Exporting Spatial Externalities*

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Abstract

Using spatial econometrics, we estimate the effect of externalities generated by neighbors' exports on place-level exports, explicitly modeling the distance to those neighbors. We find there is a positive effect of neighbors' exports on exports to both the same country and exporting generally. We also find that using a spatial weights term based on the physical distance between exporters greatly outperforms a dichotomous measure based on exporters in the same region. The results are robust to alternative definitions of the spatial weights.

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Abstract

Using spatial econometrics, we estimate the effect of externalities generated by neighbors' exports on place-level exports, explicitly modeling the distance to those neighbors. We find there is a positive effect of neighbors' exports on exports to both the same country and exporting generally. We also find that using a spatial weights term based on the physical distance between exporters greatly outperforms a dichotomous measure based on exporters in the same region. The results are robust to alternative definitions of the spatial weights.

1 Introduction

Most manufacturing industries are spatially concentrated (Ellison and Glaeser 1997), as is the export sector (Nuadé and Matthee 2010). Exporters not only cluster around ports and areas of relatively high productivity, but they also cluster domestically by the foreign destinations that they ship to. This was first noted by Lovely, Rosenthal, and Sharma (2005) using data from U.S. states. Koenig (2009), Koenig, Mayneris, and Poncet (2010), and Choquette and Meinen (2012) find the likelihood that a particular firm exports to a particular destination increases with the number of other firms exporting to that destination from the same region, controlling for standard gravity variables of GDP and physical distance. Using a panel of firm-level data from Spain, Ramos and Moral-Benito (2015) show exporter agglomeration by destination is statistically significant for most countries that firms export to, in particular countries that do not speak the same language or are culturally distinct. Cassey and Schmeiser (2013a) show the estimates obtained from regressions of standard gravity equations are sizably biased because they do not account for an externality term based on the aggregate weight of exporting neighbors.

While destination specific externalities have been shown to exist, there still remains a lack of clarity about the nature of spatial export-destination externalities. That is, though we know that export-destinations exists, because of the relatively blunt methods of modeling space in the literature we neither have a consensus estimate of their magnitude nor whether the externality is limited to destination-specific pairs or if third-country effects exist. This is an important problem because not accounting for this externality may lead to omitted variables bias and erroneous conclusions about the economic impacts of trade liberalization episodes or analysis of international trade policy. Hence we do a formal analysis of the spatial relationship between exporter locations, destination countries, and export externalities.

After converting firm-level data to the level of places in space, we estimate the significance of neighbors' exports to the same country as well as—for the first time—third-country effects using spatial econometric estimators. We study places in space because we have data on the physical location of exporters and thus we are able to use the distance between exporters as a weight on a spatial externality variable. This advances the literature as previous work used a spatial weights matrix that assigned a value of one for the presence of other exporters within some politically defined region such as a state and zero otherwise.[1] Using a zero-one weighting scheme has been shown to bias other measures of agglomeration (Feser 2000). Thus a major aim of this paper is to improve upon previous results by modeling the distance between exporting neighbors formally. Our methods are similar to Bode, Nunnenkamp, and Waldkirch (2013) who, using spatial econometrics, find foreign direct investment in U.S. states generates Marshallian externalities that positively affect productivity elsewhere, whereas externalities from domestic firms are negative.

Based on Kerr and Kominers (2010), we start exploring the nature of destination-specific externalities by assuming their strength decreases with the physical distance to other potential exporters. As Kerr and Kominers argue, the strength of an externality diminishes with distance because of the increased difficulty of meeting with or observing others at a distance. Thus we model the export-destination externality with a distance decay function. We estimate the effect of the exports of neighboring locations on exports to the same and different countries from the exporting location under consideration using a gravity equation modified by distance-weighted spatial lag terms.

There are potential opposing economic forces associated with the behavior of nearby exporters on the exports and destinations from any specific location. Consider the exports from a location ℓ to a country c as well as exports from other locations to country c. First, exports from neighbors to c may cause the exporters in location ℓ to choose some otherwise less desirable market where they

[1] Ramos and Moral-Benito (2015) have data with firm locations as we do. They use the Duranton and Overman (2005) statistic for documenting that Spanish exporters are statistically likely to be clustered around foreign destinations, but they have neither an estimate of the causal impact of the export externality directly nor for third countries.

can avoid the competition and have greater market power. In that case, we would observe diffusion in export destinations. The sign of the externality term for same countries would be negative.

Second, as suggested by Cassey and Schmeiser (2013a) and Koenig et al. (2010), nearby exporters may positively affect exports to the same country because of formal or informal sharing of information on legal, cultural and language barriers or sharing of distributional and transportation channels. In this case, the sign of the externality term for same countries would be positive.

Additionally we test for export externalities from third country effects: exports from other nearby locations within the same exporting country to other importing countries affecting exports from location ℓ to country c. Third country effects have been documented to exist and have a positive effect for foreign direct investment (Baltagi, Egger, and Pfaffermayr 2007; Blonigen, Davies, Waddell, and Naughton 2007). Furthermore, the FDI literature shows that proximity to other locations receiving FDI is important for the strength of these externalities. A positive coefficient on a spatial lag term to other countries indicates a beneficial export externality from exporting in general. Such a finding would be consistent with the idea of formal or informal sharing of export information regardless of the destination or there being a common pool of workers experienced in international trade.

Using firm-level export data from Russia in 2003, we estimate a statistically and economically significant positive effect of neighbors' exports to their foreign destinations on a location's exports to the same country, indicating a beneficial exporter-by-destination externality. Additionally, we find a positive sign on third country effects. Because we have positive signs on both externalities, we can rule out that the larger economic force is that neighbors' exports cause firms to choose different export destinations. Instead we find that in addition to potential knowledge and transportation spillovers to same country destinations, there may be a pool of common resources in terms of international trade. Alternatively, having exporting activity nearby may create a conducive exporting environment generally and on net.

