playing field through the provision of public services and regulation and guarantees of property rights. Instead we focus on a more limited definition based on the dependency of local governments on its population for income, and the amount they expend for direct services extended to the local population. This index is defined as the product of the proportion of local government expenditure on welfare, security and economic development and the proportion of its income from local sources. Data on detailed income and expenditure of local governments are sourced from the Department of the Interior and Local Government, Bureau of Local Government Finance. The proposed local government inclusiveness index ranges theoretically between 0 and 1, wherein a value of unity indicates perfect inclusiveness.

Like the other factors mentioned, fiscal policies, especially tax and incentive policies, also affect incomes of firms. Firms tend to refrain from locating in areas where there are higher taxes. This is supported by findings of Bartik (1985, 1989) where his results showed a significant and negative fiscal policy effect at the US state-level. Meanwhile, Kriesel and McNamara (1991) as well as Rainey and McNamara (1999) found that fiscal policy factors also have a significant but negative effect at the country-level. Similar with Lambert, McNamara and Garrett (2006), we use effective business tax rate, computed as the quotient of business tax revenue and the total number of establishments in a municipality, to capture the effect of fiscal policy on firm location choice.

Lastly, we control for geophysical characteristics of municipalities by using the natural logarithm of average annual precipitation computed using global climate raster data by Hijmans, Cameron, Parra, Jones and Jarvis (2005). We capture the effect of possible path dependence on location choice by using parish year of establishment-fixed effects. With the establishment in the 16th century of the Spanish colonial government in the Philippines, villages were organized around parishes, which evolved into the present-day municipalities. Differences in the year of first parish establishment, which can proxy for effective subjugation of the local population, may have resulted to differences in the development stages among the municipalities. Year of establishment and location of churches are sourced from the Catholic Bishops' Conference of the Philippines (2002, 2008).

We isolate the effect of province fixed-effects on location choice by subtracting province averages from the following variables: infrastructure index, local government inclusiveness index, proportion of working age population with high school diploma, population, and effective business tax rate. This procedure centers the variables used in the GMM Poisson models at zero, and decreases the correlation among the variables.

While estimates of marginal effects, under certain conditions, are not sensitive to the spatial weight matrix used (LeSage and Pace, 2010; LeSage and Pace, 2011), we employ a grid search to find the optimal spatial weight matrix to be used in our GMM SAR Poisson model. We define element w_{rs} of the spatial weight matrix W as the inverse distance between geographic centroids of two municipalities r and s if the distance between the two points are less than or equal to some set truncation distance d, and zero if otherwise. As is common in the literature, the spatial weight matrix W is row-standardized. Since we have no a priori information on the optimal truncation distance, a grid search over the interval 1.0 and 6.0 degrees (2.0 degree ≈ 111.3 km) at 0.1 degree increments was utilized to identify a proximate optimal truncation distance.

For each truncation distance, we estimated a GMM SAR Poisson model of municipality MSME count on precipitation as exogenous variable, and MSME spatial lag, with first and second order spatial lags of precipitation as instruments. The optimal distance truncation is chosen based on three measures: (a) root-mean-square error (RMSE), which measures the average distance between actual and predicted MSME counts, (b) Pseudo-R^2 computed as squared correlation between actual and predicted MSME count, which measures the degree of linear association between actual and predicted values, and (c) Hansen's J-statistic p-value, which measures the validity of the instruments used. A plot of the three measures under different truncation distances is shown in Figure 1. Based on the plot, the three measures has scree at around 4.5 degrees (≈ 500 km): RMSE and Pseudo-R^2 plateau, while Hansen's J-statistic p-value starts to drop beyond 4.5 degrees. We use this as justification for using 4.5 degrees as truncation distance in our spatial weight matrix. Later in the discussion, we test the sensitivity of our coefficient estimates to the truncation distance used.

RESULTS

Agglomeration economies are formed from positive externalities that arise from spatial concentration of existing economic activities. It represents the savings acquired by firms for locating in areas with relatively large concentrations of other firms. Cost savings may be in the form of reduced cost of access to external services, reduced cost of infrastructure provision and gain of access to a base of workers with specialized skills (Richardson 1973; Henderson and McNamara 1997; Henry and Drabensott 1996; Rainey and McNamara 1999). Due to these incentives, the large concentration of other firms has become an important consideration in the location choice of firms.

The spatial distribution of MSMEs presented in Figure 2.A shows that firms are largely concentrated in three areas: the greater Manila area in Luzon, Western and Central Visayas regions in the Visayas, and Davao Region in Mindanao. With respect to the presence of large firms (Figure 2.B), there appears to be greater number of MSMEs in and around municipalities that are host to large firms, than in municipalities that does not have large firms located within its boundaries. This observation is consistent with the findings by Li, Lu and Wu (2012) on the positive correlation between firm size and degree of industrial agglomeration.

Meanwhile, similar to findings in Kim (1995), and in Holmes and Steven (2002), the Pearson correlation of the counts of MSMEs and large enterprises at the municipality level is positive and highly significant (Pearson's rho = 0.84, p-value < 0.001). This may be indicative of possible agglomerating dynamics between MSMEs and large firms. Moran's I statistic (MSME: I = 0.1064, z-score = 48.6; Large: I = 0.03, z-score = 3.2) shows that the number of firms by size are significantly positively spatially auto-correlated, indicating clustering among firms.

