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Contagious Migration: Evidence from the Philippines

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Abstract

Outward migration data from the Philippines exhibit spatial clustering. This is likely due to information spillover effects - fellow migrants share information with other neighboring migrants, thereby lowering the costs of migration. To verify this, we use spatial econometrics to define a geography-based network of migrants and estimate its effect on the growth in the number of succeeding migrants. We find that current and past migration from one municipality induces contemporaneous and future migration in neighboring municipalities, even while controlling for demographic, economic and institutional factors that may be common across municipalities.

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1. Introduction

Is migration contagious? Research on migrant networks suggest that individuals who have migrated outward provide valuable information to other potential migrants, thereby lowering the costs of subsequent migration. As predicted by Massey, et. al. (1990) and Carrington, Detragiache, and Vishwanath (1996), growing migrant networks induce ever increasing migration as more and more households are able to participate.

Such migrant networks have largely been defined in terms of kinship ties. Information spreads among migrants' relatives, making it easier for other family members to migrate. However, kinship-based networks may not adequately capture the spread of information. Winter, de Janvry and Sadoulet (2001) find that the community can exert as much influence on the decision to migrate as the migrant's relatives. If this is true, then one should be able to observe a contagion-like spread in the number of migrants among neighboring regions. That is, the spatial distribution of migrants would not be random.

Of course, relatives can very well live within the same community, in which case a geography-based migrant network would more or less coincide with a kinship-based network. Nevertheless, it is important to make the distinction. Note that while geography is fixed and exogenous, the location of kin can be endogenous in that it can be related to other factors affecting migration. For instance, poor employment opportunities in one region which can induce a person to migrate outward can also prompt her relatives to move elsewhere. If that person's network were composed of her kin, then this network would be expanding as the number of migrants would be growing and at the same time that employment opportunities would be deteriorating. This would then make it difficult to attribute the growth in the number of migrants to the (information provided by the) migrant network.

This has important policy implications. If information about migration spreads across space, then initial support for migrants need only be provided in key regions or areas. The presence of local government units allows less costly, targeted implementation. In contrast, targeting migrants' families and kin may be more difficult, especially if they live in different regions. Furthermore, if migration is (spatially) contagious, then the benefits from migration are likely to be spatially clustered as well, which makes it easier to tap such benefits. In fact, the literature finds that remittances from migrants enable entire rural communities to develop. Providing institutional and financial support to these migrant-communities to, say, establish microenterprises would be cheaper because of scale effects.

Thus, in this paper, we determine to what extent geography-based migrant networks affect the number of future migrants. Using data on international migrants in the Ilocos Region of the Philippines, we first confirm the spatial correlation of the number of migrants across the different municipalities in Ilocos. Then, using Anselin, Le Gallo and Jayet's (2008) time-space simultaneous model with unobserved heterogeneity, we define the geography-based network and model its contemporaneous and future effects on succeeding migration in the immediate and in neighboring municipalities. With this specification, we are able to show that the benefits of the network spread across space and time.[1]

We estimate the model using Elhorst's (2010) bias-corrected least squares dummy variable (BCLSDV) technique, and find that geography-based migrant networks significantly affect subsequent migration, with spillover effects to neighboring municipalities being particularly large.

The rest of the paper is organized as follows. Section 2 analyzes the data and defines the geography-based migrant network. Section 3 explains the time-space simultaneous model and estimation technique, and Section 4 presents the results and compares them with those obtained from (non-spatial) OLS estimation. Section 5 concludes.

2. Data

Migration patterns within a source/home country or region can exhibit spatial clustering. Figure 1 plots outward migration data from the 125 municipalities[2] of the Ilocos Region in the Philippines in the periods 1990, 1995 and 2000, taken from the country's National Statistics Office (NSO):

< Figure 1 >

With a few pockets of municipalities with large levels of migrant workers stock at the start of each period, levels in neighbouring areas have increased in an outward direction from these municipalities.

[1] Spatial econometrics have thus far been used to model migrant networks between origin and destination countries, to show, for instance, how individuals migrate to countries or regions to which their own countrymen have gone (cf. e.g. LeSage and Pace (2005), Baghdadi (2005), Epstein and Gang (2006), and Bauer, Epstein and Gang (2000).) Our model is different in that we look at the effect of a network on one's decision to migrate, and not where to migrate. A similar notion is found in Lundberg (2002) who uses spatial econometrics to analyze net migration in Sweden.

[2] A municipality is composed of contiguous *barangays* (villages). The Ilocos Region in the Philippines is selected as the region of study because of its long history of local and international migration. (See Findlay (1987) for an exposition.)

Such spatial clustering is confirmed by Moran's I statistics, which is 0.11 (p-value = 0.000) for the 1990 data, and increases to 0.12 (p-value = 0.000) for 1995, and to 0.17 (p-value = 0.000) for 2000. This implies that the degree of clustering in migrant workers stock among neighbouring municipalities has intensified.