That spatial externalities exist around exporting has only recently begun to be understood with empirical trade studies using two-country international trade models that yield the standard bilateral gravity equation. It is in the literature on FDI where the empirical importance of third country effects was discovered and where formally modeling the distance between firms and destination countries was introduced in an international context. We combine the theoretical methods from the trade literature on agglomeration and the empirical methods from the FDI literature to estimate spatial terms calculating the importance of country specific and third-country effects on exports.

After discussing the modified gravity equation that is the basis for our regressions in section 2, we discuss the data we use as well as computational challenges in using spatial econometric methods in this framework in section 3. The results and robustness checks are in section 4.

2 A Modified Gravity Equation with Spatial Weight Matrix

There is a single country where exporters are located. That country has L locations where exporters exist. Each location is a zero-dimensional spot on a map and there may be zero, one, or multiple exporters at each location. There are C foreign destinations that exporters may sell to. Consider the benchmark gravity equation:

$$X_{\ell c} = \alpha Y_{\ell}^{b_1} Y_{c}^{b_2} D_{\ell c}^{b_3} \theta_{c}^{b_4} \theta_{\ell}^{b_5}$$

where $X_{\ell c}$ are exports from location ℓ to foreign country c, α is a constant, the Y's are the market size variables (GDP), and $D_{\ell c}$ is the great circle distance between the export location and the foreign country. Exports from location ℓ to foreign country c, $X_{\ell c}$, are aggregate in that they are the sum of the value of exports from the zero, one, two, or more exporters that are located in ℓ that export to c. Since Anderson and van Wincoop (2003), it is well-known that the gravity equation also requires exporter and importer unilateral variables representing the aggregate price index or weighted trade barriers, often called multilateral resistance terms. These are denoted by θ_c and θ_ℓ.

Cassey and Schmeiser (2013a) develop and solve a firm-level model of exports with spatial externalities derived from the supply side. Derived from the underlying firm-level structure of the economy, their main theorem shows the resulting aggregate-level benchmark gravity equation should be augmented with a destination-specific externality term so that $X_{\ell c}$ also depends on exports by neighbors. But when Cassey and Schmeiser take data to their theory, they use a simple method for describing space that gives full weight to neighbors in the same region and zero to those in different regions including contiguous regions. Using the same underlying theory as Cassey and Schmeiser but differing in estimation techniques, we use the physical distances between locations rather than arbitrary regions to spatially weight the externality:

$$X_{\ell c} = \alpha Y_{\ell}^{b_1} Y_c^{b_2} D_{\ell c}^{b_3} \theta_c^{b_4} \theta_{\ell}^{b_5} \left(\beta \prod_{\substack{m=1 \\ m \neq \ell}}^{L} (X_{mc})^{\delta w_{\ell m}} \right) F_{\ell c}^{b_6}$$

where β is a constant, L is the total number of locations where exporters exist, $w_{\ell m}$ is the spatial weight on the distance between exporting location ℓ and exporting location $m \neq \ell$, δ is the elasticity of locational effects, and $F_{\ell c}$ is an unobservable bilateral variable that may be considered as the fixed costs associated with exporting from location ℓ to country c. Importantly, our product index runs over all neighboring locations $m = 1, ..., L$ *except* for the location itself, $m \neq \ell$. In this way, the $X_{\ell c}$ export vector on the left hand side does not include itself among the $L - 1$ export vectors X_{mc} on the right hand side.[2] The exact specification of these spatial weights is important and discussed in detail below.

Taking logs and expressing the result in vector and matrix form yields

$$x_{\ell c} = b_0 + b_1 y_{\ell} + b_2 y_c + b_3 d_{\ell c} + \delta W x_{mc} + b_4 \theta_c + b_5 \theta_{\ell} + \epsilon_{\ell c} \tag{1}$$

where $x_{\ell c}$ is the $L \cdot C \times 1$ vector of log export values from each location to each destination country, $b_0 = \ln(\alpha) + \ln(\beta)$, x_{mc} is the vector of log exports from all $L - 1$ other individual locations 1 through L to country c except for location ℓ, and $\epsilon_{\ell c} = b_6 \ln F_{\ell c}$. The spatial weight matrix is W and lower-case letters denote natural logs. There is of course concern about endogeneity in this specification when data are brought to bear. We discuss how we control for endogeneity when we discuss our results in section 4.

We test if the exports from nearby locations have an effect on exports under four specifications. The first specification is the benchmark gravity equation without a spatial weights term so that W is made up of only zeros. In the second specification, we build W by assigning a weight of one

[2] Technically we set $w_{\ell\ell} = 0$ for all locations, which is the standard method described in Fischer and Wang (2011) to avoid a problem with joint and simultaneous determination of the spatial variables.

to exports from the same geographic or political structure to the same destination as the exporter under observation and zero otherwise. This is essentially the method used by Koenig (2009), Koenig et al. (2010), and Cassey and Schmeiser (2013a). Thus our results from this specification are directly comparable to the literature. We call this the Naive Spatial Lag.

In the third specification, we follow the technique described in Fischer and Wang (2011) to construct W using the great circle distances between exporting locations. There are L unique locations shipping exports. These locations are separated from each other by distance $D_{\ell m}$. Because there are C countries, there are $C \cdot L$ observations. This means W is a $C \cdot L \times C \cdot L$ spatial weight matrix. If C and L are large, then the computational burden of such a weighting matrix is high. But because it is implausible that exports from location ℓ to country c depend on exports from *all* other possible combinations of locations and countries (Kerr and Kominers 2010), we reduce the size of the spatial weight matrix. Thus in the third specification, we posit that exports from location ℓ to country c only spatially depend on exports from all locations to the same country c. This means we construct a $L \times L$ weight matrix. We apply this weight matrix to the $L \times 1$ vector of exports from each location to a single destination and then stack the matrices for all C destinations. This results in a spatially lagged term Wx_{mc} that is $C \cdot L \times 1$ including the exporting location itself, which we zero out to avoid simultaneity. We call this the Same Country Spatial Lag. LeSage and Fischer (2010) advocate this stacking procedure in order to decrease the computation burden.[3]