Factors Affecting Location Choice

Parameter estimates of the non-spatial GMM and GMM SAR Poisson models are provided in Table 2. We estimated three specifications of each model type to provide indication of the robustness of the parameter estimates. It is noteworthy that all parameter estimates related to our covariates have the expected sign consistent with previous findings in the literature. Furthermore, parameter estimates of the non-spatial GMM Poisson models (Table 2, Panels 1 to 3), which assume that all the covariates are exogenous, are larger in magnitude than parameter estimates in the other models which account for endogeneity of some covariates. As noted, however, MSME count and the presence of large firms may exhibit dynamic complementarity, making the presence of large firms as a right-hand side variable endogenous thus possibly biasing the estimated parameters.

We follow the procedure proposed by Wooldridge (2001) to test endogeneity in cross-section count data models. Specifically, we test the endogeneity of the presence of large firms in a municipality and of the first-order spatial lag of the outcome variable in our model, using the presence of special economic zones in a municipality and its first order spatial lag, as well as first and second order spatial lags of the natural logarithm of mean annual precipitation, as instruments. Table 3 provides the result of the endogeneity test, which rejects the hypothesis that the two variables are exogenous. The first stage F-statistics are likewise provided, showing the high level of association between the instruments and the endogenous variables.

We specify non-spatial instrumental variable (IV)-GMM Poisson and IV-GMM SAR Poisson models to correct for the endogeneity of the presence of large firms and of the spatial lag of MSME count in the municipality among the explanatory variables. With the number of instruments greater than the number of endogenous variables, we are able to test and affirm the validity of the over-identifying restrictions that the instruments and disturbance process are orthogonal in the GMM models that we specified through Hansen's (1982) J-statistic. Following the discussion by Stock, Wright and Yogo (2002), weak instruments may result to various pathologies in nonlinear GMM models, including different point estimates when using two-step and iterated GMM procedures. We test if our IV-GMM models possess this pathology by comparing model estimates of two-step and iterated GMM procedure using Hausman's (1978) specification test. Results of the tests indicate that our non-spatial and spatial autoregressive IV-GMM models do not share this pathology.

The parameter estimates of the non-spatial IV-GMM Poisson model (Table 2, Panels 4 to 6) are generally higher than that of the IV-GMM SAR Poisson model (Table 2, Panels 7 to 9). It is worthwhile to note, however, that the parameter estimates are not entirely comparable. Coefficient estimates in the non-spatial Poisson model may be interpreted as the expected *total* proportional change in the number of firms with a marginal change in an explanatory variable in the *same* municipality, holding other variables constant. On the other hand, in the SAR Poisson model, this corresponds only to the direct effects, excluding any feedback effects, to a municipality of a marginal change in the explanatory variable in that *same* municipality. However, *total* effect in the SAR Poisson model includes the total indirect impacts to *other* municipalities.

Agglomeration economies are an important factor that drives MSME locational decision. Urban centers with high population are both source of labor supply and of consumption demand, thus attracting MSMEs to cluster around them. Coefficient estimate related to population from the non-spatial IV-GMM Poisson model indicates an expected proportional 2.8 percentage change in the number of MSMEs with a marginal increase of 10,000 persons in the population.

With a national annual average population growth rate of 2 percent, this marginal increase is possible within a year in Cebu City, in Davao City, and among the megacities in the National Capital Region. The presence of large firms has an agglomerating effect which attracts the establishment of MSMEs. In 2000, only about 20 percent of municipalities were hosts to large firms; this leaves large space for expansion to entice the establishment of large firms as well as MSMEs. These results suggest that local governments in highly populated areas as well as areas where large firms are located should have the necessary support to MSMEs, since MSMEs are more likely to locate in those areas.

Inclusiveness of local governments plays a significant role in the choice of decision-makers on where to locate their firms. Within provinces, the number of MSMEs is expected to be higher in municipalities with more inclusive local government. Although the coefficient related to physical infrastructure is not significant for the non-spatial IV-GMM Poisson model, the sign is as expected in the literature: better physical infrastructure is related with higher concentration of firms. Fiscal policy and labor quality likewise enter the decision process of where MSMEs locate. Within provinces, municipalities with higher tax rates are expected to have lower number of MSMEs, holding other variables the same. On the other hand, municipalities with better labor quality, here proxied by the proportion of the working age population with high school diploma, have higher expected number of firms located in them.

Interestingly, climate condition also affects the choice of where MSMEs locate, wherein a one percentage change in mean annual precipitation is related to a 0.72 percentage decrease in the number of MSMEs in a municipality. This result may be indicative of risk aversion among MSMEs, wherein firms locate in areas where climate conditions are relatively better. This is expected of firms in the Philippines, where an average of about 18 typhoons reach landfall annually costing the economy more than USD200 million in damages every year (Israel, 2010).

Spatial Externalities

The non-spatial IV-GMM Poisson model assumes that municipalities are spatially independent, which may not necessarily be true as shown by our spatial auto-correlation test. We model this spatial dependence among municipalities through a spatial autoregressive process in the number of MSMEs located within municipalities. The IV-GMM SAR Poisson model (Table 2, Panels 7 to 9) seems to perform well relative to the non-spatial Poisson models based on a pseudo-R^2

measure computed as the squared correlation of the logged actual and expected number of firms in municipalities. The Pseudo-R^2 of the IV-GMM SAR Poisson models is about 5 to 13 percentage points higher than that of its non-spatial counterpart. This indicates that the SAR Poisson model, by relying on characteristics of neighboring municipalities in addition to own-municipality attributes, is able to capture more variation in the data than the non-spatial Poisson models specified.