The pattern, however, might only be coincidental. It might happen that neighboring municipalities share common characteristics. For instance, institutions are usually determined at the aggregate level and seldom vary across smaller units, and many growth and development projects are undertaken at the regional to national scale. Also, neighboring areas might face similar demographic pressures which induce or prevent family members to seek employment elsewhere. To the extent that these factors affect the opportunities for, and costs of, migration for the entire region, migration would naturally occur region-wide.

Since institutions do not vary much over short periods of time, we can control for their effects by constructing a panel of municipal-level data over the periods 1990, 1995 and 2000 and treating institutions as a fixed effect. However, demographics and economic factors change over time. Thus, to control for economic opportunities, we compute the proportion of household heads with tertiary education (to those with no tertiary education) in each municipality. To capture demographic pressures, we contruct two age dependency ratios. One is the young-age dependency ratio - the proportion of the number of individuals in the municipality who are less than 15 years old to the number of individuals who are 15 to 64 years old, while the other is the old-age dependency ratio – the proportion of the number of individuals greater than 64 years old to the number of individuals 15 to 64 years old. Although the effects of such demographics are not clear cut, one can posit that a high young-age dependency ratio can pressure older family members to augment household income, while a high old-age dependency ratio can prevent individuals from leaving in order to take care of aging family members.[3]

Aggregating household data to the municipal level also allows us to control for possible feedback from the number of migrants to the demographic and economic factors affecting migration. For instance, we do not expect municipality age dependency ratios to be affected by the stock of migrants in the same time period since the population distribution has evolved independently of the decision of individual household members to migrate, unless households with migrant workers comprise a significant proportion of the population, which is not true in our case. The same logic applies to the relationship of education level of household heads and level of migrant workers in a municipality.

Table 1 shows the distribution of migrant workers, age dependency ratios, and proportion of household heads with tertiary education in the Ilocos Region across municipalities for each of the three time periods in the panel. Because we are interested in the growth of municipal-level migrant workers stock relative to the growth of other municipality-level characteristics, we also provide log values and use a double-log specification in our regressions.

<Table 1>

[3]Note that in the Philippines, retirement homes are almost non-existent, and younger members of the household are expected to care for elderly members.

Such regressions ultimately aim to identify the effect of having neighboring migrants on the decision to migrate. That is, after controlling for institutional, economic, and demographic variables, some remaining variation in the number of migrants may be attributed to the strength of the geography-based social network of fellow migrants.

Before constructing a suitable proxy for this main variable of interest, we first point out that most studies on migrant networks at the micro level define networks based on kinship ties. However, as pointed out by Palloni et al. (2001), kinship-based networks are not necessarily the most important type of network that determines migration decisions. Winters, de Janvry and Sadoulet, for instance, find that community and family networks are substitutes in providing assistance to prospective migrants. Kinship-based networks become less important as migration becomes well established in a community. To the extent that communities are established by geographical location thus makes a geography-based network a better proxy for the influence of community ties.[4]

Strong migrant networks can induce more migration by providing information, thereby lowering the costs of migration (cf. e.g. Mincer (1978), Taylor (1986) Massey et al (1987), Massey (1986, 1990), Marks (1989), Grossman (1989), and Munshi (2003).) Using a geography-based network is thus appropriate in that information is likely to spread not only to family members and relatives but among neighbours as well. The formal and informal interactions in and across villages and municipalities afford regular exchange of news and gossip, allowing information about fellow migrants to spread easily.

Migrant networks can also alleviate information asymmetry across the source region/country and the destination region/country. Javorcik et al. (2010), for instance, find that the presence of migrant networks in the US is positively related to US foreign direct investment in the migrant home countries. The authors argue that networks that transcend national borders can help ease information asymmetries and stimulate trade among economies. Although the network in this case pertains to the groups of migrants in the destination country, they nevertheless underscore the role of networks in providing information.

Nevertheless, networks at the source/home region can also increase the benefits of migration by spreading income and remittances from migration widely across the community. This is how McKenzie and Rapoport (2007), for instance, find that migration reduces poverty and inequality in rural communities. Woodruff and Zenteno (2007) also find that migrants' remittances alleviate capital constraints and help microenterprises in the source/home region achieve higher investment levels and profits.

A good proxy for a geography-based migrant network is one that captures the flows of information, credit and/or income remittances, within and across neighborhoods. These flows occur through space and across time, which is why in constructing the proxy, we specify not

[4]Nevertheless, a geography-based network can also encapsulate kinship ties to the extent that families and close relatives can live near each other.

only the contemporaneous (geographic/spatial) cluster of migrants, but also its lagged effects on succeeding migration flows.