In the fourth and fifth specifications, we allow exports from location ℓ to country c to depend on exports from other locations within the exporting country to other importing countries besides c itself. We do this to test for third country effects as they have been found to be important for foreign direct investment (Baltagi et al. 2007; Blonigen et al. 2007) as well as gravity models with spatial weights estimated by least squares (LeSage and Pace 2008). Using the method of Blonigen et al. (2007), we include a single matrix term $\overline{W}$ spatially weighting exports to third countries. To construct $\overline{W}$, we first apply a weight based on the distances among countries to the other importing

[3]We cannot do the moments method advocated by LeSage and Pace (2008) because we do not have a closed system: the number of exporting locations is not the same as the number of importing countries in our data.

destinations. Then we interact that with the weight for the distance between locations.[4] Therefore this second weight matrix $\overline{W}$ is applied to the vector of exports from all locations to all *other* importing countries $x_{m,-c}$. Thus we have:

$$x_{\ell c} = b_0 + b_1 y_\ell + b_2 y_c + b_3 d_{\ell c} + \delta W x_{mc} + \gamma \overline{W} x_{m,-c} + b_4 \theta_c + b_5 \theta_\ell + \epsilon_{\ell c}. \qquad (2)$$

where the fourth specification only includes the third-country spatially lagged term $\overline{W}_{m,-c}$ and the fifth specification includes both spatial lags. As with (1), it should be understood that the right hand side does not include the single observation for $x_{\ell c}$ but rather just the L-1 x_{mc} for all locations $m \neq \ell$. Likewise the $x_{m,-c}$ term is nonnull only for $m \neq \ell$. There is additional concern from simultaneity in (2) because though the observation for $x_{\ell c}$ does not show up on the right hand side, it does appear as the neighbor of some other observation x_{jc} on the right hand side. We will address endogeneity in section 4.

The spatial weights that make up of the elements of W and $\overline{W}$ must be defined. We assume the spatial weights in the location-to-location weight matrix, W, decrease with distance so that neighboring exporters that are farther away from the exporting location have decreased impact on the exports from that particular location. Similarly, we assume the spatial weights in the third countries weight matrix, $\overline{W}$, decrease with the distance between the other counties as well as the interaction with the distance between exporting locations.

As in Bode et al. (2013), we define the spatial weights to be inverse exponential distances, $w_{\ell m} = e^{-\tau d_{\ell m}}$. The exogenous parameter τ is a constant distance decay parameter that determines the percentage diffusion loss per unit of distance. The inverse exponential form of the spatial weights implies that the distance losses are, in absolute terms, higher for the first than for subsequent kilometers. We set the parameter $\tau = 0.02$. This level implies that 86.5% of the externality is gone after 100 kilometers.

To account for externalities arising from the presence of more than one exporter in the same location, we set the weight for the own location $w_{\ell\ell}$ to be zero when there is one exporter and

[4]We allow for the elasticity of exports from location ℓ to country c with respect to exports from other locations m to the same country c to differ from that of other locations exporting to other countries $-c$.

one otherwise. For robustness, we also use inverse distance weights $w_{\ell m} = d_{\ell m}^{-1}$ as well as squared inverse distance and inverse square roots of distance weights. We set the weight on exports to other countries from the same location to be one in all cases. As is common in the literature to ease interpretation, we row-standardize W_ℓ. The row-standardized matrix captures the relative distance between locations rather than absolute distances.

3 Data and Computational Issues

We use firm-level data on the location of the exporter, the destination of the shipment, and the value of the sale from the 2003 Russian External Economic Activities (REEA) data set, described in Cassey and Schmeiser (2013b).[5] We limit our study to Russian exporters because we have firm-level export data for Russia only and not for other countries. (Firm-level data are extremely difficult to obtain in general.) As is common in the literature, we only use observations of manufacturing exporters to avoid issues of bulk commodities from multiple firms and locations being mixed and exported from a third site (Bradshaw 2008; Cassey 2009).

Russia is divided into postal codes that are similar to U.S. ZIP codes. Our export data have the postal code for the exporter in each transaction. Thus we know the physical location of each exporter. In 2003, there was at least one export transaction for 2,458 Russian postal codes that we were able to identify. We map Russian postal codes into coordinates in space. But as with ZIP codes in the U.S., many of the postal codes are so physically tiny that they are not distinguished in coordinates to four decimal places. Thus, we aggregate observations over postal codes to the level of 4-decimal places in space. This leaves 697 unique physical places in Russia in 2003 that had at least one export transaction. It is these unique places that we identify with locations in the model. We calculate the great circle distance between these places in Russia.

There are 145 destination countries that receive at least one Russian shipment and that we have 2003 GDP data for from the *World Economic Outlook Database* (IMF 2006). However, while there were positive exports to all 145 countries, many receive very few exports and for many of these

[5]We do not have data on domestic sales from either exporters or domestic-only firms. We do not consider this a problem as domestic sales would not affect either information spillovers, economies of scale in international shipping, or overseas competitiveness.

Table 1. Summary Statistics

Variable	Mean	Median	Std. Dev.	Min	Max
Exports	194,263	0	3,611,601	0	404,348,464
Distance to Destination	7.682	7.587	0.707	4.466	9.265
Naive Spatial Lag	38.113	11.585	78.948	0	780.004
Same Country Spatial Lag	1.889	0.522	3.768	0	34.224
Third Countries Spatial Lag	0.085	0.004	0.255	0	9.460
GDP Destination	11.127	11.295	1.982	7.150	16.211

Source: Author's calculations based on data from various sources described in the text.

countries only a few locations in Russia export there. Thus, we limit the sample to those countries that receive shipments from at least 10 locations. This leaves a data set with 80 destination countries and eliminates one of the locations to leave us with 696. Our usable data set thus consists of 55,680 location-destination observations. We calculate the great circle distance between the capital of each of these destinations and the 696 Russian locations. We take the distance between the 80 destination countries from CEPII. Table 1 presents the summary statistics.

As is common with disaggregated trade data, most of the observations are zero (Bernard and Jensen 2004). While all 696 locations export to at least one country and all 80 countries receive exports from at least ten locations, many location-country pairs do not trade, at least in 2003. That there is such a preponderance of zeros poses additional econometric challenges. We discuss those challenges below.