Estimates of the spatial autoregressive parameter ρ appear to be stable, wherein estimates under the three specifications are all within two standard deviations from each estimate. We test the theoretical restriction that ρ lies within $(-1,1)$, and fail to reject the hypothesis that it is (p-value = 0.99). The positive and significant estimates indicate that MSMEs exhibit spatial clustering. This likewise signifies that spatial externalities are present, and that MSME location decision is affected not just by the characteristics of a municipality of interest but also of neighboring municipalities'. With an estimate that lies within $(-1,1)$, the spatial externalities are expected to decay with distance. Relative to estimates of the spatial parameter available in the literature, our estimates are close to the 0.83 estimated by Alama-sabater, et. al. (2011) using Spanish municipality data, and the 0.25-0.33 estimated by Alama-sabater, et. al. (2011) for Autant-Bernard (2006) using French regional data and a spatial Durbin-type conditional logit model. This strengthens the claim that spatial externalities are more important at the local level than at higher levels of geographic aggregation.

With an estimated 0.77 spatial autoregressive parameter in the full IV-GMM SAR Poisson model (Table 2, Panel 9), the expected proportional change in the number of MSMEs as a response to a marginal increase in an explanatory variable, holding others constant, is 3.4 times greater than the estimated coefficient. This captures both direct impact, including feedback effects, to the *same* municipality and indirect impacts to *neighboring* municipalities. Thus, treating estimated coefficients in the SAR Poisson model as the same as that in the non-spatial Poisson model greatly understates the impact of marginal changes in the explanatory variables.

Table 4 presents the partitioned coefficients based on the full IV-GMM SAR Poisson model. It is apparent that the indirect effect coefficients are more than thrice the direct effect coefficients. This is indicative of the presence of strong spatial externalities in the factors affecting locational choice of MSMEs. The presence of spatial externalities implies that policies implemented in one municipality affect neighboring municipalities. Thus local governments may not be fully realizing the effects of their investment as some benefits spill over to nearby municipalities. This may foster perverse behavior among local administrators to free-ride on the investments made in neighboring municipalities, or for investing municipalities to under-invest. Hence, higher administrative level intervention, including regional cooperation, may be necessary to correct for possible under investing and free-riding in factors that promote the creation of MSMEs in municipalities.

We test the sensitivity of our estimates to distance truncation used in defining the spatial weight matrix employed in our SAR Poisson model. Figure 3 provides box-and-whisker plots of the distribution of partitioned coefficients of the IV-GMM SAR Poisson model using truncation distance between 2.0 and 6.0 degrees at 0.5 degree intervals. Estimated median of the partitioned coefficients appear not to be very sensitive to changes in distance truncation used in defining spatial weight matrices. Simulated distributions of direct effect coefficients are very similar across distance truncation. On the other hand, indirect and total effect coefficients appear to be higher and more dispersed with higher truncation distance. This is not very surprising, however. Higher truncation distance means that more municipalities are related with each other, thus more geographic space to which effects can be passed on to. Although the box-and-whisker plots indicate more dispersed distribution of indirect effect (thus total effect) coefficients, the dispersion is largely away from zero, thereby not affecting the statistical significance of the estimated coefficients. These results support the claim by LeSage and Pace (2010, 2011) that partitioned marginal effects in SAR models are robust to spatial weight matrix definition if the model is properly specified.

Policy Simulation

In light of limited resources, an important policy question to ask is, “Which MSME intervention provides the most benefit to the economy?” Using the full-specification IV-GMM SAR Poisson Model, we estimate the marginal change in Gross Value Added brought about by funding one policy intervention costing USD226.3 million[4], representing about 0.17 percent of GDP in 2011. More specifically, we consider the following interventions: (a) provision of tax breaks to all firms, (b) full cycle basic education spending, (c) 100 percent electrification of barangay

[4] This value represents the approximate Php10 billion public spending leakage investigated in aid of legislation by the Senate of the Philippines Committee on Accountability of Public Officers and Investigations in 2013.

(villages), and (d) local government grants to finance local spending on welfare, security and economic development. Each policy intervention corresponds to a variable in our MSME location choice model.

The National Statistics Office estimates that in 2011 there are 820,225 firms in the Philippines, of which about 99.6 percent are MSMEs. With USD226.3 million, a grant amounting to USD230 may be given to 987,437 firms. As mentioned in the previous discussion, municipalities with higher effective tax rates are expected to have lower number of MSMEs. Hence, implementing tax breaks will encourage establishment of new MSMEs. If transferred to local governments, the same amount could also increase the proportion of local government expenditure spent on welfare, security and economic development by 2.9 percentage points, thereby resulting to an increase in inclusiveness index by 0.97 percentage points. Alternatively, the same value can finance the fully cycle basic education of about 161.5 thousand workers,[5] which would result to an increase in the proportion of working age population with high school diploma by 0.3 percentage points. Finally, if invested in electrification, it could fill the 0.11 percentage point gap to achieve full barangay electrification, which would result to an increase in the infrastructure index by 1.1 percentage points.[6]

The marginal effect of USD226.3 million-worth policy interventions on the proportional change in the number of MSMEs and its resulting contribution to the economy is shown in Table 6. It is important to note that the estimates correspond to static partial equilibrium effects through the MSME sector, and does not represent the overall impact of policy interventions to the economy. For instance, improvements in average human capital may result to more efficient production, as well as better governance, which have positive effects to output that is not fully captured in the model.

What is apparent in these results is that with spatial externalities at play, investing a certain amount to implement a policy translates into results which are much larger in value than the initial investment. This can be attributed to the presence of indirect effects of the policy to neighboring regions which is observably larger than the direct effect itself. Failing to account for

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[5] Computed using an estimated Php61,923 average basic education 10-year cycle cost based on the 2007 National Transfer Account deflated at 2000 prices. For an overview of NTA theory, estimation and applications, including in the Philippines, see Lee and Mason (2011).

