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LeSage, James P.; Fischer, Manfred M.

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# MCMC estimation of panel gravity models in the presence of network dependence

James P. LeSage
Texas State University
San Marcos, TX, USA
james.lesage@txstate.edu

and

Manfred M. Fischer
Vienna University of Economics and Business
Vienna, Austria
manfred.fischer@wu.ac.at

## Abstract

Past focus in the panel gravity literature has been on multidimensional fixed effects specifications in an effort to accommodate heterogeneity. After introducing fixed effects for *each origin-destination dyad* and time-period specific effects, we find evidence of cross-sectional dependence in flows.

We propose a simultaneous dependence gravity model that allows for network dependence in flows, along with computationally efficient MCMC estimation methods that produce a Monte Carlo integration estimate of log-marginal likelihood useful for model comparison.

Application of the model to a panel of trade flows points to network spillover effects, suggesting the presence of network dependence and biased estimates from conventional trade flow specifications.

KEYWORDS: origin-destination panel data flows, cross-sectional dependence, log-marginal likelihood, sociocultural distance, convex combinations of interaction matrices.

JEL: C18, C33, C51

## 1 Introduction

The panel data gravity literature has focused on multidimensional fixed effects specifications in an effort to accommodate heterogeneity. We show that even after introducing fixed effects for *each origin-destination dyad*, as well as time-period specific effects, there is strong evidence of cross-sectional dependence in the dependent variable representing flows. Different sources of cross-sectional dependence based on various sociocultural factors such as common borders, language and currency, trade unions and colonial ties, are explored.

In a panel data model setting, distance as well as sociocultural factors (which we can view as generalized distance variables) are generally time invariant, so they are treated as fixed effects. Balazsi, Matyas and Wansbeek (2018) explore econometric implications of using a host of alternative multidimensional fixed effects in panel data gravity models, but assume trade flows to be independent. We apply two of the more widely used multidimensional fixed effects transformations from the empirical trade literature to a panel of $N = 70$ countries trade flows covering the $T = 38$ years from 1963 to 2000, in a model specification that allows for the presence of simultaneous cross-sectional dependence. One approach uses $N$ origin and $N$ destination country fixed effects plus $T$ time-specific effects proposed by Matyas (1997) as an extension of conventional fixed effects panel data model (e.g., Baltagi, 2005) to the multidimensional situation that arises in the case of gravity models. These models take an $N^2T \times 1$ vector of dependent variables reflecting the matrix of trade flows between the $N$ countries (assuming flows between all countries) at each time period, resulting in a dummy matrix of fixed effects with column rank of $2N + T - 2$. The second approach makes use of fixed effects proposed by Cheng and Wall (2005) that introduce fixed effects for origin-destination dyads as well as time periods, resulting in a dummy matrix with column rank of $N^2 + T - 1$, frequently adopted in the empirical trade literature.

Apart from accommodating heterogeneity in flows using fixed effects, the dependent variable vector of $N^2 \times 1$ trade flows for each time period are assumed to be independent, so flows between countries that have a common currency, language, border or colonial ties are no more likely than flows between countries having nothing in common. Cross-sectional dependence in flows suggests that flows between countries with sociocultural similarity (e.g., common language, colonial ties, spatial neighbors, member of trade unions, etc.) are likely to exhibit dependence as opposed to independence. We set forth a model specification that allows for this type of dependence in flows across the $N^2T$ country-time dyads. Vasilis and Wansbeek (2012) provide an overview of econometric specifications for dealing with cross-sectional dependence, consisting of two main approaches, spatial econometric and common factor models. We take the spatial econometric approach here, but note that a common factor specification could also be employed to address the issue we raise. The nature of dependence that we model would be better labeled *network dependence* rather than spatial or cross-sectional dependence, because we introduce dependence between network nodes involving origin- and destination-dyads as well as covariance across these. Common factor cross-sectional dependence specifications would need to be extended to address the type of dependence that we consider here.[1] We use the terms network and cross-sectional dependence interchangeably here, but note that the network dependence specification introduced here reflects a special case of cross-sectional dependence that can arise in the case of origin-destination flows that has not received a great deal of attention in the literature. Although we focus our discussion on trade flows the econometric issues of heterogeneity, network dependence and time-invariant fixed effects raised here would also apply to migration, airline flows across the network, etc.

Estimates from the network dependence model specification suggest that sociocultural proximity can reflect transmission channels that can be viewed as a source of cross-sectional dependence. Model specifications that accommodate network dependence are set forth, along with computationally efficient MCMC estimation methods. Ignoring network dependence implies biased estimates from panel trade flow models that rely on fixed effects and the assumption of independence between flows.

An innovative aspect of our MCMC estimation approach is use of Metropolis-Hastings guided samples from the joint posterior distribution of the dependence parameters to construct a Monte Carlo integration estimate of the log-marginal likelihood useful for model comparison. Our MCMC estimation approach allows for estimation and posterior inference on a vector of dependence parameters that determines the relative importance of network dependence, as well as a Monte Carlo integration estimate of the log-marginal likelihood which can be used for model

[1] See also Baltagi and Maasoumi (2013), who provide an introductory discussion for a series of articles in a special issue devoted to dependence in cross-section, time series and panel data models.

comparison purposes.[2] In our case, we rely on Markov Chain Monte Carlo sampling to estimate the model parameters with the dependence parameters sampled using a Metropolis-Hastings procedure. Since this approach produces draws of the dependence parameters that are steered by Metropolis-Hastings accept/reject decisions to areas of high density of the joint posterior, we can produce an efficient Monte Carlo integration of the log-marginal likelihood.

Another methodological innovation is use of convex combinations of network dependence weight matrix structures (see Pace and LeSage, 2002; Debarsy and LeSage, 2017, 2018; Hazir, LeSage and Autant-Bernard, 2018; LeSage and Fischer, 2018). The weight matrix structures are constructed to reflect spatial proximity between countries, as well as numerous types of sociocultural proximity such as common currency, language, colonial ties, and so on. A convex combination of these multiple weight matrices is used to form a single weight matrix. This approach allows us to treat sociocultural factors (for example, common currency, common language, historical colonial relationships, trade agreements, and so on) as sources of network dependence in the panel gravity model.

Section 2 introduces conventional panel gravity models as used in the empirical trade literature, along with a discussion of the two multidimensional fixed effects specifications that we explore.[3] Section 3 discusses an extension of the conventional panel gravity model that allows for origin- and destination-based network dependence following ideas set forth by LeSage and Pace (2008). A computationally efficient approach to Markov Chain Monte Carlo (MCMC) estimation is set forth. Section 4 sets forth computational challenges to estimation of the network dependence variant of the conventional panel gravity model, along with an MCMC estimation approach that overcomes these challenges. Section 5 applies our model to panel data on trade flows between 70 countries covering the 38 years from 1963 to 2000. In our application of the model we introduce an extension that allows for convex combinations of multiple sociocultural connectivity structures, that can be used in conjunction with log-marginal likelihood estimates to determine the relative importance of each type of connectivity. We find strong evidence of network dependence in trade flows pointing to network spillover effects, and suggesting that

[2] Monte Carlo integration evaluates the expression to be integrated using random draws of the parameter values, but a drawback to this approach is inefficiency because many of the random draws for the parameters are not in areas of high density of the function being integrated.

[3] Choice of these two approaches from the myriad approaches available was based on their popularity in the empirical trade literature.

ignoring the presence of this type of cross-sectional dependence will result in biased estimates from conventional trade flow specifications. Section 6 provides conclusions, and Appendix A presents information on data used as well as sources.