If we had not stacked the weight matrix for each destination, we would have had a $55,680 \times 55,680$ spatial weight matrix. Also, as mentioned in section 2, we do not model the export elasticity of each destination country. It is doubtful that there is enough variation in the data to separately identify 80 such elasticities and the computational burden is large. That is why we assume that the elasticity of *other* destinations can differ from the target destination but not from each other in (2).

We are unable to include product-level controls in our regressions due to our aggregation method. However, we do not believe this biases our results as Cassey and Schmeiser (2013a) show that when product controls are included, statistical significance is robust to the inclusion.

4 Results and Robustness

The coefficients on the spatial lag terms are the estimates of the strength of location-destination externalities in exporting, with the statistical significance indicating whether they exist. Given there is evidence of externalities, the signs of the coefficients will indicate how these externalities behave. If the coefficient on the spatial lag term for the same country is positive then that suggests there is a beneficial externality from neighbors exporting to the same destination. If, in addition, the coefficient on the spatial lag term for other countries is positive then that suggests there is also a beneficial export externality from neighbors exporting anywhere. Both of these would be consistent with the existence of information about how to export in general or how to export to a specific country spilling over from neighbors. If the coefficient on the spatial lag term for the same country is negative when the coefficient on the spatial lag term for other countries is positive then that would indicate market competition is leading exporters to serve different destinations than their neighbors, creating diffusion among destinations. Of course, if the coefficients on both spatial lag terms are negative that suggests a negative externality on exporting to the same country and exporting in general.

To address possible endogeneity concerns, we estimate (1) and (2) by replacing the multilateral resistance terms θ_ℓ and θ_c with exporter and importer fixed effects. Because the data are cross sectional, the fixed effects subsume the GDP variables y_ℓ and y_c. Furthermore, the exporter fixed effects will control for variables such as high productivity in a particular place or exporters being close to ports of exit regardless of the destination of their shipment. Similarly, because all of our export locations are places within Russia, the importer fixed effect will control for variables such as speaking Russian commonly and tariff and non tariff barriers or free trade agreements as these do not vary across Russian locations.[6] The importer fixed effects also control for exports from the rest of the world to each destination c because this variable does not vary across Russian exporting places ℓ. Only the distance between the location of the exporter and the export destination can be included from among the gravity variables. Using fixed effects to control for observable and unobservable unilateral variables in a gravity equation was introduced by Feenstra (2002) and

[6]At the beginning of 2003, Russia was part of a free trade agreement with only Georgia, Kyrgyzstan, and Serbia. A free trade agreement with Armenia began in 2003.

is now the standard way of econometrically controlling for Anderson and van Wincoop's (2003) multilateral resistance terms.

Table 2 shows results from the fixed effects regression on (1) and (2). All standard errors are White heteroskedasticity consistent. The first column is a standard gravity equation without any spatial terms, only the location and country fixed effects and distance are included. The coefficient on distance is negative, statistically significant at the one percent level, and at the high end of the range of estimates from the vast gravity equation literature.

The second column includes our naive spatial lag as a benchmark. This is essentially the method used by Koenig (2009), Koenig et al. (2010), and Cassey and Schmeiser (2013a), and like them, we find the coefficient is positive and significant at the 1% level. Thus there is evidence that exporters generate positive externalities, at least somewhat crudely.

In the third column, we include the spatial lag of exports to the same destination country, using the inverse exponential weights on distance between locations. The coefficient on that term is positive and highly statistically significant, which we take as evidence of a positive externality in exporting from nearby locations to the same destination country. Such a finding is consistent with the idea that destination-specific export information is spilled over from geographically nearby neighbors. The direct interpretation of the magnitude is that if exports from *all* other locations to country c, weighted by distance from location ℓ, increased by 1% then exports from ℓ to c would increase by 0.57%. Though we find this estimate to be economically relevant and quite plausible, we do not think it is the most instructive interpretation for our analysis, a point we discuss below. Also, though the coefficient on distance is still negative and statistically significant, it is an order of magnitude weaker than in the first two columns as the spatial lag term for same country is accounting for some of what the distance variable formerly picked up. This suggests that not including the spatial lag using internal distances creates omitted variable bias.

In the fourth column, we include the spatial lag of exports to countries other than the destination country, which are themselves spatially weighted by the distance from the destination country. The resulting coefficient is also positive and statistically significant. That the coefficient on the third country term is positive suggests that there is a beneficial externality from neighbors exporting to any country, not just to the same country. The direct interpretation of the coefficient is that if exports from *all* other locations to *all* other destinations increased by 1% then exports from location ℓ to country c would increase by 3.17%. Though this seems large in magnitude, it applies to the unlikely case that exports from all locations to all destinations increase. Again, that is why the sign of the coefficient, rather than the point estimate, is most instructive to our findings at this point.

Finally, we include both spatial lags. We find they are both positive and statistically significant. Thus we find robust support that there are spatial complementarities from exporting, and that these positive externalities have both a "same country" component and an "exporting generally" component. On net, there is no evidence that exporters choose destination markets to avoid the sales of their exporting neighbors as this would cause the spatial lag coefficients to be negative.

In the discussion of specifications (3) and (4), we commented on the point estimates and their immediate interpretation. But while we believe those point estimates are economically important and plausible, we do not think they are the most instructive for our analysis because of the implausibility of exports from all locations to a single country or exports from all locations to all countries increasing uniformly. Rather, we prefer to multiply the estimated coefficients for the naive spatial lag from column (2) and from the two spatial lags included in specification (5) with the median of the lag in Table 1, giving values of 0.070, 0.282 and 0.008, respectively.[7] Thus, evaluated at the median, the spatial lag of exports to the same country accounts for far more of the exports data than the naive lag. Note too that the value for exports to the same destination is larger than for third countries. This indicates that though there is a beneficial externality from exporting in general, the effect is quite a bit larger for exporting to the same destination. That is consistent with there being informational spillovers on exporting generally, but more important informational spillovers on exporting to a specific country.