[6] This implies an electrification cost of USD5.03 million for each of the 45 un-electrified barangays as of 2011. The National Electrification Authority considers a barangay energized if at least 20 households living in that barangay had been given electricity connection.

spatial externalities could lead to under-valuation of the impact of interventions. Limiting the measure of economic impacts on direct effects only could result to policies not to be undertaken, as in the case of our simulation for barangay electrification[7] and basic education spending, because of wrongfully attributing negative economic returns. Interestingly, fiscal governance and government inclusiveness have the largest impact on the locational decision of MSMEs, and consequently to the economy. This highlights the importance of institutions on firm productivity.

CONCLUSION

This paper examined the role of location heterogeneity and spatial externalities on the location choice of micro-, small and medium enterprises (MSME). The traditional economic theory on discrete location choice is augmented to capture spatial dynamics, to be able to link the theory with recent developments in the empirical specification of spatial models of count data. Using municipality level data in the Philippines, we provided evidence that agglomeration economies, labor supply quality, fiscal policies and infrastructure support are important factors considered by entrepreneurs when choosing the location of their firms. Identification of these factors is useful to local administrators as this finding provides them various possible areas of intervention to promote MSME establishment and foster their growth. We have shown that spatial effects have large influence on locational decisions of firms, thereby supporting the findings in previous studies.

Our results have important implications in terms of regional and national policy. Although local-level programs to support MSME directly impacts the growth of firms in the same locality, indirect impacts on neighboring localities prove to be significant. In light of limited resources, the presence of spatial spillovers shall enable local as well as national administrators to focus their efforts on key investment locations to promote MSME creation and growth. Spatial clustering among MSMEs provides an avenue for more efficient targeted interventions.

On the flipside, the presence of spatial spillovers may foster perverse behavior among local administrators to free-ride on the investments made by other administrators in nearby localities. This possibility suggests that the support to MSMEs may be sub-optimal at the local

[7] An alternative specification is to use the proportion of barangay energized, instead of the infrastructure index. The estimated total change in GVA increases to USD0.6 billion. This may be attributed to the variable being correlated with other infrastructure services, thus capturing their effects.

level. Hence, regional cooperation or higher administrative level intervention may be necessary to correct for possible underinvesting in factors that promote the creation of MSMEs in municipalities.

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Figure 1. Grid search for distance truncation

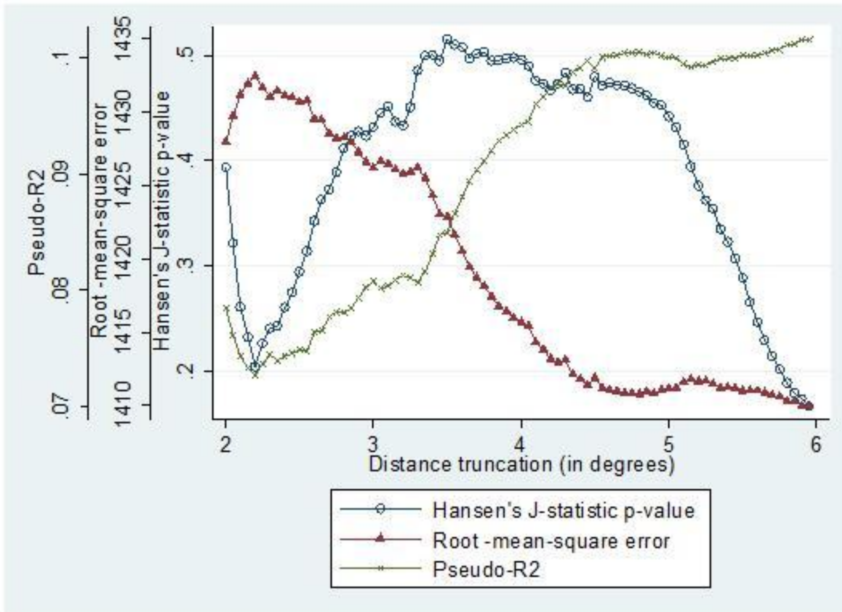
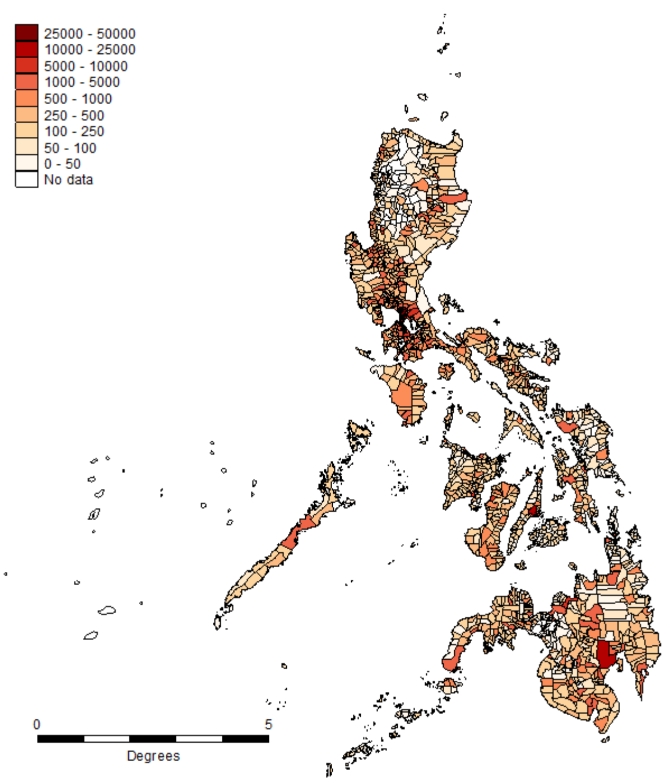