## 2 Empirical panel data gravity models

As noted, Matyas (1997) made an early attempt to introduce multidimensional fixed effects for gravity model specifications such as that in (1), where the dependent variable $y_{ijt}$ reflects an $N^2T\times 1$ vector of (logged) trade flows between $N$ countries $i$ and $j$ at time $t$, so $i = 1, \ldots, N, j = 1, \ldots, N$, and $t = 1, \ldots, T$.[4]

$$y_{ijt} \quad = \quad x_{ijt}\beta + \alpha_i + \gamma_j + \lambda_t + \varepsilon_{ijt}, \tag{1}$$

where $\beta$ is a $K\times 1$ vector of parameters on the $N^2T\times K$ (logged) covariates $x_{ijt}$, which are usually measures of economic size of destination and origin dyads $(i, j)$. We note that distance between the countries is time-invariant and not in the set of covariates. The fixed effects parameters $\alpha_i, \gamma_j$ represent destination-specific and origin-specific country effects while $\lambda_t$ are time-period specific fixed effects. It is assumed that $\varepsilon_{ijt}$ are normal *i.i.d.* (independent, identically distributed) idiosyncratic disturbances with zero mean and scalar $(\sigma^2_\varepsilon)$ variance.[5]

We can write the fixed effects as an $N^2T \times (2N + T)$ matrix:

$$D = \begin{pmatrix} I_N \otimes \iota_{NT}, & \iota_N \otimes I_N, & \iota_{N^2} \otimes I_T \end{pmatrix},$$

with column rank $(2N + T - 2)$, where $I_N$ is an identity matrix of dimension $N$ and $\iota_N$ is an $N-$dimensional column vector of ones. One can use a projection matrix of size $N^2T \times N^2T$ to eliminate the fixed effects in $D$, corresponding to the usual scalar transformation involving what have been labeled "Within" transformations.

There are of course other specifications for the fixed effects. For example, Egger and Pfaffermayr (2003) propose bilateral specific fixed effects $\gamma_{ij}$, where $D = \begin{pmatrix} I_N \otimes I_N \otimes \iota_T \end{pmatrix}$, of size

[4] See Baltagi, Egger and Pfaffermayr (2014) for an explanation of theoretical models that give rise to this log-linear specification.

[5] It is also assumed that the covariates and the disturbance terms are uncorrelated, ruling out endogeneity of the measures of country size.

$N^2T \times N^2$ with full column rank $N^2$. A variant of this, proposed by Cheng and Wall (2005), that is popular in the empirical trade literature is shown in (2),

$$y_{ijt} = x_{ijt}\beta + \gamma_{ij} + \lambda_t + \varepsilon_{ijt}, \quad (2)$$

where $D = \begin{pmatrix} I_N \otimes I_N \otimes \iota_T & I_N \otimes \iota_N \otimes I_T \end{pmatrix}$ of size $N^2T \times (N^2 + T)$, with column rank $(N^2 + T - 1)$. Of course, there is a projection matrix and corresponding scalar "Within-type" transformation that can be used to eliminate this more extensive set of fixed effects. Balazsi, Matyas and Wansbeek (2018) point out that the model in (1) represents a special case of that in (2), and there is an analogy of this 3D situation in (2) to 2D panel data models, where individuals in the 2D situation are treated as $(i, j)$ pairs in the 3D setting. In other words, individual effects are now assigned to $(i, j)$ dyads.

We note that the model specifications in (1) and (2) assume that the dependent variable vector of $N^2 \times 1$ trade flows for each time period are statistically independent, so flows between countries that have a common currency, language, border or colonial ties are no more likely than flows between countries having nothing in common. Network dependence in flows suggests that flows between countries with sociocultural similarity (e.g., common language, colonial ties, spatial neighbors, member of trade unions, etc.) are likely to exhibit dependence as opposed to independence. In the next section, we set forth a model specification that allows for this type of dependence in flows across the $N^2T$ country-time dyads.

## 3 Panel data gravity specifications for network dependence

We set forth an extension of the conventional panel gravity model that allows for origin- and destination-based network dependence. The matrix expressions in (3) represent a panel data extension of the cross-sectional *gravity model for origin-destination flows* introduced in LeSage and Pace (2008).

$$y = \rho_o I_T \otimes (W \otimes I_N)y + \rho_d I_T \otimes (I_N \otimes W)y + \rho_w I_T \otimes (W \otimes W)y + Z\delta + \varepsilon, \quad (3)$$

where $y$ is the $N^2T \times 1$ dependent variable vector of origin-destination flows for each time period, organized with $t$ being the slow index for elements $y_{ijt}$ in the vector $y$. The $N^2T \times K$ matrix $Z$ contains covariates with the associated $K \times 1$ parameter vector $\delta$, and the $N^2T \times 1$ vector $\varepsilon$ represents the normally distributed *i.i.d.* scalar variance disturbances.[6]

The model in (3) indicates that flows at *each time period* $t = 1, \dots, T$ exhibit dependence on flows of countries *neighboring* the origin country captured by the $N^2T \times 1$ vector $I_T \otimes (W \otimes I_N)y$ with the associated scalar parameter $\rho_o$ measuring the strength of that dependence. The matrix $W$ is an $N \times N$ matrix that defines neighbors and for now, we define neighboring countries as those with common borders (spatial neighbors), as in the model of LeSage and Pace (2008).[7] A neighboring country is indicated by a non-zero $(i, j)$ element in the $N \times N$ matrix $W$, which has zeros on the main diagonal. The matrix $W$ is normalized to have row-sums of unity, resulting in the $N^2 \times 1$ vector $(W \otimes I_N)y$ reflecting a linear combination of trade flow values from countries that are *neighbors* to the origin country.

The model also allows for dependence of flows in each time period from countries neighboring the destination country, captured by the vector $I_T \otimes (I_N \otimes W)y$, with associated scalar parameter $\rho_d$, and we note that this vector relies on the same matrix $W$ used to define (spatial) neighbors. LeSage and Pace (2008) point out that while the matrix $(I_N \otimes W)$ defines neighbors to the destination, the matrix $(W \otimes I_N)$ identifies neighbors to the origin, when the vector of flows for time $t$ arises from a conventional $N \times N$ origin-destination flow matrix, organized with dyads $(i, j)$ representing flows from origin $j$ to destination $i$.

Another type of dependence is also included in the model, reflected by the $N^2T \times 1$ vector $I_T \otimes (W \otimes W)y$ and associated scalar parameter $\rho_w$, which captures dependence of flows from countries that are neighbors to both the origin and destination countries. LeSage and Pace (2008) motivate this type of dependence using the (cross-sectional) specification in (4), where

[6]For notational convenience, we assume that the matrix $D$ of fixed effects has been eliminated from the model through the use of a scalar transformation of the type described in Balazsi, Matyas and Wansbeek (2018).

[7]We consider more general definitions of neighboring countries based on other connectivity constructs such as common currency, common language, etc. later.

they argue that the matrix $A$ can be viewed as a spatial filter.

$$\begin{aligned} Ay &= \alpha\iota_{N^2} + Z\delta + \varepsilon, \quad (4) \\ A &= (I_{N^2} - \rho_d W_d)(I_{N^2} - \rho_o W_o) \\ &= (I_{N^2} - \rho_d W_d - \rho_o W_o + \rho_w W_w), \\ W_d &= I_N \otimes W, \\ W_o &= W \otimes I_n, \\ W_w &= W_d \otimes W_o = W_o \otimes W_d = W \otimes W. \end{aligned}$$

The argument is that the existence of origin- and destination-based dependence between trade flows $(W_o y, W_d y)$, logically implies a covariance between these two types of dependence which is reflected in $W_w y$. They note that this filter implies a restriction that $\rho_w = -\rho_o \rho_d$, but argue this restriction need not be imposed during estimation, so we address the more general case here and allow for an unrestricted parameter $\rho_w$.[8]

LeSage and Pace (2008) also point out that the matrix of covariates reflecting origin-destination dyads can be written as $Z = \begin{pmatrix} X_{ot} & X_{dt} \end{pmatrix}$, where $X_{ot} = X_t \otimes \iota_N$ and $X_{dt} = \iota_N \otimes X_t$ with $X_t$ being an $N \times K$ matrix of covariates measuring the (economic) size of each country at time $t$.