That export externalities exist has been established in the literature using the naive weight. Thus we want to know how much better the results using the inverse exponential weights are. To do this, we use the adjusted R-squared and the Akaike and Bayesian information criteria (AIC and BIC, respectively). These are three ways of measuring the amount of variation in the export data the spatial lag terms account for. Entering the naive spatial lag in addition to distance and the

[7]Using means instead of medians results in similar relative magnitudes.

Table 2. Fixed Effects Results: Inverse Exponential Distance Weights

	(1)	(2)	(3)	(4)	(5)
Distance	-1.551^{***}	-1.331^{***}	-0.140^{**}	-1.347^{***}	-0.0705
	(0.093)	(0.096)	(0.068)	(0.086)	(0.066)
Naive spatial lag		0.006^{***}			
		(0.001)			
Same country lag			0.567^{***}		0.541^{***}
			(0.011)		(0.011)
Third country lag				3.167^{***}	2.065^{***}
				(0.236)	(0.186)
Adjusted R^2	0.158	0.168	0.388	0.202	0.406
F(.)	16.93	15.51	86.99	19.39	86.03
AIC	276092	275461	258372	273134	256707
BIC	276806	276184	259095	273857	257439

In all specifications, there are 55,680 observations and location and country fixed effects are included: $x_{\ell c} = b_0 + b_3 d_{\ell c} + \delta W x_{mc} + \sum_\ell \gamma_\ell (1)_\ell + \sum_c \eta_c (1)_c + \epsilon_{\ell c}$. Standard errors are robust. The naive spatial lag takes values of one for locations within the same region and 0 otherwise. AIC is the Akaike information criterion and BIC is the Bayesian information criterion.

*** p<0.01,** p<0.05

fixed effects increases the R-squared modestly, by 0.01 or 6%, and lowers the information criteria modestly as well. In contrast, entering the spatial lag to the same country raises the R-squared by 0.23 or 145%, and lowers the information criteria value substantially. The “naive” spatial indicator that has been used in the literature does not adequately account for the significant externalities generated by other exporters and thus vastly underestimates their complementarity. Even entering the spatial lag to other countries raises the R-squared by much more than the naive lag and both together raise it over 0.40. Thus to account for more variation in the data, not only must an externality term measuring the exports of neighbors be included, but that term should be weighted using the distance to those neighbors. Using a naive weight based on arbitrary political boundaries such as states does not seem to be enough.

Though our inclusion of exporter and importer fixed effect accounts for some of the endogeneity concerns, there are other concerns resulting from export values that are contained in the spatial terms and also in the dependent variable. While this is a direct result of the nature of spatial estimation and we always omit the own exports in the construction of the spatial term, we also

Table 3. Instrumental Variable Results: Inverse Exponential Distance Weights

	(3)	(4)	(5)
Distance	-0.0225	-1.279^{***}	0.041
	(0.0039)	(0.0418)	(0.0363)
Lag same country	0.599^{***}		0.572^{***}
	(0.004)		(0.0039)
Lag third country		3.666^{***}	2.149^{***}
		(0.0651)	(0.0555)
Adjusted R^2	0.468	0.183	0.483
Wald χ^2	$51,404.7$	$23,621.3$	$54,332.5$

In all specifications, there are 55,680 observations and location and country fixed effects are included: $x_{\ell c} = b_0 + b_3 d_{\ell c} + \delta W x_{mc} + \sum_\ell \gamma_\ell (1)_\ell + \sum_c \eta_c (1)_c + \epsilon_{\ell c}$. Standard errors are robust.

*** p<0.01.

check our results using a panel instrumental variable specification. The results are shown in table 3.

We use the weight of exports as an instrument, as in Cassey and Schmeiser (2013a), and create the spatial lags from that instrument. Export weight and value are not strongly correlated as many high value export goods are not massive. The first-stage F-statistics are very large, so these spatially lagged export weights appears to be good instruments.[8] The IV-results provide very similar coefficients on our spatial variables of interest. The IV estimates imply that a 1% increase in exports from the median location neighbor to the same country is 0.299% and a 1% increase in the median neighbor to the third country is 0.009% effect.

It is important for the robustness of our results that they do not hinge on the way we have calculated our weights. As shown in Bode et al. (2013), the choice of distance decay function can make a difference. We replace the inverse exponential weights of table 2 with simple inverse distance weights (Blonigen et al. 2007) and squared inverse distance and inverse square roots of distance weights (Baltagi et al. 2007) while keeping $\tau = 0.02$. The qualitative results using both spatial lags, in column (1) of appendix tables A.1-A.3 are unaffected. Using all three alternative distance decay functions, the coefficients for both the same country spatial lag and the third country spatial lag remain positive and statistically significant. Furthermore, the size of the coefficient on the spatial lag to the same destination is about the same in all cases. The size of the coefficient on the spatial

[8] Some observations do not have a corresponding export weight. In those cases, we set the weight to zero.

lag to other countries does change. This is perhaps not surprising as we construct that weight matrix by first using the distance between countries and then the distance between locations. Thus changing the distance decay function causes two changes in the weight matrix.

One downside of including the multilateral resistance terms in a cross-section is that the GDP gravity variables cannot be included. Thus, as another robustness check, we omit the multilateral resistance terms and include GDP of the Russian location and of the destination country instead. Though we do not have GDP at the place-level, we do at the region-level, which is equivalent to U.S. states. We use *Russia: All Regions Trade & Investment Guide* (CTEC Publishing 2004, 2006) for economic data for the 89 Russian regions that existed in 2003. (Russia has since combined some regions.) Since GDP for Russia is at the region (oblast) level and GDP of the destination country is at the country level, we now cluster standard errors on both region and destination country in order to avoid the well-known bias from repeated observations and analysis that includes different levels of aggregation (Moulton 1990). Results are shown in Table 4. First note that GDP variables have the expected sign, although they are not always statistically significant at the ten percent level, which is a result of the clustering procedure. More importantly, our findings for the spatial lag variables are perhaps stronger. Not only do the signs and statistical significance of both spatial lag variables remain as in Table 2, but the relative magnitudes are similar as well. The inclusion of the spatial lag of exports to the same country now raises the R-squared by 0.387 relative to the basic gravity specification. These results also hold up to changing the distance decay function, as seen in column (2) of Tables A.1-A.3. Thus once again, we see the importance of the export externality to same country as well as the importance of using a more sophisticated weight matrix than the naive method.