Figure 2. Geographic distribution of firms

A. Micro-, Small and Medium Enterprises



B. Large Enterprises

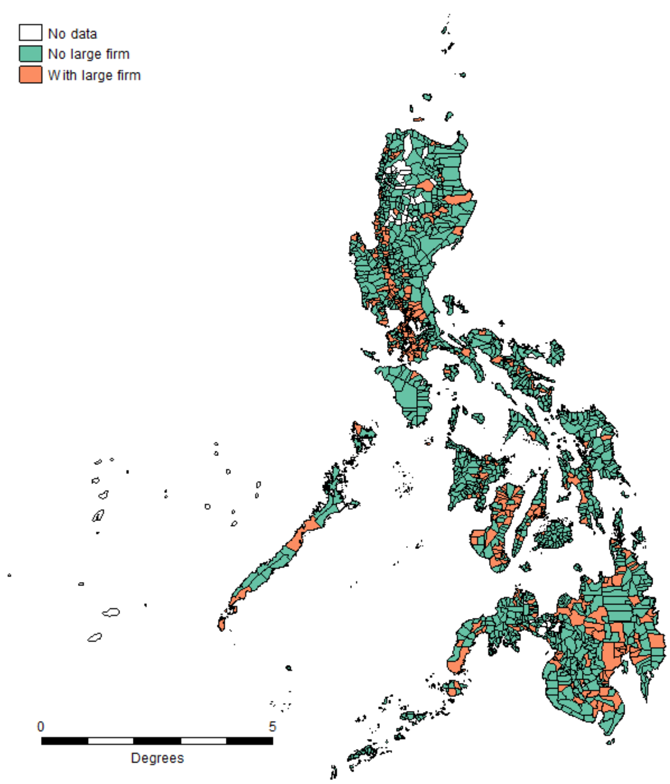


Table 1. Descriptive statistics

	Mean	SD	Min	Max	N
MSME count	458.32	1488.00	1.00	35636.00	1581
Log of mean annual precipitation (cm)	7.80	0.22	7.14	8.44	1581
With large firm (1 = Yes, 0 = No)	0.20	0.40	0.00	1.00	1581
Infrastructure index	0.00	0.10	-0.42	0.67	1581
Local government inclusiveness index	0.00	0.05	-0.20	0.43	1502
Working age population with HS diploma (%)	0.00	0.07	-0.29	0.28	1581
Population ('00,000)	0.00	0.78	-3.24	18.44	1581
Bussiness tax rate (0'000Php)	0.00	3.64	-19.33	114.48	1503
With parish since 1500s (1 = Yes, 0 = No)	0.07	0.25	0.00	1.00	1581
With parish since 1600s (1 = Yes, 0 = No)	0.08	0.27	0.00	1.00	1581
With parish since 1700s (1 = Yes, 0 = No)	0.10	0.31	0.00	1.00	1581
With parish since 1800s (1 = Yes, 0 = No)	0.24	0.43	0.00	1.00	1581

Note: Infrastructure index, Local government inclusiveness index, working age population with high school diploma, population, and business tax rate are centered using provincial average.

Table 2. Poisson model estimates

	GMM Poisson									IV-GMM Poisson									IV-GMM SAR Poisson								
	(1)			(2)			(3)			(4)			(5)			(6)			(7)			(8)			(9)		
	Est.	SE	Sig.	Est.	SE	Sig.	Est.	SE	Sig.	Est.	SE	Sig.	Est.	SE	Sig.	Est.	SE	Sig.	Est.	SE	Sig.	Est.	SE	Sig.	Est.	SE	Sig.
Log of mean annual precipitation (cm)	-0.77	0.31	**	-0.86	0.33	**	-0.86	0.33	***	-0.44	0.31		-0.58	0.31	*	-0.72	0.31	**	-0.36	0.21	*	-0.37	0.20	*	-0.35	0.21	*
With large firm (1 = Yes, 0 = No)	2.07	0.29	***	1.53	0.41	***	1.39	0.36	***	2.91	0.34	***	2.12	0.28	***	2.04	0.26	***	2.46	0.40	***	1.04	0.26	***	1.17	0.29	***
Infrastructure index				0.40	0.22	*	0.49	0.21	**				0.07	0.33		0.25	0.27					0.61	0.30	**	0.61	0.31	**
Local government inclusiveness index				2.28	1.07	**	2.20	1.02	**				1.97	0.80	**	1.61	0.79	**				3.14	0.79	***	2.85	0.81	***
Working age population with HS diploma (%)				3.28	0.37	***	2.70	0.44	***				3.07	0.48	***	2.49	0.52	***				3.42	0.44	***	3.11	0.47	***
Population ('00,000)				0.32	0.08	***	0.30	0.08	***				0.32	0.08	***	0.28	0.07	***				0.43	0.10	***	0.39	0.09	***
Bussiness tax rate (0'000Php)				-0.05	0.01	***	-0.05	0.01	***				-0.06	0.01	***	-0.05	0.01	***				-0.05	0.01	***	-0.05	0.01	***
With parish since 1500s (1 = Yes, 0 = No)							0.70	0.13	***							0.58	0.12	***							0.25	0.10	***
With parish since 1600s (1 = Yes, 0 = No)							0.81	0.15	***							0.73	0.15	***							0.36	0.12	***
With parish since 1700s (1 = Yes, 0 = No)							0.38	0.12	***							0.38	0.13	***							0.14	0.10	
With parish since 1800s (1 = Yes, 0 = No)							0.25	0.11	**							0.24	0.10	**							0.09	0.09	
Constant	11.23	2.40	***	11.92	2.62	***	11.65	2.57	***	8.53	2.40	***	9.59	2.46	***	10.48	2.42	***	4.57	1.68	***	3.72	1.58	**	3.85	1.66	**
rho																			0.65	0.11	***	0.86	0.11	***	0.77	0.10	***
Observations		1581			1502			1502			1581			1502			1502			1581			1502			1502	
Hansen's J Chi2											1.36			1.57			0.20			0.20			1.07			1.37	
Hausman-Wu H Chi2											0.06			2.33			0.29			0.04			0.02			0.33	
Correlation-squared		0.28			0.29			0.29			0.28			0.29			0.29			0.34			0.36			0.42	