Thus, for a given region with N municipalities, let elements w_{ij} , $i, j = 1,2, \ldots N$, capture the pair-wise spatial interaction between a municipality i and another municipality $j \neq i$, and let the $N \; x \; N$ matrix formed by these elements be denoted by W.

If y_t denotes the $N \; x \; 1$ vector capturing the stock of migrant workers in the N municipalities as of time t, we can weight this stock of migrants by the extent of spatial interactions W among them to form the geography-based network Wy_t of migrants. If this network affects the extent of current migration, that is, if Wy_t affects y_t, then the lagged value y_{t-1} incorporates the effect of the previous network Wy_{t-1} on previous migration y_{t-1}. Thus, to capture both contemporaneous and delayed effects on migration, we can use both Wy_t and y_{t-1} as proxies for the network.

Values of y_t and y_{t-1} are given by the NSO data on the (log) number of migrants in the Ilocos Region for 1990, 1995, and 2000 (summarized in Table 1). The particular weight W that we use is constructed from geographic information from the NSO Data Kit of Official Philippine Statistics (DATOS). Using such data, we first calculate distances d_{ij} between pairs of centroids of municipality i and j, then compare with a given distance d^*, beyond which we assume pair-wise spatial interaction to be non-existent, i.e. $w_{ij} = 0$.

We consider three distance bands: $d^* = 0.4^o, 0.5^o, 0.6^o$[5], and compute elements w_{ij} in two ways:

$$w_{ij}^{bin} = \begin{cases} 1, & if \; d_{ij} < d^* \\ 0, & if \; otherwise \end{cases}$$

and

$$w_{ij}^{inv} = \begin{cases} \dfrac{1}{d_{ij}}, & if \; d_{ij} < d^* \\ 0, & if \; otherwise \end{cases}$$

to form matrix W^{bin} and W^{inv}, respectively.[6] We find that W^{bin} with distance band $d^* = 0.5^o$(approximately 55 km) fits the data best, and thus use as the weight of y_t in the succeeding regression analysis.[7]

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[5] As is common in map data, coordinates in the map of DATOS are measured in degrees.

[6] The elements of both matrices are row-standardized to ensure that the maximum eigenvalue of each matrix is at most one. See LeSage and Pace (2009).

[7] In theory, a distance band between observations that will maximize the fit of the model may be simultaneously estimated with the other parameters. In spatial econometrics practice, however, distance bands that best fit the data are ex ante chosen. Note that choosing too narrow a radius would exclude observations which are otherwise spatially related. On the other hand, choosing too wide a radius would dampen spatial dependence among units that are actually spatially related.

3. Estimation

3.1. Empirical Model

Using Wy_t and y_{t-1}, we can then adopt a time-space simultaneous model with cross-sectional fixed effects (as in Anselin, Le Gallo and Jayet):

$$y_t = \tau y_{t-1} + \rho W y_t + x_t \beta' + u + e_t \tag{1}$$

where $\tau \in (-1, 1)$ captures the effect of the lagged dependent variable (incorporating, among others, the delayed effect of networks, or the effect of past networks), and ρ the contemporaneous effect of the network, assumed to be constrained within $(\frac{1}{r_{min}}, 1)$, where r_{min} is the minimum eigenvalue of the matrix W when its elements are row-standardized (see LeSage and Pace for details). x_t is a $N\ x\ K$ vector of controls (e.g. (log) age dependency ratios and (log) number of household heads with tertiary education) with corresponding $1\ x\ K$ vector β of parameters, and u a $N\ x\ 1$ vector of unobserved heterogeneity which we allow to be correlated with the explanatory variables. The unobserved heterogeneity, modelled as area-fixed effects, accounts for all other time-invariant factors (e.g. institutions and long-term policies) which may affect the stock of migrants. Lastly, e_t is a $N\ x\ 1$ vector of random errors which are assumed to be independent and identically distributed as $N(0, \sigma^2)$.

Manipulation of the model in (1) shows that the data-generating process of the model may be specified as[8]:

$$y_t = (I_N - \rho W)^{-1}(\tau y_{t-1} + x_t \beta' + u + e_t) \tag{2}$$

$$\begin{aligned} y_t = &\left\{ y_0 \prod_{k=1}^{T} \tau\, (I_N - \rho W)^{-1} \right\} + \left\{ \sum_{k=1}^{T} \tau^{k-1} (I_N - \rho W)^{-k} x_{t-(k-1)} \beta' \right\} \\ &+ \left\{ \sum_{k=1}^{T} \tau^{k-1} (I_N - \rho W)^{-k} (u + e_t) \right\} \end{aligned} \tag{3}$$

where I_N is a $N\ x\ N$ identity matrix.