## 4 Estimating the network dependence panel data gravity model

One issue that arises when considering estimation of the model in (3) is that multiple dependence parameters $\rho_o, \rho_d, \rho_w$ would require use of a multivariate optimization routine to produce estimates based on maximum likelihood. It is also the case that the dependence parameters are (well) defined over the $(-1, 1)$ interval, meaning that constrained optimization would be required to ensure values $-1 < \rho_o + \rho_d + \rho_w < 1$.[9]

Another challenge to maximum likelihood estimation is the log-determinant term that arises in the (log) likelihood function, specifically (log): $|I_{N^2T} - \rho_o I_T \otimes (W \otimes I_N) - \rho_d I_T \otimes (I_N \otimes W) - \rho_w I_T \otimes (W \otimes W)|$. In the case of conventional spatial regression models involving a single weight

[8] Of course, given unrestricted estimates of $\rho_o, \rho_d, \rho_w$ one could test if the restriction $\rho_w = -\rho_o \rho_d$ is consistent with the sample data.

[9] The lower bound of $-1$ is typically used for convenience in applied practice and ensures the existence of the matrix inverse for the reduced form of the model.

matrix, there is a great deal of literature on approaches to efficiently calculating or approximating the log-determinant term that appears in the (log) likelihood $|I_N - \rho W|$, (see LeSage and Pace, 2008, Chapter 4). These approaches are not directly applicable to the model considered here, complicating maximum likelihood estimation, since the log-determinant expression needs to be evaluated for multiple dependence parameter values during optimization. In the case of Markov Chain Monte Carlo estimation, the log-determinant term appears in the conditional distribution for the dependence parameters requiring multiple evaluations during sampling.

Because of the issues outlined above, we set forth estimation based on Markov Chain Monte Carlo, with no prior distributions assigned to the parameters $\beta, \sigma^2$. Parameter restrictions are imposed on the dependence parameters during MCMC sampling using methods described later. Since emphasis is on modeling situations involving large samples of observations, prior information would not play a role in determining posterior estimates of the parameters, so MCMC is used as a computational device to produce estimates that should be identical to those from maximum likelihood estimation. MCMC estimation involves sequentially sampling each parameter (or set of parameters) from their conditional distributions (or joint conditional distribution in the case of a set of parameters). Expressions for the conditional distributions are frequently easier to calculate than those required to evaluate the (log) likelihood, which is true for the models considered here.

Another aspect of this model regards proper interpretation of the partial derivative impacts on the dependent variable vector arising from changes in the explanatory variables, e.g., $\partial E(y)/\partial X^r$ for the $r$th explanatory variable. We take this issue up in a later section.

The model from (3) can be written as shown in (5).

$$\begin{aligned} \tilde{y}\omega &= Z\delta + \varepsilon, \quad \varepsilon \sim \mathcal{N}(0, \sigma^2 I_{N^2T}), \qquad (5) \\ \tilde{y} &= \left[ \begin{array}{cccc} y, & I_T \otimes (I_N \otimes W)y, & I_T \otimes (W \otimes I_N)y, & I_T \otimes (W \otimes W)y \end{array} \right], \\ \omega &= \begin{pmatrix} 1 \\ -\rho_o \\ -\rho_d \\ -\rho_w \end{pmatrix}. \end{aligned}$$

A key feature of $\tilde{y}$ is that this expression separates dependence parameters to be estimated from sample data describing the simultaneous dependence, with the scalar dependence parameters in the vector $\omega$. We assume normally distributed $\mathcal{N}(0, \sigma^2 I_{N^2T})$, zero mean, constant variance ($\sigma^2$) disturbances.

MCMC estimation proceeds by sampling sequentially from the conditional distributions of each parameter (or set of parameters). The conditional distributions for the model parameters $\delta, \sigma^2, \omega$ needed to implement MCMC estimation are set forth next.

## 4.1 Conditional distributions for the model parameters

Since our focus is on large samples $N^2T$, we can rely on uninformative priors for the parameters $\delta$, as these would not likely impact posterior estimates. For the same reason, we rely on an uninformative inverse Gamma$(\bar{a}, \bar{b})$, where we let $\bar{a}, \bar{b} \to 0$ for $\sigma^2$. Since the dependence parameters in $\omega$ are at the center of inference, we employ uniform priors for these dependence parameters which are constrained to lie in the open interval $(-1, 1)$. There is also the need to impose stability restrictions on these parameters discussed later. Given the limited prior information, the conditional distribution for the parameters $\delta$ of the model in (5) takes the form of a multivariate normal with mean and variance-covariance shown in (6).

$$
\begin{aligned}
p(\delta|\sigma^2, \omega) &= \mathcal{N}(\tilde{\delta}, \tilde{\Sigma}_\delta), \\
\tilde{\delta} &= (Z'Z)^{-1}(Z'\tilde{y}\omega), \\
\tilde{\Sigma}_\delta &= \sigma^2 (Z'Z)^{-1}.
\end{aligned}
\tag{6}
$$

We note that $(Z'Z)^{-1}Z'\tilde{y}$ consists of only sample data information, so this expression can be calculated once prior to MCMC sampling, and this is true of $(Z'Z)^{-1}$ as well. This means that sampling new values of the parameters $\delta$ (given values for the parameters $\sigma^2, \omega$) can take place in a rapid, computationally efficient way.

The conditional posterior for $\sigma^2$ (given $\delta, \omega$) takes the form in (7), when we set the prior parameters $\bar{a} = \bar{b} = 0$.

$$
\begin{aligned}
p(\sigma^2|\delta,\omega) &\propto (\sigma^2)^{-(\frac{N}{2})}\exp\left(-\frac{1}{2\sigma^2}(e'e)\right), \\
e &= (\tilde{y}\omega - Z\delta) \\
&\sim \mathcal{IG}(\tilde{a},\tilde{b}), \\
\tilde{a} &= N/2, \\
\tilde{b} &= (e'e)/2.
\end{aligned} \tag{7}
$$

The joint conditional distribution for the dependence parameters in $\omega$ can be obtained by analytically integrating out $\delta, \sigma^2$ leading to a (log kernel) expression for the joint posterior of the dependence parameters in $\omega$.

$$
\begin{aligned}
log\ p(\omega|y,Z,W) &\propto log[D(\omega)] - (N^2T/2)log(\omega' F\omega), \\
F &= (\tilde{y} - Z\delta_d)'(\tilde{y} - Z\delta_d), \\
\delta_d &= Z(Z'Z)^{-1}\tilde{y},
\end{aligned} \tag{8}
$$

where $log[D(\omega)]$ is a Taylor series approximation to the log-determinants in the model, described in detail later. For now we note that this log-determinant term depends on the dependence parameters in the vector $\omega$, indicated by $D(\omega)$. We note that $F$ consists of only sample data, so this expression can be calculated prior to MCMC sampling, leading to a computationally efficient expression reflecting a quadratic form: $log(\omega' F\omega)$, that can be easily evaluated for any vector of dependence parameters $\omega$.

One motivation for working with the joint conditional posterior distribution for the dependence parameters is the need to impose stability restrictions on these parameters. Specifically, $-1 < \rho_o + \rho_d + \rho_w < 1$. Working with the joint conditional posterior distribution for these parameters allows us to adopt a block sampling Metropolis-Hastings (M-H) scheme for the dependence parameters (described in detail later). Block sampling means that a vector of dependence parameters in $\omega$ are proposed and compared to the current vector of dependence parameters. The proposed vector is either accepted or rejected. This allows proposals of dependence parameters that obey the stability restriction, so any vectors that are accepted by the Metropolis-Hastings procedure will always obey the needed restrictions.

A second motivation is that having analytically integrated out the parameters $\delta, \sigma^2$, further integration of the joint conditional posterior over the set of dependence parameters in $\omega$, would yield the log-marginal likelihood for these models. We can use Monte Carlo integration to accomplish this task. Monte Carlo integration evaluates the expression to be integrated using random draws of the parameter values. A drawback to this approach is inefficiency because many of the random draws for the parameters are not in areas of high density of the function being integrated. In our case, the Metropolis-Hastings sampling procedure used to produce draws of the dependence parameters steers these parameter values to areas of high density of the joint posterior. This allows us to produce an efficient Monte Carlo integration of the log-marginal likelihood.

Given an estimate of the log-marginal likelihood for a model $M_i$ ($logM_i$), we can calculate: $prob(M_i) = \exp(logM_i)/\sum_{i=1}^{Q}\exp(logM_i))$ (in the case of $Q$ different models). Of course, there is a great deal of interest in comparing alternative models, for example, models based on different spatial weight matrices, or different fixed effects specifications.