As pointed out by Santos Silva and Tenreyro (2006), one problem in gravity equations is the preponderance of zeros and our data are no exception. There are many location-destination pairs for which no exports are recorded. As shown in Table 1, the median export value in our data is zero. Santos Silva and Tenreyro (2006) show that the use of a poisson estimator can eliminate the bias associated with these zeros without eliminating those observations. Thus we repeat our fixed effects regressions using the poisson estimator and robust standard errors. Results are shown in Table 5. All spatial lag variables continue to have positive and highly statistically significant

Table 4. Double Clustering Results: Inverse Exponential Distance Weights

	(1)	(2)	(3)	(4)	(5)
GDP Russian location	0.269	0.113	0.0870	0.237	0.0783
	(0.220)	(0.225)	(0.0790)	(0.197)	(0.0748)
GDP destination country	0.182***	0.138***	0.00134	0.217***	0.0255
	(0.0549)	(0.0418)	(0.0107)	(0.0604)	(0.0162)
Distance	−1.184***	−0.836***	0.0428	−0.977***	0.0965
	(0.172)	(0.163)	(0.0507)	(0.195)	(0.0617)
Naive spatial lag		0.00816***			
		(0.00262)			
Spatial lag same country			0.658***		0.633***
			(0.0232)		(0.0251)
Spatial lag other countries				3.567***	1.745***
				(0.578)	(0.272)
Adjusted R-squared	0.059	0.082	0.446	0.116	0.459
F(.)	134.4	116.9	5844.0	222.6	4736.0
AIC	300280	298888	270789	296766	269448
BIC	300315	298932	270834	296811	269502

In all specifications, there are 55,680 obs: $x_{\ell c} = b_0 + b_1 y_\ell + b_2 y_c + b_3 d_{\ell c} + \delta W x_{mc} + \epsilon_{\ell c}$. Standard errors are clustered on both region and country. The naive spatial lag takes values of one for locations within the same region and 0 otherwise. AIC is the Akaike information criterion and BIC is the Bayesian information criterion.

*** p<0.01.

coefficients. As is common when using the poisson estimator, our estimated coefficients in Table 5 are attenuated to those in Table 2 by about one third. But as this is true for both the spatial lag of exports to the same and to other destinations, their relative importance remains about the same. Again, the Akaike and Bayesian information criteria favor the specification with both lags included over any other specification. Thus we continue to find support for export externalities to both same country and generally. As a further benefit, **?** recommend the Poisson spatial autoregressive estimator to address the possible simultaneity in specifications (4) and (5) (but not (3)) coming from the possibility that an observation of the left hand side variable could show up as a right hand side variable for a neighbor.

As evidenced by the standard deviation exceeding the mean by a large margin, our export data are considerably over dispersed. Supported by a Vuong test, we estimate the spatial lag variables with a zero-inflated negative binomial estimator. Coughlin (2014) advocates using a negative

Table 5. Poisson Fixed Effects Results: Inverse Exponential Distance

	(1)	(2)	(3)	(4)	(5)
Distance	-1.295^{***}	-1.206^{***}	-0.157	-1.292^{***}	-0.185
	(0.201)	(0.195)	(0.214)	(0.200)	(0.218)
Naive spatial lag		0.003^{***}			
		(0.001)			
Spatial lag same country			0.183^{***}		0.179^{***}
			(0.018)		(0.018)
Spatial lag other countries				0.797^{***}	0.474^{***}
				(0.156)	(0.152)
Wald χ^2	22674	24213	32241	32020	35529
AIC	2.520e+10	2.480e+10	1.800e+10	2.470e+10	1.790e+10
BIC	2.520e+10	2.480e+10	1.800e+10	2.470e+10	1.790e+10

In all specifications, there are 55,680 obs and location and country fixed effects are included: $X_{\ell c} = \exp(b_0 + b_3 d_{\ell c} + \delta W x_{mc} + \sum_\ell \gamma_\ell (1)_\ell + \sum_c \eta_c (1)_c)\epsilon_{\ell c}$. Standard errors are in parentheses. The naive spatial lag takes values of one for locations within the same region and 0 otherwise. AIC is the Akaike information criterion and BIC is the Bayesian information criterion.

*** p<0.01.

binomial estimator on export data with many zeros. The results are in Table 6. The results are again largely identical to those from the OLS and Poisson estimators. The point estimates are further attenuated by about another third from the estimates from the Poisson estimator, but again the relative contribution of the two spatial lags remains.

Looking at the results in columns (3) and (4) in tables A.1 to A.3 using different distance decay function for defining the spatial weight matrices shows that the results are extremely robust and there is very little variation in the size of the coefficients. The one exception is the spatial lag of exports to other destinations for two of the weight schemes in the Poisson model where it becomes insignificant or significant at the ten percent level. However, this is more a reflection of the difficulty of convergence of this model in the presence of a large number of fixed effects than non-robustness of the results.

We conduct one final robustness check. Since there are 696 location observations for each destination country, we run separate regressions for each destination, including the spatial lag of exports to the same destination. Since there are 80 coefficients and standard errors, we show the results graphically. Figure 1 shows the spatial lag coefficient and its confidence interval for each of

Table 6. Zero-Inflated Negative Binomial Fixed Effects Results: Inverse Exponential Distance

	(1)	(2)	(3)	(4)	(5)
Distance	-0.846^{***}	-0.846^{***}	-0.211^{***}	-0.851^{***}	-0.215^{***}
	(0.072)	(0.072)	(0.073)	(0.072)	(0.073)
Naive spatial lag		$-1.57e{-}05$			
		(0.000)			
Spatial lag same country			0.122^{***}		0.121^{***}
			(0.004)		(0.004)
Spatial lag other countries				0.490^{***}	0.338^{***}
				(0.095)	(0.081)
Wald χ^2	412051	412270	1.753e+06	347588	1.564e+06
AIC	204773	204775	203829	204730	203801
BIC	211736	211747	210801	211701	210781

In all specifications, there are 55,680 obs and location and country fixed effects are included. Standard errors are in parentheses. The naive spatial lag takes values of one for locations within the same region and 0 otherwise. AIC is the Akaike information criterion and BIC is the Bayesian information criterion.