As shown in (3), the model may be partitioned as the sum of three components. The first component $\{y_0 \prod_{k=1}^{T} \tau\, (I_N - \rho W)^{-1}\}$ may be seen as a 'first-movers' component (Component 1) to the extent that it is based on the initial (log) stock of migrant workers. The second component $\{\sum_{k=1}^{T} \tau^{k-1} (I_N - \rho W)^{-k} x_{t-(k-1)} \beta'\}$ is an evolving component (Component 2) which is based on time-varying exogenous variables x. The last component $\{\sum_{k=1}^{T} \tau^{k-1} (I_N - \rho W)^{-k} (u + e_t)\}$ is an unobserved component (Component 3), which may be partitioned further as (a) unobserved heterogeneity and as (b) white noise.

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[8]Another specification of the data-generating process is $y_t = (1 - \rho W - \tau L)^{-1}(x_t \beta' + u + e_t)$, where L is a temporal lag operator, which highlights the spatio-temporal multiplier effect$(1 - \rho W - \tau L)^{-1}$.

One can see how these components spread spatio-temporally by looking at the function $f((I - \rho W)^{-1},\ \tau)$. Taking the expectation of the equation in (3), and assuming that $\sum_{j=1}^{N} w_{ij} = 1$, if $|\tau| < |1 - \rho|$, for sufficiently large time T, the first-movers component (Component 1) becomes diluted by more recent dynamics brought about by shocks in the evolving component (Component 2). This does not mean that first-movers are not important determinants of present (logged) levels of migrant workers stock, but it may signify that more recent dynamics in home areas and in neighbouring geographic regions are more relevant. On the other hand, if $|\tau| > |1 - \rho|$, the role of the first movers is magnified as time T tends to infinity. In any case, however, note that a shock in any spatial unit i at time t through any of the components will have spillover impacts to other units that are spatially inter-related.

Although the true residuals in the vector e_t are assumed to be independent identically distributed $N(0, \sigma^2)$, the observed residuals $\{(1 - \rho W)^{-1} e_{it}\}$ are spatially correlated, which makes inference using ordinary least squares generally invalid, unless spatial correlation is controlled for. The unobserved heterogeneity in a non-spatial fixed-effects panel model may capture this spatial interaction if the unobserved effects are time-invariant. If ρ equals 0, the model in (1) collapses to the usual non-spatial panel model with fixed effects, which assumes cross-section independence across observations.

3.2. Estimation Issues

The presence of the endogenous variable Wy_t on the right-hand side of the equation in (1) complicates estimation of this model. Although classic two-stage and three-stage least squares estimators may account for feedback simultaneity in the model, these estimators are inappropriate in accounting for both spatial autoregressive simultaneity and spatial cross-regressive simultaneity (Jeanty, Partridge and Irwin, 2010). Elhorst provides a review of different estimators of the time-space simultaneous model with area-fixed effects, especially when T is small[9]. Due to limitations on data, however, Elhorst's one-step[10] bias-corrected least squares dummy variable (BCLSDV) based on Yu, de Jong and Lee (2008) is used in this study. Elhorst finds that the BCLSDV fare relatively well, even for small T.

The one-step BCLSDV begins by concentrating out the fixed effects in the model by demeaning each of the variables y_t, y_{t-1} and x_t by observation across time periods. Since the true error term e_t are assumed to be independent identically distributed $N(0, \sigma^2)$, the uncorrected LSDV may be estimated via maximum likelihood estimation, similar to the cross-section spatial autoregressive case, using the demeaned variables y_t^*, y_{t-1}^* and x_t^*. The likelihood function to be maximized is given by Elhorst as follows:

$$\log L = -\frac{NT}{2}\log\left(2\pi\sigma^2\right) + T\log|I_N - \rho W| \\ - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{it}^* - \tau y_{t-1}^* - \rho\left(\sum_{j=1}^{N} w_{ij} y_{jt}\right)^* - x_t^* \beta'\right)^2$$

[9] Elhorst studies the case when $T = 5$

[10] A two-step estimator is likewise available

LeSage and Pace (2009) discuss computationally efficient procedures to estimate the parameters of the likelihood function, especially in relation to manipulation of the matrix$|I_N - \rho W|$. Computational search algorithms are utilized to maximize the (log-) likelihood function.

As is well-known, the LSDV estimator is biased if the model contains a dynamic lag of the dependent variable. The estimated parameters are corrected using the asymptotic bias of LSDV estimators for fixed-effect models with both dynamic and spatial lags, as derived by Yu, de Jong and Lee.

To assess the goodness of fit, we use a quasi-R^2 measure, computed as the squared correlation of the predicted and the actual (logged) level of migrant workers stock. It must be noted that the predicted values of the BCLSDV model are generated using equation (2).