### 4.2 A Taylor's series approximation to the log-determinant term

We have motivated that (8) represents a computationally efficient expression for the joint posterior, but this involves the log-determinant term $log[D(\omega)]$ in (9), where: $W_1 = I_T \otimes (W \otimes I_N), W_2 = I_T \otimes (I_N \otimes W), W_3 = I_T \otimes (W \otimes W)$, which could be difficult and slow to calculate.

$$\ln|I_{N^2 \times T} - \rho_o W_1 - \rho_d W_2 - \rho_w W_3|. \tag{9}$$

An approximation to the log-determinant term works to preserve the computational efficiency of the expression (8). A fourth-order Taylor series expansion for the log-determinant term can be expressed using traces of a sequence of matrix products, shown in (10), where $\Psi = \begin{pmatrix} \rho_o, & \rho_d, & \rho_w \end{pmatrix}$.

$$
\begin{aligned}
\ln|I_{N^2\times T} - \rho_o W_1 - \rho_d W_2 - \rho_w W_3| &= -\sum_{j=1}^{\infty} \frac{\Psi^j \operatorname{tr} \tilde{W}^j}{j} \\
&\simeq -\sum_{j=1}^{q} \frac{\Psi^j \operatorname{tr}(\tilde{W}^j)}{j}, \\
\tilde{W} &= \begin{pmatrix} W_1 & W_2 & W_3 \end{pmatrix}.
\end{aligned} \tag{10}
$$

From the definitions of $W_1, W_2, W_3$ we see that the first-order trace of $(\tilde{W}^1)$ for the matrix $W_1$ is zero because diagonal elements of the matrix $W$ are zero. The same is true for the first-order trace of $W_2$ and $W_3$. Higher-order traces are shown in (11), where LeSage and Pace (2009) discuss computationally efficient ways to calculate these.

$$
\begin{aligned}
\operatorname{tr}(\tilde{W}^2) &= \sum_{i=1}^{3}\sum_{j=1}^{3} \operatorname{tr}(W_i W_j), \\
\operatorname{tr}(\tilde{W}^3) &= \sum_{i=1}^{3}\sum_{j=1}^{3}\sum_{k=1}^{3} \operatorname{tr}(W_i W_j W_k), \\
\operatorname{tr}(\tilde{W}^4) &= \sum_{i=1}^{3}\sum_{j=1}^{3}\sum_{k=1}^{3}\sum_{l=1}^{3} \operatorname{tr}(W_i W_j W_k W_l).
\end{aligned} \tag{11}
$$

For a set of pre-calculated traces, we need only calculate powers of the parameters $\Psi^j$ and multiply these times the (already calculated) traces during MCMC sampling from the conditional (or joint posterior) distribution. A fourth-order Taylor's series approximation seems sufficient to produce accurate estimates. Specifically, for the case of our three matrices the second-order traces interacted with the parameter vector $\Psi$ takes the form in (12). Of course, the 3rd order terms increase to 27 and 4th order to 81 terms.

$$
\begin{aligned}
\Psi^2 \operatorname{tr}(\tilde{W}^2) &= \Psi' Q^2 \Psi, \\
\Psi' &= \begin{pmatrix} \rho_o & \rho_d & \rho_w \end{pmatrix},
\end{aligned} \tag{12}
$$

$$
Q^2 = \begin{pmatrix} \operatorname{tr}(W_1^2) & \operatorname{tr}(W_1 W_2) & \operatorname{tr}(W_1 W_3) \\ \operatorname{tr}(W_2 W_1) & \operatorname{tr}(W_2^2) & \operatorname{tr}(W_2 W_3) \\ \operatorname{tr}(W_3 W_1) & \operatorname{tr}(W_3 W_2) & \operatorname{tr}(W_3^2) \end{pmatrix}. \tag{13}
$$

A key aspect of these calculations is that traces of products of the weight matrices can be pre-calculated prior to MCMC sampling. This means that updating the log-determinant expression for any set of dependence parameters $(\rho_o, \rho_d, \rho_w)$ involves simple multiplications, where the dependence parameters in $\omega$ can be separated from these matrix products.

### 4.3 Block sampling the dependence parameters $\omega$

As noted above, a second computational challenge for estimation of these models is the need to impose stability restrictions on the dependence parameters $(-1 < \rho_o + \rho_d + \rho_w < 1)$. Debarsy and LeSage (2018) set forth a block-sampling approach that proposes a vector of candidate values for a similar set of dependence parameters in the context of a model involving a convex combination of weight matrices. Dependence parameters that do not meet the stability restriction can be rejected, so any values accepted are consistent with stability.

The conditional distributions for the current and proposed dependence vectors that we can label $\omega^c, \omega^p$ are evaluated with a M-H step used to either accept or reject the newly proposed vector $\omega^p$. Block sampling the dependence parameter vector $\omega$ has the virtue that accepted vectors will obey any restrictions and reduce autocorrelation in the MCMC draws for these parameters. However, block sampling is known to produce lower acceptance rates which may require more MCMC draws in order to collect a sufficiently large sample of draws for posterior inference regarding $\omega$. To address this issue, Debarsy and LeSage (2018) as well as LeSage, Chih and Vance (2018) propose a hybrid approach that begins with a reversible jump sampling procedure and switches to a tuned random-walk proposal procedure for proposing vectors $\omega$ after some initial number of start-up samples are drawn.

We rely on a reversible jump procedure to produce proposal values for the vector of parameters $\rho_o, \rho_d, \rho_w$. For each scalar parameter we rely on a three-headed coin flip. By this we mean a uniform random number on the open interval $\textit{coin flip} = U(0, 1)$, with head #1 equal to a value smaller or equal to 1/3, head #2 a value larger than 1/3, but smaller or equal to 2/3 and head #3 a value larger than 2/3 and smaller than one. Given a head #1 result, we set a proposal $\rho_o^p$ using a uniform random draw on the open interval $(-1 < \rho_o^p < \rho_o^c)$, where $\rho_o^c$ is the current value. A head #2 results in setting the proposal value equal to the current value $(\rho_o^p = \rho_o^c)$, while a head #3 selects a proposal value based on a uniform random draw on the open interval ($\rho_o^c < \rho_o^p < 1$). Of course, a similar approach is used to produce proposals for the parameters $\rho_d, \rho_w$. Proposed vectors of these parameters inconsistent with the stability restrictions are eliminated via rejection sampling.

The reversal jump approach to proposing the block of dependence parameters has the virtue that accepted vectors will obey the stability restriction and will also reduce autocorrelation in the MCMC draws for these parameters. However, proposals from the reversible jump procedure based on the large intervals between ($-1 < \rho_o^c$) and ($\rho_o^c < 1$) will not produce candidates likely to be accepted when these parameters are estimated with a great deal of precision, as would be the case for problems involving large $N^2T$. This can result in a failure to move the chain adequately over the parameter space. To address this issue, standard deviations, $\sigma_{\rho_o}, \sigma_{\rho_d}, \sigma_{\rho_w}$ for each parameter are calculated based on the first 1,000 draws (and updated thereafter using an interval of $m = 1,000$ draws). These are used in a tuned random-walk procedure to produce candidate/proposed values. Specifically, we use a tuning scalar $c$ for each parameter that is adjusted based on acceptance rates for each parameter. This is used in conjunction with the standard deviations to produce proposals: $\rho_o^p = \rho_o^c + c\mathcal{N}(0,1)\sigma_{\rho_o}$, with the same approach used for $\rho_d, \rho_w$.

The proposed estimation method relies on a great many approximations, raising the issue of whether resulting estimates have desirable properties such as small bias and mean-squared error as well as good coverage. By coverage we mean that the (say) 2.5% and 97.5% intervals from the empirical distributions of the effects estimates on which practitioners base conclusions regarding statistical significance of the effects estimates cover the true values 95% of the time.

Debarsy and LeSage (2018) present results from Monte Carlo experiments for the case of a cross-sectional convex combination of weights SAR model that relies on the same fourth-order Taylor series approximation to the log-determinant and the reversible-jump, hybrid tuned random-walk procedure for estimating the spatial dependence parameters. They show small bias and mean-squared error as well as good coverage across a range of negative and positive dependence parameters.