*Note: *, **, *** denote significance at the 1, 5 and 10 percent alpha level, respectively. Hausman-Wu test compares 2-step and iterated GMM estimates.*

Table 3. Endogeneity test

	Chi2	df	Sig.	First-stage F
W*MSME count	15.67	1	***	143.29
With large firm (1 = Yes; 0 = No)	37.94	1	***	39. 92
Joint test	49.89	2	***	

Table 4. Partitioned coefficients estimates

	Direct Effects				Indirect Effects				Total Effects			
	Est.		95% C.I.		Est.		95% C.I.		Est.		95% C.I.	
Log of mean annual precipitation (cm)	-0.35	*	-0.71	0.00	-1.18	*	-8.63	0.01	-1.52	*	-9.28	0.01
With large firm (1 = Yes, 0 = No)	1.18	***	0.73	1.68	4.00	***	1.88	20.81	5.18	***	2.92	21.86
Infrastructure index	0.61	**	0.11	1.18	2.06	**	0.20	17.20	2.67	**	0.30	18.12
Local government inclusiveness index	2.87	***	1.57	4.40	9.71	***	2.88	68.92	12.58	***	4.70	73.24
Working age population with HS diploma (%)	3.13	***	2.31	3.99	10.58	***	4.52	68.02	13.71	***	7.33	71.61
Population ('00,000)	0.39	***	0.25	0.56	1.32	***	0.48	8.66	1.71	***	0.78	9.14
Bussiness tax rate (0'000Php)	-0.05	***	-0.06	-0.04	-0.16	***	-0.86	-0.07	-0.20	***	-0.90	-0.11

*Note: Confidence intervals are based on 2,000 Monte Carlo simulation iterations. Significance refer to one-sided statistical significance. *, **, *** denote significance at the 1, 5 and 10 percent alpha level, respectively.*

Table 5. Change in Gross Value Added under different policy scenarios

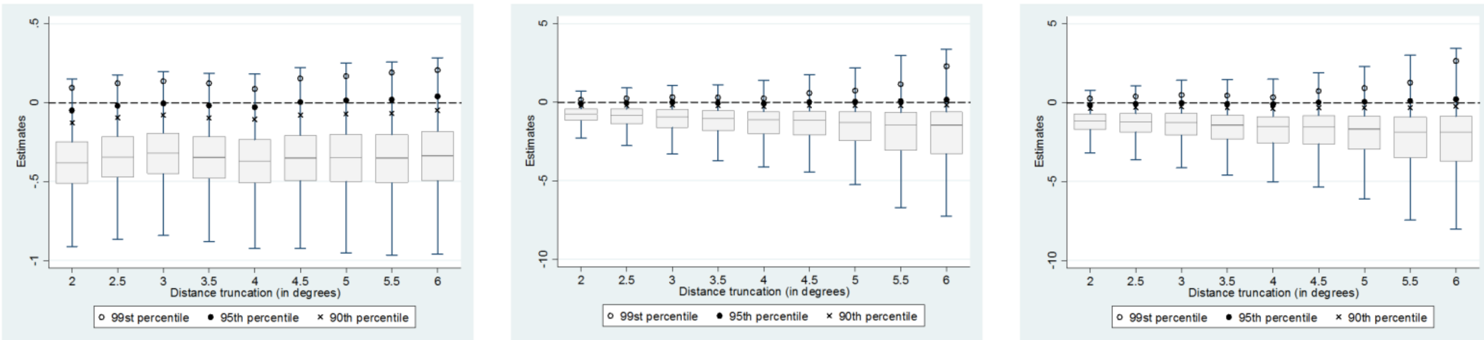
	% Change in	Change in Gross Value Added (USD Billion)		
Policy	MSME Count	Direct Effect	Indirect Effect	Total Effect
Tax breaks	20.5	0.6	2.0	2.6
100% Barangay Electrification	3.0	0.1	0.3	0.4
Full Cycle Basic Education	3.6	0.1	0.4	0.5
Local Development Expenditure	8.8	0.4	1.2	1.6

Note: Gross Value Added estimates are in 2000 prices. USD1 ≈ PhP44

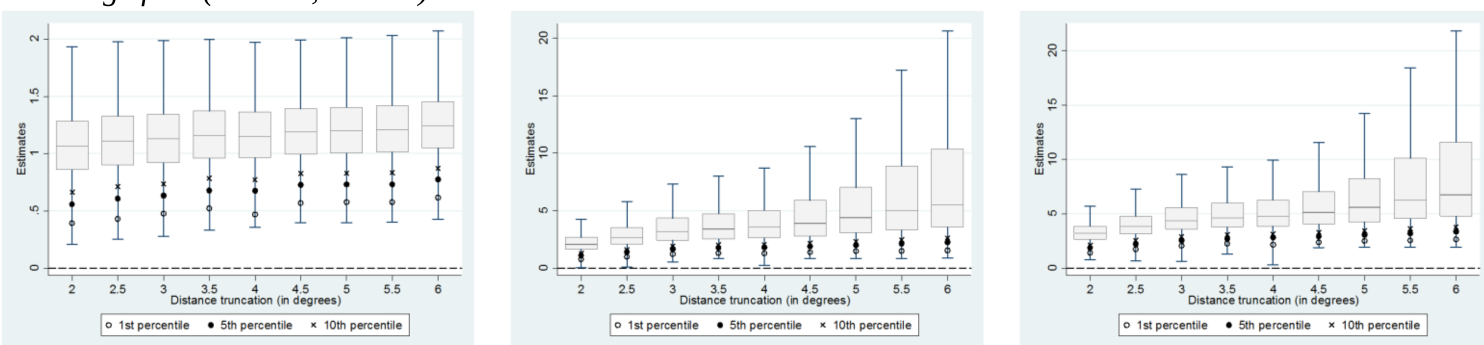
Figure 3. Sensitivity of estimates to distance truncation