*** $p<0.01$.

the 80 export destinations. Each dot shows the point estimate for one country and the vertical line is the 95 percent confidence interval. We see that almost always, exporting to a country provides a positive externality to neighbors that export to that same country. Only one point estimate is negative and only 9 of 80 are not statistically significant at the 5% level. We conclude that our results do not depend on a few influential observations, but that they are in fact quite general.

There is robust evidence that there are externalities from nearby exporters that decrease with distance that are very strong for exports to the same destination. As expected, export complementarities are weaker with exports to other destinations, but these are also found to be statistically significant. The economic importance of these terms indicates that failure to include them leads to perhaps severe omitted variable bias in gravity estimations of international trade.

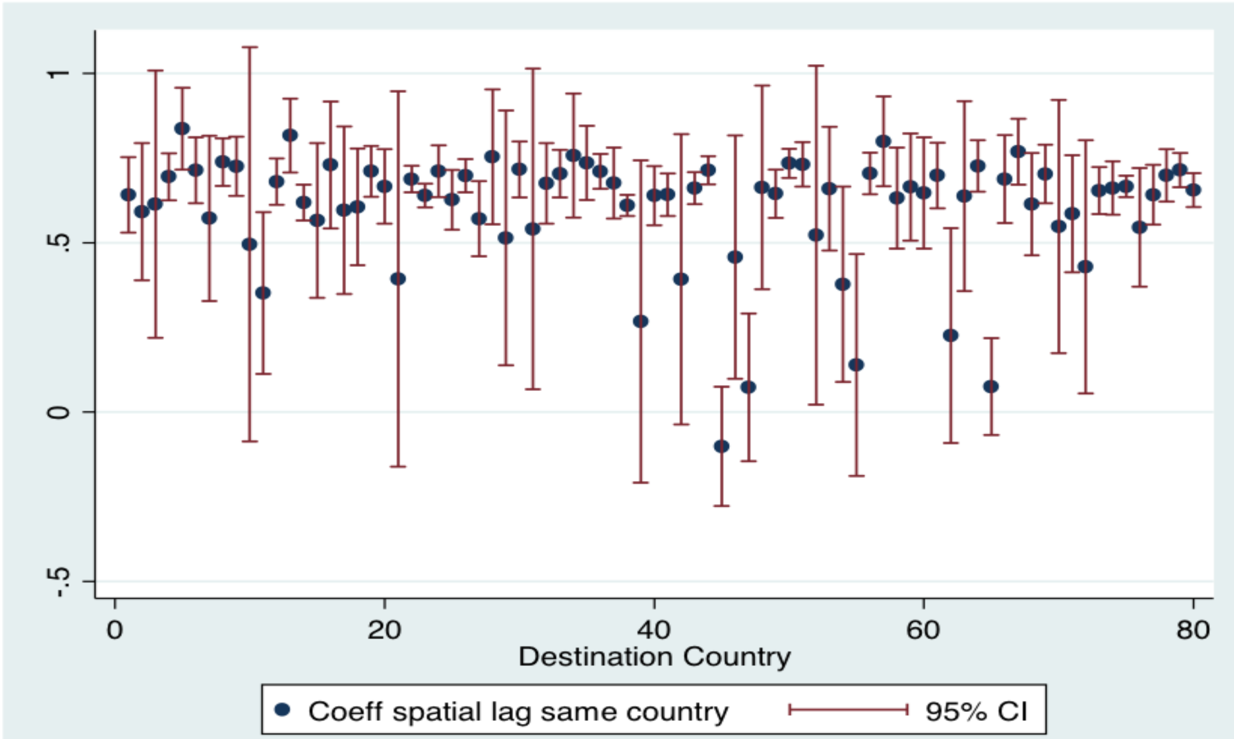

Figure 1. Destination Specific 'Same Country' Spatial Lag

5 Conclusion

Industrial localization is a well documented economic occurrence that has now been recognized to occur across industries and products to extend to the destination country of exports. We confirm previous findings of a beneficial externality from nearby exporting neighbors. We show that the naive spatial weight matrix used previously may have been sufficient to document beneficial export externalities, but that it is too simple to fully capture the effects. Using spatial econometrics techniques on data on the physical distance between export locations within the same country, we are better able to account for export externalities and relieve the missing variable bias in gravity equation estimates that do not include a same country and third country term. Thus our estimates improve upon the literature in showing the strength of destination-specific externalities. Additionally we are the first to show evidence of the importance of third country effects in export externalities. Although the literature has found similar variables to be important in analyzing FDI flows, the export literature has been focused on political regions (such as states) as the boundary of exporting externalities.

Though we find beneficial export externalities exist to same destinations and exporting generally, we leave it to future work to identify the source of these externalities. While our results effectively rule out that competition causes exporters to choose destinations to get away from their neighbors's destinations and exploit market power on net, we are not able to distinguish between export knowledge spillovers, a common pool of workers with exporting experience, or economies of scale in transportation. Because we find a larger economic effect in the spatial lag variable for same country than for third countries, we speculate that a beneficial export externality coming from an information spillover about how to export to a specific country regardless of product is most plausible.

Our results have policy implications in that the existence of these export externalities whose strength depends on distance suggest a role for government policies based not only on export status or industrial similarity, but rather on market similarity. In other words a policy could be for a U.S. state government, say, to target specific markets for export promotion program based on the most popular destination of that state's exporting firms. Additionally boosting export activities generally would boost overall export market participation and flows.

References

, January 2004, 2006. Russia: All Regions Trade & Investment Guide. CTEC Publishing LLC, Moscow, 1st Edition.