3.3. *Interpretation of Results*

From equation (2), it is evident that the marginal effects of a change in any of the right-hand side variables, say y_{it-1}, do not correspond to its corresponding estimated parameter, in this case τ, as in the classic ordinary least squares sense. Instead, the marginal effect is given by

$$\partial y_t = (I_N - \rho W)^{-1} \tau \, \partial y_{t-1} \tag{4}$$

For simplicity, we assume that$|\rho| < 1$. Thus

$$\partial y_t = \sum_{l=0}^{\infty} (\rho W)^l \, \tau \, \partial y_{t-1} \tag{5}$$

where $W^0 = I_N$, $W^1 = W$, $W^2 = WW$, etc. $l$in the literature is the order of neighbourhood among spatial units, e.g. $l = 0$ correspond to own area, $l = 1$ correspond to actual neighbours, $l = 2$ correspond to neighbours of first order neighbours, etc.

Following LeSage and Pace (2009), we define a function

$$G_\varphi(W) = (I_N - \rho W)^{-1} \varphi \tag{6}$$

where φ is the estimated parameter related with a variable in the right-hand side of the equation in (1). The diagonal elements of $G_\varphi(W)$ correspond to direct impacts or own-partial effects since they account for the marginal effect contained within area i, including feedback effects from neighbouring spatial units$j$, for a unit change in the corresponding variable at area i. Off-diagonal elements of$G_\varphi(W)$, on the other hand, are referred to as indirect impacts or cross-partial effects or spill-over effects because these correspond to the marginal change in neighbouring unit j for a unit change in the corresponding variable in area i. Total impacts from (to) area i are defined by the row (column) sum of $G_\varphi(W)$. Scalar summary measures are given by LeSage and Pace (2009), based on mean impacts across observations, as follows:

$$Average\ Direct\ Impact = n^{-1} trace\left(G_\varphi(W)\right) \tag{7}$$

$$Average\ Total\ Impact = n^{-1}\iota_N' G_\varphi(W)\iota_N \quad (8)$$

$$Average\ Indirect\ Impact = Average\ Total\ Impact - Average\ Direct\ Impact \quad (9)$$

where ι_N is a $N\,x\,1$ vector of ones. For completeness, average effects partitioned by neighbourhood may be generated by expanding $(I_N - \rho W)^{-1}$ in $G_\varphi(W)$, as in (5).

Posterior estimates of standard errors for the estimated partial effects may be generated using Markov-chain Monte Carlo simulations, as in LeSage and Pace (2009), or by Krinsky and Robb simulation procedures, as in Jeanty, Partridge and Irwin. In this paper, bootstrapped standard errors are computed for the summary measures.

4. Results

Table 2 presents results from estimation of the spatial model (BCLSDV), and compares them with the results from a non-spatial fixed effects model (OLS on the demeaned variables). To check the sensitivity of the model to variables included as explanatory variables, we use two sets of independent variables. Set 1 includes the (log of the) lagged stock of migrant workers, and (log of) young- and old-age dependency ratios. In Set 2, we add the (log of the) proportion of household heads with tertiary education.

<Table 2>

The OLS estimates are likely biased because of the inclusion of the lag of the dependent variable. In addition, unlike BCLSDV, OLS estimation does not capture spatial spillover effects to neighbouring units j arising from marginal changes in the covariates of municipality i. Note, then, that the coefficient of young-age dependency ratio is negative by OLS, while positive by BCLSDV, estimation.

BCLSDV estimation thus allows us to capture a larger proportion of the variability in the stock of migrant workers. Using Set 2, for example, the squared-correlation using the BCLSDV is 99.7%, compared with 52.1% when using OLS. Additional variation would have otherwise been captured in OLS by the municipality-fixed effects. Note that adding the estimated unobserved heterogeneity in the OLS predicted values would raise its pseudo-R^2 measure to 98.6%. (For subsequent discussions, we use estimates in Set 2 since the models have higher pseudo-R^2.)

Although we cannot interpret directly the estimated parameters in the BCLSDV model (recall section 3.3), the estimated coefficient of the (log of the) lag of migrant workers stock, i.e. $\hat{\tau}$, may be seen as the estimated temporal rate of decay of the effect of the spatial network, while $\hat{\rho}$, the estimated coefficient of the current spatial network (log(W*migrant worker stock$_t$)), measures the contemporaneous spread. A τ or ρ coefficient close to one indicates that network effects decay slowly and/or spread quickly. That $\hat{\tau} = 0.059$ is low is expected, given that our panel data has time gaps of five years. Annual data might have otherwise generated larger $\hat{\tau}$. On the other hand, $\hat{\rho} = 0.660$ indicates that the spatial relationship among units is large, making the indirect effects of the network more pronounced. Following the data-generating process in (4), the fact that $|\hat{\tau}| < |1 - \hat{\rho}|$ indicates that more recent dynamics may be more important determinants of the growth in the stock of migrant workers than the first-movers component.