LeSage, Chih and Vance (2018) show results from Monte Carlo experiments for the dynamic space-time panel data model, which also involves three spatial weight matrices like the model described here. They also report Monte Carlo results with small bias and mean-squared error as well as good coverage across a range of negative and positive dependence parameters. LeSage (2018) discusses the commonality of the cross-sectional convex combination model of Debarsy and LeSage (2018), LeSage, Chih and Vance (2018), and the model described here, as well as Monte Carlo results.

### 4.4 Interpreting the network dependence panel data gravity model

The partial derivatives used to interpret how changes in (say the $r$th) explanatory variable of the model impacts changes in the dependent variable vector are non-linear matrix expressions. The sequence of partial derivatives for this model are shown in (14), where we record the $N \times N$ matrices of changes in (logged) flows arising from changing the $r$th variable in each country $i$ $X_i^r$ using $Y_i, i = 1, \ldots, N$, to denote the $N \times N$ flow matrices associated with changing the $r$th variable in each country $i$. We define $\tilde{W}_o = (W \otimes I_N), \tilde{W}_d = (I_N \otimes W), \tilde{W}_w = (W \otimes W)$ to simplify notation in (14), and note that because the matrix $W$ does not change over time in our static panel data model, we have a set of $N^2 \times N$ matrices describing the partial derivative impacts.

$$\begin{pmatrix} \partial Y_1/\partial X_1^r \\ \partial Y_2/\partial X_2^r \\ \vdots \\ \partial Y_N/\partial X_N^r \end{pmatrix} = (I_{N^2} - \rho_o W_o - \rho_d W_d - \rho_w W_w)^{-1} \begin{pmatrix} Jd_1\beta_d^r + Jo_1\beta_o^r \\ Jd_2\beta_d^r + Jo_2\beta_o^r \\ \vdots \\ Jd_N\beta_d^r + Jo_N\beta_o^r \end{pmatrix}. \qquad (14)$$

In (14), $Jd_i$ $(i = 1, \ldots, N)$ is an $N \times N$ matrix of zeros with the $i$th row equal to $\iota_N'\beta_d$, and $Jo_i$ is an $N \times N$ matrix of zeros with the $i$th column equal to $\iota_N\beta_o$, where $\beta_o$ and $\beta_d$ denote parameters associated with origin and destination size measures. We have $N$ sets of $N \times N$ outcomes, (one for each change in $X_i^r, i = 1, \ldots, N$) resulting in an $N^2 \times N$ matrix of partial derivatives reflecting the total effect on flows from changing the $r$th characteristic of all $N$ regions, which LeSage and Thomas-Agnan (2015) label the *total effect*.

These authors provide a motivation for the expression in (14), noting that changes in the (size) characteristics of a single country $i$ will (potentially) produce impacts on all elements of the $N \times N$ flow matrix. Intuitively, a change in (say) income of a single country can impact trade flows involving immediate trading partners, as well as, trade flows involving partners to the trading partners, partners to the partners of the trading partners, and so on, potentially impacting the entire $N \times N$ flow matrix.

Since regression models typically consider changes in characteristics (say income) of all $i = 1, \ldots, N$ observations/countries, this produces a set of $N$ different $N \times N$ matrices of partial derivatives associated with changes in *each* explanatory variable in the model. LeSage and Thomas-Agnan (2015) propose scalar summary measures for the various types of effects that average over certain dimensions of the sequence of $N$ different $N \times N$ matrices. We adopt a simpler strategy here for producing scalar summary measures of the partial derivative impacts. We take an average of the diagonal elements of the $N$ different $N \times N$ matrices in (14) as a measure of own-partial derivative impacts reflecting own-country changes in flows arising from changes in (say) the typical country's income. And we use an average of the cumulative off-diagonal elements from each row of the $N$ different $N \times N$ matrices in (14) to summarize network effects arising from changes in (say) income in a typical country. Network effects represent a scalar summary measure of the spillover impacts on other countries associated with changes in an explanatory variable in the model (say income). The scalar summary averages over all countries, and since the model is a static panel data model, over all time periods as well. We can delineate between origin and destination specific effects using the expressions involving $\beta_o, \beta_d$, which allows us to determine the relative importance of changes in (say) income at origin versus destination countries on trade flows.

In addition to point estimates of the partial derivative impacts, there might also be a need to calculate empirical measures of dispersion for the effects that could be used for inference. An empirical distribution of the scalar own- and cross-partial derivatives (labeled direct and network effects here) can be constructed using MCMC draws for the parameters $\rho_o, \rho_d, \rho_w, \beta_o, \beta_d$ in expression (14). However, this would require inversion of the $N^2 \times N^2$ matrix $(I_{N^2} - \rho_o W_o - \rho_d W_d - \rho_w W_w)$ thousands of times for each set of draws for $\rho_o, \rho_d, \rho_w$, making this computationally intensive.[10]

A compromise approach would be to use posterior means of the estimated parameters $\rho_o, \rho_d, \rho_w$ to calculate a single matrix inverse: $(I_{N^2} - \rho_o W_o - \rho_d W_d - \rho_w W_w)^{-1}$ in conjunction with the MCMC draws for the parameters $\beta_o, \beta_d$. However, this would ignore stochastic variation in

[10]Given sparse matrices $W$ it would not be difficult to calculate the matrix inverse for situations involving the typical sample of 100 to 200 countries used in trade flow models.

the effects estimates that arise from the fact that there is uncertainty regarding the parameters $\rho_o, \rho_d, \rho_w$. Ideally, we would like to use draws for these dependence parameters from their posterior distributions when simulating the empirical distribution of effects estimates.

## 5 Application of the network dependence panel model

We consider panel model specifications that use a panel of trade flows as the dependent variable vector $y$ over the 38 years from 1963 to 2000. The (single) explanatory variable is (logged) gross domestic product per capita (GDP) lagged one year to cover the period from 1962 to 1999. The trade flows are from Feenstra et al. (2005), while the GDP data at market prices (current US$) and population data come from World Bank's (2002) World Development Indicators. A usable sample of 70 countries (see Table A.1 in Appendix A) was constructed for which GDP, population and trade flows were available over the 38 years.[11]

Given our sample of 70 countries and 38 years, this results in $N^2T = 186,200$; with $2N + T - 2 = 176$ fixed effects parameters for the case of the Matyas (1997) model in (1), and $N^2 + T - 1 = 4,937$ fixed effects parameters in the Chen and Wall (2005) approach set forth in the model from (2).

We used five different definitions for the matrix $W$ describing alternative structures of network dependence, specifically, $W_{space}$ based on the three nearest spatial neighboring countries, $W_{language}$ based on countries sharing a common language, $W_{currency}$ based on common currency, $W_{colony}$ based on countries with direct historical colonial ties, and $W_{trade}$ based on membership in the same trade union (excluding the WTO). Details regarding countries with common borders, language, currency, colonial ties and trade union membership can be found in Appendix A.

Estimates from the model in (15) where the parameters $\rho_o, \rho_d, \rho_w$ are (significantly) different from zero point to the existence of cross-sectional dependence.

$$
\begin{aligned}
y &= \rho_o W_o y + \rho_d W_d y + \rho_w W_w y + GDP_o \beta_o + GDP_d \beta_d + \varepsilon, \qquad (15) \\
W_o &= I_T \otimes (W \otimes I_N), \quad W_d = I_T \otimes (I_N \otimes W), \quad W_w = I_T \otimes (W \otimes W).
\end{aligned}
$$

[11] We eliminated countries from our sample that had one or more zero rows in any of the five weight matrices. This resulted in a few countries such as South Korea, Japan and India for which data was available to be excluded from our sample.