Direct Effect	Indirect Effect	Total Effect

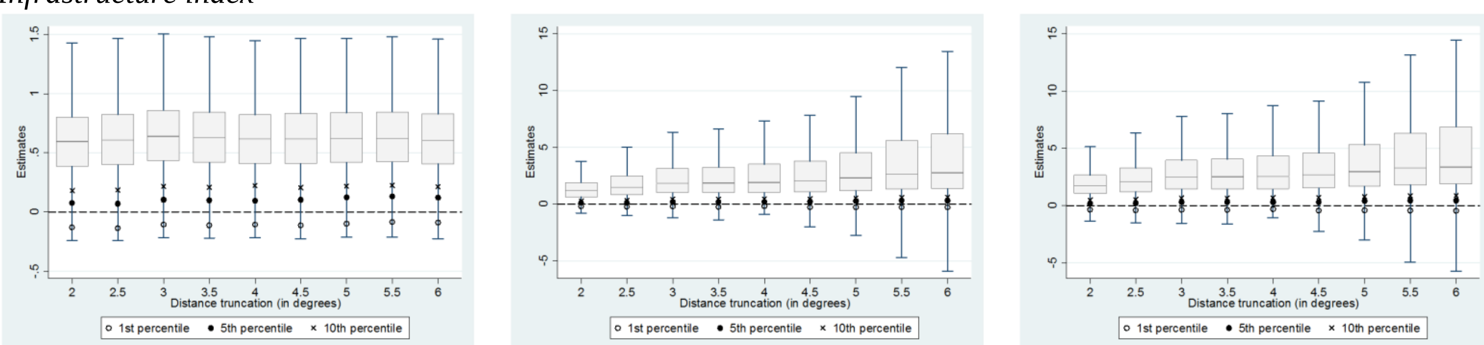
Log of mean annual precipitation (cm)



With large firm (1 = Yes, 0 = No)



Infrastructure index



Local government inclusiveness index

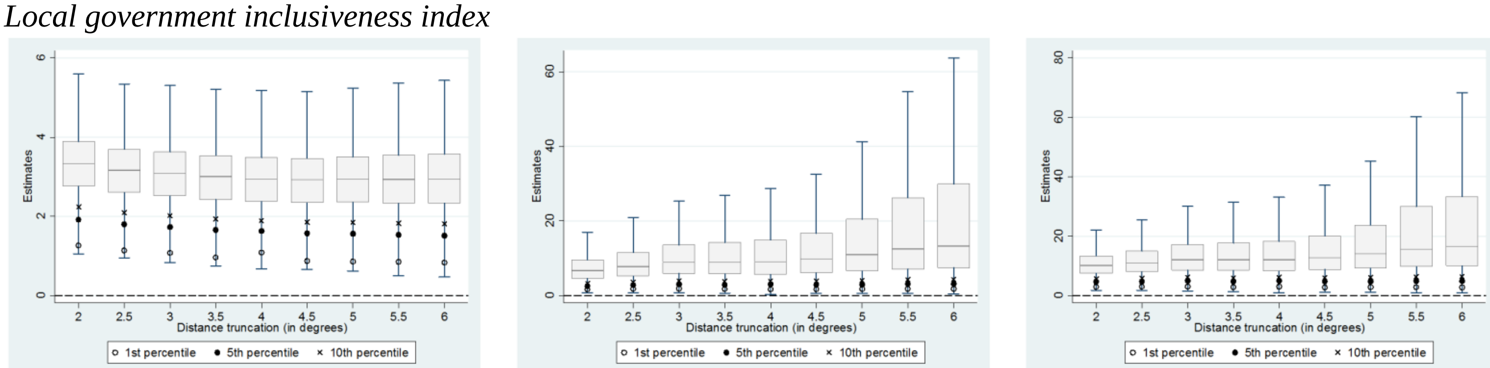
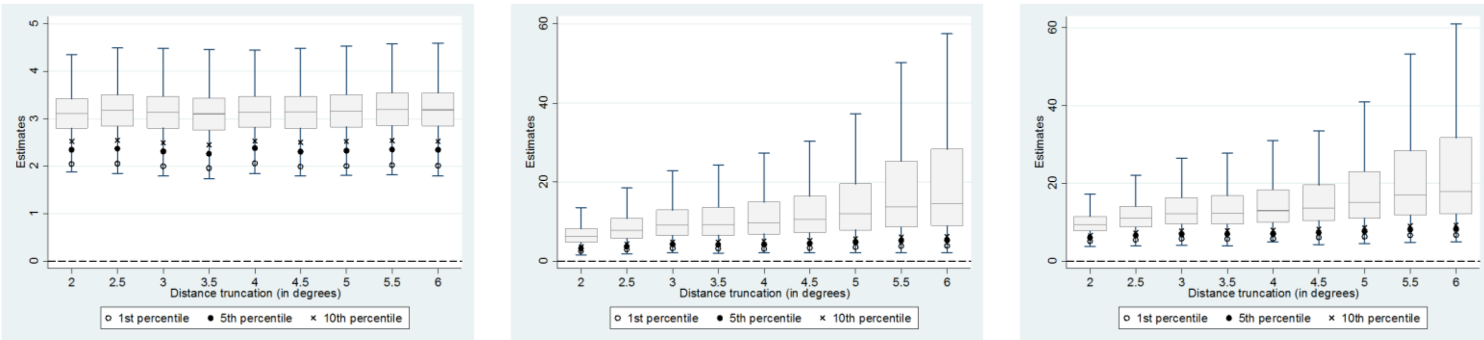