Because of the double log specification, the estimates can be interpreted as elasticities. However, recall from section 3.3 that the estimated coefficients from BCLSDV are not equal to the marginal effect of the covariates since the latter incorporates the (contemporaneous) network effect. The estimated coefficients from BCLSDV underestimate the mean effect of a change in the covariates. As a consequence, this average effect may be significant even if the estimated BCLSDV parameters are statistically insignificant. Note, then, that while $\hat{\tau}$ is insignificant, the partitioned mean effect of the lag of migrant workers stock is significant, as shown in Table 3.

<Table 3>

That is, since the average effect incorporates the contemporaneous spillovers across municipalities, the average total effect of the lagged stock of migrant workers is still significant, in spite of the large (5-year) time gaps in our panel data (and the low and insignificant $\hat{\tau}$). However small the effect of the lagged stock of migrant workers on its own municipality's stock in the current period, this effect spreads quickly to neighboring municipalities because $\hat{\rho}$ is high. Thus, the estimated average total effect from a one percent increase in the stock of migrant workers in the previous period is a 0.178% increase in the stock of migrant workers in the current period - while the direct effect (from municipality i to i) is only 0.060%, the indirect effect (from i to neighbor j) is 0.118%. [11]

All the other partitioned average effects are significant, with the exception of the young-age dependency ratio. Nevertheless, note that the effects for the young- and old-age dependency ratios are of opposite signs, which would not have been detected if age-dependency ratio had been defined as a single measure, and not disaggregated. Recall our earlier hypothesis (section 2) that the presence of young members in the household induces the adult members to migrate to augment income, while the presence of old members dissuades them from doing so since retirement homes are almost non-existent in the Philippines. Such pressures rapidly spill over to neighboring units, as indicated by the large indirect effects. The partitioned average effects of income (as proxied by the proportion of household heads with tertiary education) are also positive and significant.

Overall, our results confirm that migration is contagious across space and time. Stimulating migration in one municipality would positively impact (contemporaneous and future) growth in migration in neighbouring municipalities.

[11] Note that interpreting the OLS result of 0.068% as the migrant network effect would have greatly underestimated the spillover impacts from migration.

5. Conclusion

For the Ilocos Region in the Philippines, the spatial distribution of migrant workers is not random, but instead exhibit spatial clustering. Migrant networks positively impact the growth of migrant workers stock, confirming the role of spatial contagion in the growth of the number of migrant workers. However, first-mover conditions are found to be less important than more recent (contemporaneous) dynamics.

This paper contributes to the migration and development literature in two ways. Firstly, we introduce a geography-based definition of migrant networks as an alternative to the kin-based networks commonly analyzed in the literature. Secondly, we use spatial econometrics to explain how networks affect the decision to migrate, rather than the choice of where to migrate or how individuals move between origin and destination regions.

References

Anselin, Luc, Julie Le Gallo, and Hubert Jayet. 2008. "Spatial Panel Econometrics", In *The Econometrics of Panel Data, Fundamentals and Recent Developments in Theory and Practice (3rd Edition)*, ed. L. Matyas and P. Sevestre. Dordrecht: Kluwer.

Baghdadi, Leila. 2005. "Mexico-U.S. Migration: Do Spatial Networks Matter?" Unpublished manuscript, Universite Paris I. http://dse.univr.it/espe/documents/Papers/A7/A7_2.pdf

Bauer, Thomas, Gil Epstein and Ira N. Gang. 2000. "What are Migration Networks?" *IZA Discussion Paper No. 200*. Institute for the Study of Labor, Bonn, Germany.

Carrington, William J., Enrica Detragiache, and Tara Vishwanath. 1996. "Migration with Endogenous Moving Costs". *The American Economic Review*, 86(4): 909-930.

Elhorst, J. Paul. 2010. "Dynamic panel with endogenous interaction effects when T is small". *Regional Science and Urban Economics*, in Press.

Epstein , Gil S., and Ira N. Gang. 2006. "The Influence of Others on Migration Plans." *Review of Development Economics*, 10(4):652–665.

Findley, Sally E. 1987. "An Interactive Contextual Model of Migration in Ilocos Norte, the Philippines." *Demography*, 24(2): 163-190.

Grossman, James R. 1989. *Land of hope: Chicago, black southerners, and the great migration*. Chicago: University of Chicago Press.

Javorcik, Beata S. , Çağlar Özden, Mariana Spatareanu, and Cristina Neagu. 2010. "Migrant networks and foreign direct investment." *Journal of Development Economics*. In Press.

Jeanty, P. Wilner, Mark Partridge, and Elena Irwin. 2010. "Estimation of a spatial simultaneous equation model of population migration and housing price dynamics." *Regional and Urban Economics*, In Press.

LeSage, James P., and R. Kelley Pace. 2009. *Introduction to Spatial Econometrics*. Taylor and Francis Group, Inc.