Table 1: Log-marginal likelihood estimates for alternative models

| Model | Matyas (1997) fixed effects | $\rho_o + \rho_d + \rho_w$ | Cheng and Wall (2005) fixed effects | $\rho_o + \rho_d + \rho_w$ |
|---|---|---|---|---|
| $W$-trade | −5.1401e+05 | 0.8988 | −5.0487e+05 | 0.8708 |
| $W$-language | −5.5419e+05 | 0.6597 | −5.3048e+05 | 0.6741 |
| $W$-colony | −5.5610e+05 | 0.5726 | −5.3548e+05 | 0.5911 |
| $W$-currency | −5.6827e+05 | 0.6091 | −5.4406e+05 | 0.5708 |
| $W$-space | −5.2307e+05 | 0.8459 | −5.0988e+05 | 0.8137 |

In the presence of cross-sectional dependence, estimates from conventional models that ignore cross-sectional/network dependence can be shown to be biased and inconsistent (see LeSage and Fischer, 2018). The presence of network dependence also implies spillover impacts arising from changes in neighboring countries $j \neq i$ income on country $i$'s trade flows. In our model, neighbors are defined to include spatial neighbors in the case where $W_{space}$ is used when estimating the model. More broadly, sociocultural neighbors arise when the matrix $W$ used is based on common language, currency, trade union membership or direct colonial ties. Specifically, changes in income of countries $j$ that have spatial, common language, currency, trade agreements, or colonial ties with country $i$ will impact flows in the SAR model, provided that the scalar dependence parameters $\rho_o, \rho_d, \rho_w$ are different from zero and the parameters $\beta_o, \beta_d$ are non-zero.

Table 1 shows log-marginal likelihood function values for models based on the alternative definitions of the weight matrix as well as the two alternative approaches to including fixed effects. The sum of posterior means for $\rho_o + \rho_d + \rho_w$ are also reported, since non-zero values of these parameters point to significant network dependence. From the table, we see that models using the Cheng and Wall (2005) fixed effects have higher log-marginal likelihoods than the corresponding Matyas (1997) model based on the same weight matrix, indicating these models are more consistent with our sample data. A second finding indicated by the estimated log-marginal likelihoods in the table is that the rank-ordering of preferred models for the various types of weight matrices is very similar for both types of fixed effects. Specifically, the weight matrix based on $W_{trade}$ has the highest log-marginal likelihood, $W_{space}$ is next highest, followed by $W_{language}$. Turning to estimates for the dependence parameters, we see that the sum of these are substantially positive, pointing to the presence of network dependence.

Table 2: Estimates for the $W_{trade}$ models

| | Matyas (1997) fixed effects | | | | |
|---|---|---|---|---|---|
| Parameter | Mode | Mean | Median | MC error | Geweke |
| Constant | −9.0215 | −9.0177 | −9.0187 | 0.00660826 | 0.997389 |
| $\beta_o$ | 0.2863 | 0.2865 | 0.2864 | 0.00030498 | 0.997029 |
| $\beta_d$ | 0.3182 | 0.3178 | 0.3177 | 0.00024616 | 0.995985 |
| $\rho_o$ | 0.6811 | 0.6815 | 0.6816 | 0.00032737 | 0.997605 |
| $\rho_d$ | 0.6342 | 0.6339 | 0.6340 | 0.00045538 | 0.998746 |
| $\rho_w$ | −0.4165 | −0.4166 | −0.4162 | 0.00061022 | 0.996369 |
| Variable | Lower 0.01 | Lower 0.05 | Mean | Upper 0.95 | Upper 0.99 |
| Constant | −9.3420 | −9.2677 | −9.0177 | −8.7669 | −8.6804 |
| $\beta_o$ | 0.2753 | 0.2779 | 0.2865 | 0.2949 | 0.2973 |
| $\beta_d$ | 0.3065 | 0.3093 | 0.3178 | 0.3266 | 0.3289 |
| $\rho_o$ | 0.6753 | 0.6770 | 0.6815 | 0.6862 | 0.6875 |
| $\rho_d$ | 0.6272 | 0.6287 | 0.6339 | 0.6386 | 0.6408 |
| $\rho_w$ | −0.4248 | −0.4234 | −0.4166 | −0.4109 | −0.4097 |

| | Cheng and Wall (2005) fixed effects | | | | |
|---|---|---|---|---|---|
| Parameter | Mode | Mean | Median | MC error | Geweke |
| Constant | −12.4699 | −12.5429 | −12.5429 | 0.00780577 | 0.998862 |
| $\beta_o$ | 0.2964 | 0.2985 | 0.2985 | 0.00019371 | 0.998628 |
| $\beta_d$ | 0.4891 | 0.4920 | 0.4920 | 0.00044417 | 0.997119 |
| $\rho_o$ | 0.4706 | 0.4671 | 0.4671 | 0.00055234 | 0.995611 |
| $\rho_d$ | 0.6375 | 0.6347 | 0.6347 | 0.00033448 | 0.998707 |
| $\rho_w$ | −0.2363 | −0.2308 | −0.2308 | 0.00062930 | 0.992945 |
| Variable | Lower 0.01 | Lower 0.05 | Mean | Upper 0.95 | Upper 0.99 |
| Constant | −13.6988 | −13.3789 | −12.5429 | −11.6729 | −11.3569 |
| $\beta_o$ | 0.2877 | 0.2901 | 0.2985 | 0.3067 | 0.3086 |
| $\beta_d$ | 0.4656 | 0.4727 | 0.4920 | 0.5115 | 0.5181 |
| $\rho_o$ | 0.4584 | 0.4600 | 0.4671 | 0.4720 | 0.4748 |
| $\rho_d$ | 0.6299 | 0.6310 | 0.6347 | 0.6382 | 0.6399 |
| $\rho_w$ | −0.2387 | −0.2370 | −0.2308 | −0.2236 | −0.2221 |

## 5.1 Estimates for the best models

Table 2 presents estimates for the best models based on $W_{trade}$ using both the Matyas (1997) fixed effects and those of Cheng and Wall (2005). The table presents the mode of the parameter estimates evaluated using the joint posterior distribution as well as the mean and median based on 5,000 retained MCMC draws (with an initial 5,000 excluded for burn-in of the sampler). Monte Carlo (MC) error estimates are reported along with Geweke's diagnostic that compares draws from the first ten percent of the MCMC sampling (after burn-in) and the last 50 percent of the draws. The test is whether the batched means are equal, which indicates convergence.

From the estimates we see that the dependence parameters $\rho_o, \rho_d, \rho_w$ are different from zero based on the credible intervals calculated from the MCMC draws. As noted in the discussion

Table 3: Partial derivative impacts for the $W_{trade}$ models

| | Matyas (1997) fixed effects | | Cheng and Wall (2005) fixed effects | |
|---|---|---|---|---|
| *Effects* | $GDP_o$ | $GDP_d$ | $GDP_o$ | $GDP_d$ |
| direct | 0.3475 | 0.3855 | 0.3395 | 0.5589 |
| network | 2.3160 | 2.5695 | 1.8371 | 3.0240 |
| total | 2.6635 | 2.9550 | 2.1766 | 3.5828 |

of model interpretation, the parameters $\beta_o, \beta_d$ do not represent partial derivative impacts of the elasticity response of trade flows to changes in origin and destination-country GDP. These need to be calculated using the non-linear matrix expressions for the own- and cross-partial derivatives. The results from doing this are presented in Table 3, where we see substantial network effects. The network effects reflect cumulated off-diagonal elements of the matrix of partial derivatives (cross-partial derivatives) averaged over all countries as described in our discussion of model interpretation.

These estimates show larger direct and network impacts arising from changes in destination country than origin country income on trade flows in the case of both types of fixed effects. The Cheng and Wall (2005) fixed effects lead to larger direct and network destination effects than those from the Matyas (1997) fixed effects specification, but smaller origin-specific direct and network effects than those from the Matyas (1997) fixed effects specification.

Least-squares estimates were $\hat{\beta}_o = 0.9818, \hat{\beta}_d = 1.1562$ for the Matyas (1997) specification, and $\hat{\beta}_o = 0.9822, \hat{\beta}_d = 1.3032$ for the Cheng and Wall (2005) specification. The total effects estimates from the cross-sectional dependence models would be comparable to the least-squares estimates, and we see that ignoring network effects that arise from cross-sectional dependence lead to a substantial downward bias in the least-squares estimates.