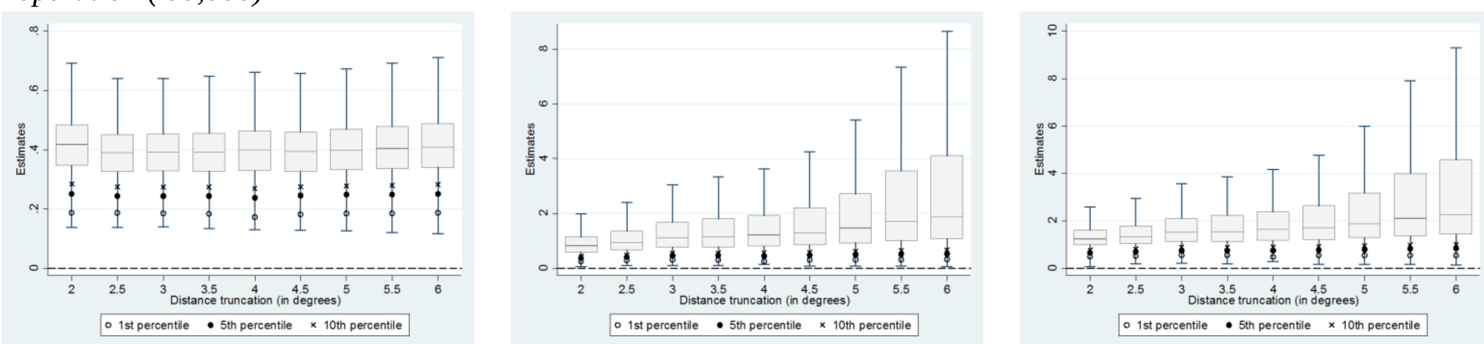
Figure 3. Sensitivity of estimates to distance truncation (con't.)

Direct Effect	Indirect Effect	Total Effect

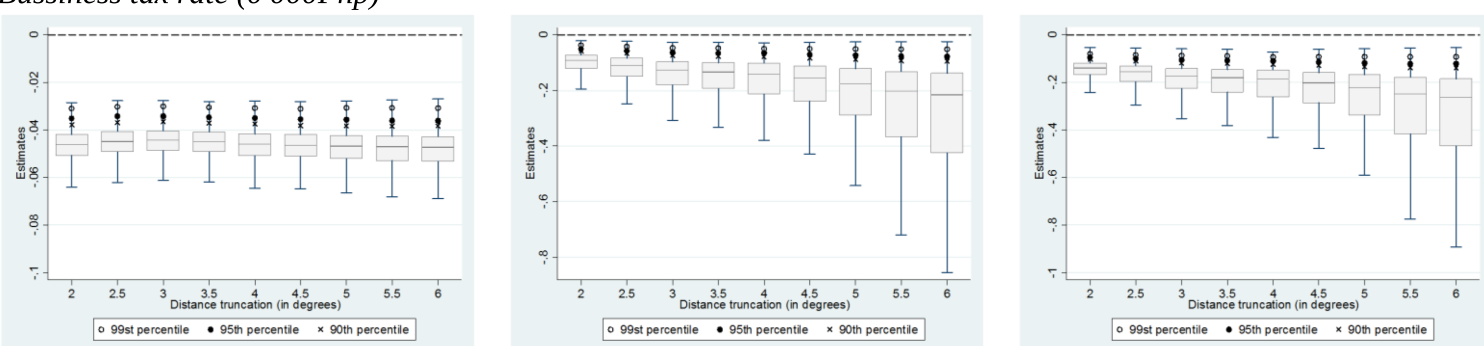
Working age population with HS diploma (%)



Population ('00,000)



Bussiness tax rate (0'000Php)



Note: Based on 2,000 Monte Carlo simulation iterations per distance truncation.

Annex A. Infrastructure index factor loading and scoring coefficient

Variable	Factor loading	Scoring coefficient
% of barangay with a street pattern/network	0.496	0.077
% of barangay with access to the national highway	0.397	0.056
% of barangay with town/city hall or provincial capitol in barangay	0.287	0.048
% of barangay with church/chapel or mosque in barangay	0.133	0.026
% of barangay with public plaza in the barangay	0.222	0.042
% of barangay with market or building with trading activities in baran	0.255	0.049
% of barangay with elementary school in barangay	0.181	0.046
% of barangay with high school in barangay	0.565	0.109
% of barangay with college/university in barangay	0.553	0.099
% of barangay with public library in barangay	0.437	0.061
% of barangay with hospital in barangay	0.538	0.094
% of barangay with health center in barangay	0.537	0.117
% of barangay with barangay hall in barangay	0.362	0.053
% of barangay with housing project in barangay	0.535	0.079
% of barangay with newspaper circulation in barangay	0.702	0.167
% of barangay with telephone in barangay	0.728	0.183
% of barangay with telegraph in barangay	0.571	0.089
% of barangay with postal service in barangay	0.674	0.139
% of barangay with community waterworks system in barangay	0.371	0.053
% of barangay with electric power in barangay	0.531	0.102

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