LeSage, James P., and R. Kelley Pace. 2005. Spatial Econometric Modeling of Origin-Destination Flows. Unpublished manuscript, University of Toledo, Department of Economics and Department of Finance, E.J. Ourso College of Business Administration, Louisiana State Univeristy. http://www4.fe.uc.pt/spatial/doc/lecture7.pdf.

Lundberg, Johan. 2002. "Using Spatial Econometrics to Analyze Local Growth in Sweden". *Cerum Working Paper 52:2002.* Center for Regional Science, Umea University.

Marks, Carole. 1989. *Farewell- We're good and gone: The great black migration*. Bloomington: Indiana University Press.

Massey, Douglas S. 1986. "The Social Organization of Mexican Migrants to the United States." *Annals of the American Academy of Political and Social Science*, 487:102-113.

Massey, Douglas S. 1990. "Social Structure, Household Strategies, and the Cumulative Causation of Migration." *Population Index*, 56(1):3-26.

Massey, Douglas S., Rafael Alarcon, Jorge Durand, and Humberto Gonzalez. 1987. *Return to Aztlan: The Social Process of International Migration from Western Mexico*. Berkeley, Calif./London, England: University of California Press.

Mckenzie, David, and Hillel Rapoport. 2007. "Network effects and the dynamics of migration and inequality: Theory and evidence from Mexico." *Journal of Development Economics*, 84:1–24.

Mincer, Jacob. 1978. "Family Migration Decisions." *Journal of Political Economy*, 86:749-773.

Munshi, Kaivan. 2003. "Networks in the Modern Economy: Mexican Migrants in the U. S. Labor Market." *The Quarterly Journal of Economics*, 118(2):549-599.

Palloni, Alberto, Douglas S. Massey, Miguel Ceballos, Kristin Espinosa, Michael Spittel. 2001. "Social Capital and International Migration: A Test Using Information on Family Networks." *The American Journal of Sociology*, 106(5):1262-1298.

Taylor, J. Edward. 1986. "Differential Migration, Networks, Information and Risk." In *Research in Human Capital and Development, Vol. 4, Migration, Human Capital, and Development*, edited by Oded Stark, pp. 147-71. Greenwich, Conn.: JAI Press.

Winters, Paul, Alain de Janvry, and Elisabeth Sadoulet. 2001. "Family and Community Networks in Mexico-U.S. Migration." *The Journal of Human Resources*, 36(1): 159-184.

Woodruff, Christopher, and Rene Zenteno. 2007. "Migration networks and microenterprises in Mexico." *Journal of Development Economics*, 82: 509–528.

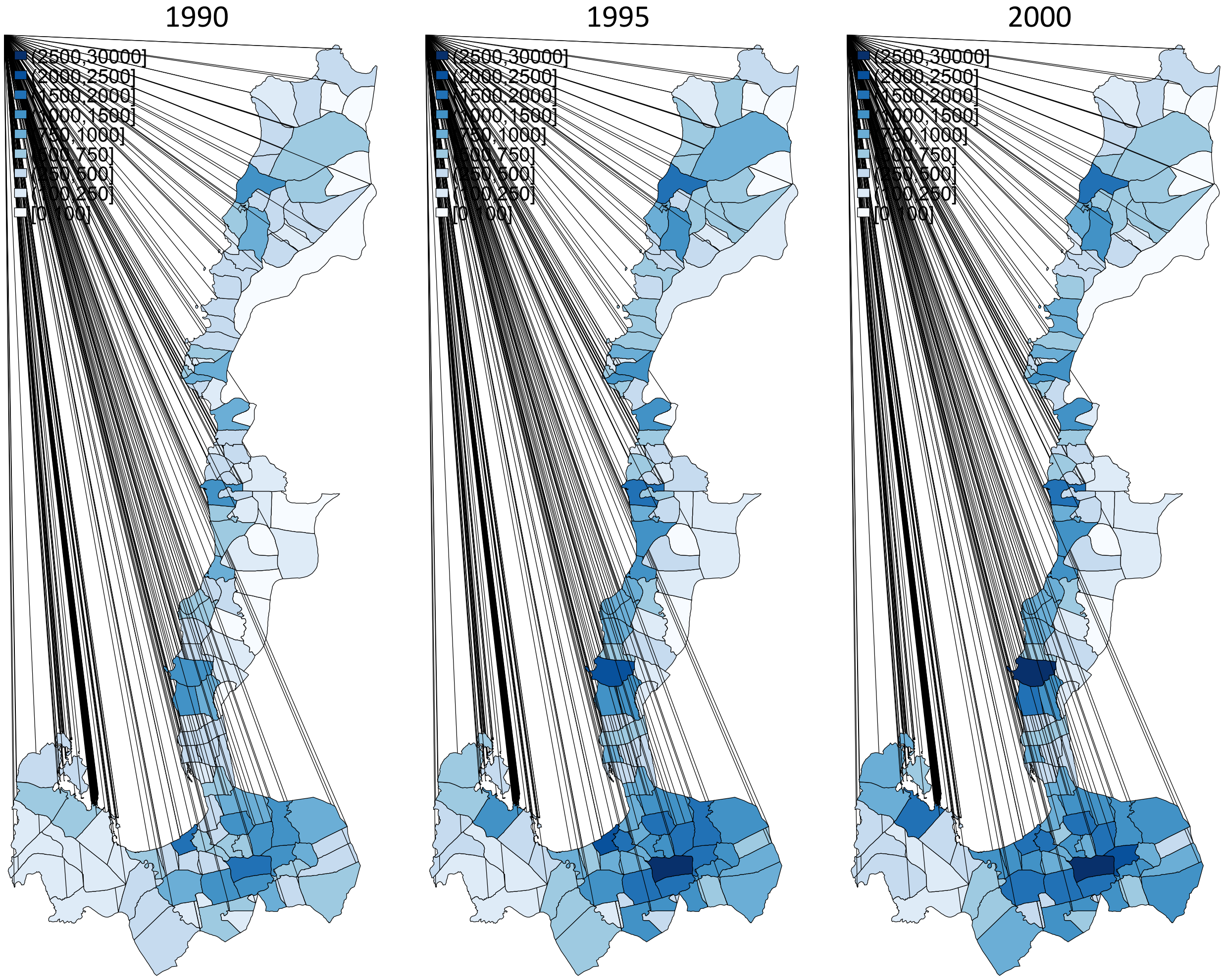
Yung, Jai, Robert de Jong, and Lung-fei Lee. 2008. "Quasi-maximum likelihood estimators for spatial dynamic panel data with fixed effects when both n and T are large." *Journal of Econometrics*, 146: 118-134