### 5.2 Extended versions of the network dependence models

We produced estimates for models based on averages of all 26 possible combinations of two or more weight matrices. For example, we define the combined weight matrix: $W_c = W_{space} + W_{trade} + W_{language} + W_{currency} + W_{colony}$, where $W_c$ is row-normalized to have row-sums of unity. Log-marginal likelihoods are presented for these models in Table 4, for the specification

Table 4: Model comparison of convex combinations of $W-$matrices (Matyas, 1997, fixed effects)

| Models | Log-marginal likelihood | Model probability | $W_{space}$ | $W_{currency}$ | $W_{language}$ | $W_{colony}$ | $W_{trade}$ |
|---|---|---|---|---|---|---|---|
| Model 1 | −519529.635 | 0.000 | 1 | 1 | NA | NA | NA |
| Model 2 | −514041.460 | 0.000 | 1 | NA | 1 | NA | NA |
| Model 3 | −512428.703 | 0.000 | 1 | NA | NA | 1 | NA |
| Model 4 | −507705.640 | 0.000 | 1 | NA | NA | NA | 1 |
| Model 5 | −534178.348 | 0.000 | NA | 1 | 1 | NA | NA |
| Model 6 | −539338.264 | 0.000 | NA | 1 | NA | 1 | NA |
| Model 7 | −513959.160 | 0.000 | NA | 1 | NA | NA | 1 |
| Model 8 | −535185.602 | 0.000 | NA | NA | 1 | 1 | NA |
| Model 9 | −512443.984 | 0.000 | NA | NA | 1 | NA | 1 |
| Model 10 | −503071.944 | 0.000 | NA | NA | NA | 1 | 1 |
| Model 11 | −510951.761 | 0.000 | 1 | 1 | 1 | NA | NA |
| Model 12 | −509278.763 | 0.000 | 1 | 1 | NA | 1 | NA |
| Model 13 | −507252.885 | 0.000 | 1 | 1 | NA | NA | 1 |
| Model 14 | −511418.909 | 0.000 | 1 | NA | 1 | 1 | NA |
| Model 15 | −505617.056 | 0.000 | 1 | NA | 1 | NA | 1 |
| Model 16 | −505331.781 | 0.000 | 1 | NA | NA | 1 | 1 |
| Model 17 | −521467.837 | 0.000 | NA | 1 | 1 | 1 | NA |
| Model 18 | −511281.957 | 0.000 | NA | 1 | 1 | NA | 1 |
| Model 19 | −502105.215 | 1.000 | NA | 1 | NA | 1 | 1 |
| Model 20 | −510301.764 | 0.000 | NA | NA | 1 | 1 | 1 |
| Model 21 | −508705.425 | 0.000 | 1 | 1 | 1 | 1 | NA |
| Model 22 | −504953.579 | 0.000 | 1 | 1 | 1 | NA | 1 |
| Model 23 | −503487.829 | 0.000 | 1 | 1 | NA | 1 | 1 |
| Model 24 | −509310.719 | 0.000 | 1 | NA | 1 | 1 | 1 |
| Model 25 | −508467.724 | 0.000 | NA | 1 | 1 | 1 | 1 |
| Model 26 | −504584.898 | 0.000 | 1 | 1 | 1 | 1 | 1 |

based on Matyas (1997) fixed effects and in Table 5 for the Cheng and Wall (2005) fixed effects specification.

In the Table 4 results, model #19 dominates all others leading to a posterior model probability of one assigned to this specification, based on $W_{currency} + W_{colony} + W_{trade}$. We also note that a comparison of the log-marginal likelihood for the best single weight matrix model from Table 1 shows that combinations of weight matrices produce a specification more consistent with our sample data. That is, the log-marginal likelihood for the model based on $W_{trade}$ alone was $-5.1401e+05$, compared to that for model #19 based on three weight matrices of $-5.0210e+05$. The next best model was model #10 based on $W_{colony} + W_{trade}$ and the 3rd best model was model #23 based on $W_{space} + W_{currency} + W_{colony} + W_{trade}$.

The Table 5 results based on the extended set of fixed effects from Cheng and Wall (2005)

Table 5: Model comparison of convex combinations of $W-$matrices (Cheng and Wall, 2005, fixed effects)

| Models | Log-marginal likelihood | Model probability | $W_{space}$ | $W_{currency}$ | $W_{language}$ | $W_{colony}$ | $W_{trade}$ |
|---|---|---|---|---|---|---|---|
| Model 1 | −507048.345 | 0.000 | 1 | 1 | NA | NA | NA |
| Model 2 | −503766.884 | 0.000 | 1 | NA | 1 | NA | NA |
| Model 3 | −502532.222 | 0.000 | 1 | NA | NA | 1 | NA |
| Model 4 | −499358.674 | 0.000 | 1 | NA | NA | NA | 1 |
| Model 5 | −518174.284 | 0.000 | NA | 1 | 1 | NA | NA |
| Model 6 | −523989.738 | 0.000 | NA | 1 | NA | 1 | NA |
| Model 7 | −504428.222 | 0.000 | NA | 1 | NA | NA | 1 |
| Model 8 | −520322.487 | 0.000 | NA | NA | 1 | 1 | NA |
| Model 9 | −503695.091 | 0.000 | NA | NA | 1 | NA | 1 |
| Model 10 | −497304.291 | 0.000 | NA | NA | NA | 1 | 1 |
| Model 11 | −501405.745 | 0.000 | 1 | 1 | 1 | NA | NA |
| Model 12 | −500300.054 | 0.000 | 1 | 1 | NA | 1 | NA |
| Model 13 | −498846.687 | 0.000 | 1 | 1 | NA | NA | 1 |
| Model 14 | −501643.920 | 0.000 | 1 | NA | 1 | 1 | NA |
| Model 15 | −498027.006 | 0.000 | 1 | NA | 1 | NA | 1 |
| Model 16 | −495841.701 | 0.000 | 1 | NA | NA | 1 | 1 |
| Model 17 | −510634.416 | 0.000 | NA | 1 | 1 | 1 | NA |
| Model 18 | −502613.916 | 0.000 | NA | 1 | 1 | NA | 1 |
| Model 19 | −496487.855 | 0.000 | NA | 1 | NA | 1 | 1 |
| Model 20 | −500274.233 | 0.000 | NA | NA | 1 | 1 | 1 |
| Model 21 | −499479.361 | 0.000 | 1 | 1 | 1 | 1 | NA |
| Model 22 | −497376.837 | 0.000 | 1 | 1 | 1 | NA | 1 |
| Model 23 | −495177.846 | 1.000 | 1 | 1 | NA | 1 | 1 |
| Model 24 | −496643.681 | 0.000 | 1 | NA | 1 | 1 | 1 |
| Model 25 | −499171.712 | 0.000 | NA | 1 | 1 | 1 | 1 |
| Model 26 | −495836.711 | 0.000 | 1 | 1 | 1 | 1 | 1 |

where we see that the best model (#23) is one based on $W_{space} + W_{currency} + W_{colony} + W_{trade}$, and the next best model (#26) included all five weight matrices, with the third-best model (#16) including $W_{space} + W_{colony} + W_{trade}$. What seems clear from the results in Table 4 and Table 5 is that membership in trade unions and historical colonial ties are an important source of interaction between countries' trade flows. The results from Table 5 place emphasis on $W_{space}$ not found for the model based on simpler fixed effects. Recall that the model based on Cheng and Wall (2005) fixed effects whose results are presented in Table 5 represents the preferred model as it has higher log-marginal likelihood values.

# 6 Conclusions

A computationally efficient approach to MCMC estimation of a network dependence gravity model specification was set forth and used to examine the presence of a specific type of cross-sectional dependence in trade flows. The alternative simultaneous network dependence gravity model specification here is based on a spatial econometric specification set forth by LeSage and Pace (2008) that allows trade flows to be dependent on flows between countries that are spatial neighbors to the origin and destination countries. The extension set forth here allows for more general types of network dependence such as common currency, language, colonial ties or membership in trade unions. In cross-sectional gravity models these are typically treated as generalized distance variables, with the interpretation being that they reflect heterogeneity impacting the intercept term. In a panel data specification, these types of commonality between countries reflect time-invariant factors that are thought to be modeled by fixed effects.

We show that after including commonly used fixed effects of the type suggested by Maytas (1997) or Cheng and Wall (2005), there is evidence that network dependence in trade flows remains. Conventional gravity models assume the variable vector of $N^2 \times 1$ trade flows for each time period are independent, so trade flows between countries that have a common currency, language, border, colonial ties or are members of a trade union are no more likely than flows between countries having nothing in common.