Table 1. Municipality Demographic Characteristics, Ilocos Region, Philippines

	1990		1995		2000	
	Mean	SD	Mean	SD	Mean	SD
Mean of Levels						
Number of Migrants	470.65	370.83	727.95	547.37	752.89	550.20
Age dependency ratio	0.77	0.06	0.7402	0.07	0.68	0.06
Young	0.67	0.07	0.64	0.08	0.58	0.07
Old	0.10	0.02	0.10	0.02	0.10	0.02
Heads with tertiary education	0.07	0.03	0.08	0.04	0.08	0.04
Mean of logged Levels						
Number of Migrants	5.77	1.10	6.26	0.94	6.30	0.92
Age dependency ratio	- 0.27	0.08	- 0.31	0.09	- 0.39	0.09
Young	- 0.41	0.11	- 0.45	0.12	- 0.55	0.12
Old	- 2.29	0.22	- 2.31	0.20	- 2.31	0.17
Heads with tertiary education	- 2.71	0.45	- 2.69	0.46	- 2.63	0.61

Source of basic data: NSO Census of Population, various years

Figure 1. Migrant workers stock, Ilocos Region, Philippines



Source of basic data: NSO Census of Population, various years

Table 2. Growth in migrant workers stock and migrant network

	OLS		BCLSDV	
	Set 1	Set 2	Set 1	Set 2
log(migrant worker stock$_{t-1}$)	0.085	0.062	*** 0.073	0.059
	(0.054)	(0.055)	(0.035)	(0.036)
log(W*migrant worker stock$_t$)	-	-	*** 0.696	*** 0.660
			(0.106)	(0.112)
log(young-age dependency ratio$_t$)	0.016	-0.050	0.177	0.126
	(0.304)	(0.302)	(0.199)	(0.200)
log(old-age dependency ratio$_t$)	** -0.596	* -0.515	*** -0.699	* -0.641
	(0.297)	(0.296)	(0.194)	(0.195)
log(hh head with tertiary education$_t$)	-	0.100	-	** 0.065
		(0.050)		(0.033)
Obs.	250	250	250	250
Pseudo-R^2 (Correlation-squared)	0.446	0.521	0.997	0.997

Figures in () are standard errors

** Significant at 10%; ** significant at 5%; *** significant at 1%*

Table 3. Partitioned Mean Effects, BCLSDV model

	Direct Effect	Indirect Effect	Total Effect
log(migrant worker stock$_{t-1}$)	* 0.060	* 0.118	* 0.178
	(0.037)	(0.070)	(0.101)
log(young-age dependency ratio$_t$)	0.130	0.253	0.383
	(0.204)	(0.334)	(0.526)
log(old-age dependency ratio$_t$)	*** -0.663	** -1.288	*** -1.950
	(0.200)	(0.560)	(0.704)
log(hh head with tertiary education$_t$)	* 0.067	** 0.131	** 0.198
	(0.034)	(0.063)	(0.089)

Figures in () are bootstrap standard errors using 5000 replicates
** Significant at 10%; ** significant at 5%; *** significant at 1%*