Our specification allows these sociocultural factors to represent a basis for trade interaction between countries, with more similar flows between countries that share common borders, currency, language etc. Application of the model to a panel of trade flows covering 38 years and 70 countries provides evidence that this is the case. Network dependence produces simultaneous dependence, which means that flows from country dyad $(i, j)$ depend on flows from other country dyads (say $k, l$), where the dependence structure is based on sociocultural factors. The most important sources of cross-sectional dependence were found to be trade organizations, historical colonial tries, common currency and spatial proximity of countries.

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# APPENDIX A

**Table A.1:** List of countries

| | | | |
|---|---|---|---|
| Algeria | Costa Rica | Kenya | South Africa |
| Australia | Denmark | Madagascar | Spain |
| Austria | Dominican Rep. | Malaysia | Sri Lanka |
| Bahamas | Ecuador | Mauritania | Sudan |
| Belgium | Fiji | Mexico | Suriname |
| Benin | Finland | Morocco | Sweden |
| Bolivia | France | Netherlands | Thailand |
| Brazil | Gabon | Nicaragua | Togo |
| Burkina Faso | Ghana | Niger | Trinidad and Tobago |
| Burundi | Greece | Nigeria | Uganda |
| Cameroon | Guatemala | Pakistan | United Kingdom |
| Canada | Guyana | Panama | United States |
| Central African Rep. | Honduras | Papua New Guinea | Uruguay |
| Chad | Hong Kong | Peru | |
| Chile | Ireland | Philippines | |
| China | Israel | Portugal | |
| Colombia | Italy | Senegal | |
| Congo, Dem. Rep. | Ivory Coast | Sierra Leone | |
| Congo, Rep. | Jamaica | Singapore | |

**Table A.2:** Language ties: Common official and second languages (Krisztin and Fischer 2015)

| | | | |
|---|---|---|---|
| **English** | **French** | **Spanish** | **Arabic** |
| Australia | Algeria | Bolivia | Algeria |
| Bahamas | Belgium | Chile | Chad |
| Cameroon | Benin | Colombia | Mauritania |
| Canada | Burkina Faso | Costa Rica | Morocco |
| Fiji | Burundi | Dominican Rep. | Sudan |
| Ghana | Cameroon | Ecuador | |
| Guyana | Canada | Guatemala | **Chinese** |
| Ireland | Cent. African Rep. | Honduras | China |
| Jamaica | Chad | Mexico | Hong Kong |
| Kenya | Congo, Dem. Rep. | Nicaragua | Malaysia |
| Nigeria | Congo, Rep. | Panama | Singapore |
| Pakistan | France | Peru | |
| Panama | Gabon | Spain | **Malay** |
| Papua New Guina | Ivory Coast | Uruguay | Malaysia |
| Philippines | Madagascar | | Singapore |
| Sierra Leone | Morocco | **Dutch** | |
| Singapore | Niger | Belgium | |
| South Africa | Rwanda | Netherlands | |
| Sri Lanka | Senegal | Suriname | |
| Suriname | Togo | | |
| Trinidad and Tobago | | | |
| Uganda | **Portuguese** | | |
| United Kingdom | Brazil | | |
| USA | Portugal | | |

**Table A.3:** Free trade and stronger forms of agreements in 2000 (Krisztin and Fischer 2015)

| | | | | |
|---|---|---|---|---|
| *APTA* | *CEMAC* | *EU* | Malaysia | *NAFTA* |
| Philippines | Burundi | Austria | Mexico | Canada |
| Sri Lanka | Cameroon | Belgium | Morocco | Mexico |
| | Central African Rep. | Demark | Nicaragua | USA |
| ASEAN [AFTA] | Chad | Finland | Pakistan | |
| Malaysia | Congo, Rep. | France | Peru | *PATCRA* |
| Philippines | Congo. Dem. Rep. | Greece | Philippines | Australia |
| Singapore | Gabon | Ireland | Singapore | Papua New Guinea |
| Thailand | | Italy | Sri Lanka | |
| | *COMESA* | Netherlands | Sudan | *SICA* |
| CAN | Burundi | Portugal | Thailand | Costa Rica |
| Bolivia | Congo, Dem. Rep. | Spain | Trinidad and Tobago | Guatemala |
| Colombia | Kenya | Sweden | | Honduras |
| Ecuador | Madagascar | United Kingdom | *LAIA* | Nicaragua |
| Peru | Sudan | Uruguay | Bolivia | |
| | Uganda | | Brazil | *EU treaties* |
| *CACM* | | *GSTP* | Chile | EU-Israel |
| Costa Rica | *ECOWAS* | Algeria | Colombia | EU-South Africa |
| Guatemala | Benin | | Ecuador | |
| Honduras | Burkina Faso | Bolivia | Mexico | *Bilateral treaties* |
| Nicaragua | Ghana | Brazil | Panama | Canada-Chile |
| | Ivory Coast | Cameroon | Peru | Canada-Israel |
| *CARICOM* | Niger | Chile | | Chile-Mexico |
| Bahamas | Nigeria | Colombia | *MERCOSUR* | Colombia-Mexico |
| Dominican Rep. | Senegal | Ecuador | Bolivia | Fiji-Papua New Guinea |
| Guyana | Sierra Leone | Ghana | Brazil | Israel-Mexico |
| Jamaica | Togo | Guyana | Chile | |
| Suriname | | | Uruguay | |
| Trinidad and Tobago | | | | |

Note: Asia Pacific Trade Agreement (APTA), Asian Free Trade Area (AFTA), Andean Community (CAN), Central American Common Market (CACM), Caribbean Community and Common Market (CARICOM), Economic Community of Central African States (CEMAC), Common Market for Eastern and Southern Africa (COMESA), Economic Community of West African States (ECOWAS), Global System of Trade Preferences among Developing Countries (GSTP), Latin American Integration Association (LAIA), Mercado Comun del Sur (MERCOSUR), North American Free Trade Agreement (NAFTA), Agreement on Trade between Australia and New Guinea (PATCRA), Central American Integration System (SICA) (Source: WTO (2014))

**Table A.4:** Common currency ties

| | |
|---|---|
| Euro: | Austria, Belgium, France, Finland, Ireland, Italy, Netherlands, Portual, Spain |
| US Dollar: | United States, Bahamas[1], Panama |
| West African CFA Franc[2,4]: | Benin, Burkina Faso, Ivory Coast, Niger, Senegal, Togo |
| Central African CFA Franc[3,4]: | Cameroon, Central African Republic, Chad, Republic of Congo, Gabon |

Notes: 1) The Bahamian dollar is bagged to the US dollar on a one-to one basis. 2) CFA stands for African Financial Community. It is issued by the Central Bank of the West African States, located in Dakar, Senegal, for the countries of the West African Economic and Monetary Union. 3) CFA stands for Financial Cooperation in Central Africa. It is issued by the Bank of Central African States, located in Yaoundé, Cameroon, for the countries of the Economic and Monetary Union of Central Africa. 4) The two CFA Franc currencies, although theoretically separate, are effectively interchangeable.

**Table A.5:** Direct colonial ties

| | | | | |
|---|---|---|---|---|
| *UNITED KINGDOM* | Nigeria | *FRANCE* | Morocco | Honduras |
| Australia | Pakistan | Algeria | Niger | Mexico |
| Bahamas | Sierra Leone | Benin | Senegal | Netherlands |
| Cameroon | South Africa | Burkina Faso | Togo | Nicaragua |
| Fiji | Sri Lanka | Cameroon | | Panama |
| Ghana | Sudan | Central African Rep. | *SPAIN* | Peru |
| Hong Kong | Trinidad and Tobago | Chad | Bolivia | |
| Ireland | Uganda | Congo, Dem. Rep. | Chile | *BELGIUM* |
| Israel | United States | Congo, Rep. | Colombia | Congo, Dem. Rep. |
| Jamaica | | Gabon | Costa Rica | |
| Kenya | | Madagascar | Ecuador | *PORTUGAL* |
| Malaysia | | Mauritania | Guatemala | Brazil |