, April 2006. World Economic Outlook Database. International Monetary Fund, Washington, DC, `http://www.imf.org/external/pubs/ft/weo/2006/01/data/index.htm` (accessed December 15, 2006).

Anderson, J. E., van Wincoop, E., March 2003. Gravity with gravitas: A solution to the border puzzle. American Economic Review 93 (1), 170–192. 2, 4

Baltagi, B. H., Egger, P., Pfaffermayr, M., September 2007. Estimating models of complex FDI: Are there third-country effects? Journal of Econometrics 140 (1), 260–281. 1, 2, 4

Bernard, A. B., Jensen, J. B., May 2004. Why some firms export. Review of Economics and Statistics 86 (2), 561–569. 3

Blonigen, B. A., Davies, R. B., Waddell, G. R., Naughton, H. T., 2007. FDI in space: Spatial autoregressive relationships in foreign direct investment. European Economic Review 51, 1303–1325. 1, 2, 4

Bode, E., Nunnenkamp, P., Waldkirch, A., February 2013. Spatial effects of foreign direct investment in US states. Canadian Journal of Economics 45 (1), 16–40. 1, 2, 4

Bradshaw, M., June 2008. The geography of Russia's new political economy. New Political Economy 13 (2), 193–201. 3

Cassey, A. J., 2009. State export data: Origin of movement vs. origin of production. Journal of Economic and Social Measurement 34 (4), 241–268. 3

Cassey, A. J., Schmeiser, K. N., 2013a. The agglomeration of exporters by destination. The Annals of Regional Science 51 (2), 495–513. 1, 2, 2, 3, 4, 4

Cassey, A. J., Schmeiser, K. N., November 2013b. Multilateral export decompositions. Open Economies Review 24 (5), 901–918. 3

CEPII, February 2014. CEPII. `www.cepii.fr` (accessed February, 2014).

Choquette, E., Meinen, P., July 2012. Export spillovers: Openning the black box, unpublished. URL `http://www.hha.dk/nat/philippm/Export_Spillovers.pdf` 1

Coughlin, C. C., March 2014. Determinants of trade margins: Inights using state export data, federal Reserve Bank of St. Louis working paper no. 2014-006A. 4

Duranton, G., Overman, H. G., 2005. Testing for localisation using micro-geographic data. Review of Economic Studies 72 (4), 1077–1106. 1

Ellison, G., Glaeser, E. L., October 1997. Geographic concentration in U.S. manufacturing industries: A dartboard approach. Journal of Political Economy 105 (5), 889–927. 1

Feenstra, R. C., 2002. Border effects and the gravity equation: Cinsistent methods for estimation. Scottish Journal of Political Economy 49 (5), 491506. 4

Feser, E. J., 2000. On the Ellison-Glaeser geographic concentration index. 1

Fischer, M. M., Wang, J., 2011. Spatial Data Analysis: Models, Methods and Techniques. Springer, Berlin. 2, 2

Kerr, W. R., Kominers, S., December 2010. Agglomerative forces and cluster shapes, NBER working paper no./ 16639. 1, 2

Koenig, P., November 2009. Agglomeration and the export decisions of French firms. Journal of Urban Economics 66 (3), 186–195. 1, 2, 4

Koenig, P., Mayneris, F., Poncet, S., May 2010. Local export spillovers in France. European Economic Review 54 (4), 622–641. 1, 2, 4

LeSage, J. P., Fischer, M. M., 2010. Spatial econometric methods for modeling origin-destination flows. In: Fischer, M. M., Getis, A. (Eds.), Handbook of Applied Spatial Analysis. Springer, New York, pp. 409–433. 2

LeSage, J. P., Pace, R. K., December 2008. Spatial econometric modeling of origin-destination flows. Journal of Regional Science 48 (5), 941–967. 2, 3

Lovely, M. E., Rosenthal, S. S., Sharma, S., March 2005. Information, agglomeration, and the headquarters of U.S. exporters. Regional Science and Urban Economics 35 (2), 167–191. 1

Moulton, B. R., 1990. An illustration of a pitfall in estimating the effects of aggregate variables on micro units. The Review of Economics and Statistics 72 (2). 4

Nuadé, W., Matthee, M., June 2010. The location of manufacturing exporters in Africa: Empirical evidence. African Development Review 22 (2), 276–291. 1

Ramos, R., Moral-Benito, E., March 2015. Agglomeration matters for trade. URL `http://www.robertoramosm.eu/Roberto_Ramos_Files/Agglomeration_Matters_for_Trade.pdf` 1, 1

Santos Silva, J. a. M. C., Tenreyro, S., November 2006. The log of gravity. Review of Economics and Statistics 88 (4), 641–658. 4

Appendix: Robustness to Alternative Distance Decay Functions

Table A.1. Inverse Distance Weights

Model	Fixed Effects	Cluster	Poisson	Zero-inflated Neg. Bin.
Distance	0.050	0.760***	−0.281	−0.269***
	(0.070)	(0.089)	(0.205)	(0.073)
Spatial lag same country	0.618***	0.641***	0.211***	0.126***
	(0.007)	(0.020)	(0.024)	(0.005)
Spatial lag other countries	28.22***	24.50***	5.486***	11.17***
	(2.006)	(2.244)	(1.639)	(1.009)
Observations	55,360	55,280	55,360	55,280
Adjusted R-squared	0.474	0.582		
Location Fixed Effects	Yes	No	Yes	Yes
Country Fixed Effects	Yes	No	Yes	Yes
Clustering	No	Both	No	No
F(.)/Wald Chi2	398.2	5801	39380	1.151e+06
AIC	248182	252977	1.650e+10	200145
BIC	248913	253030	1.650e+10	207085

Standard errors in parentheses.

*** p<0.01.

Table A.2. Squared Inverse Distance Weights

Model	Fixed Effects	Cluster	Poisson	Zero-inflated Neg. Bin.
Distance	-0.300^{***}	-0.0598	-0.185	-0.237^{***}
	(0.0696)	(0.0451)	(0.215)	(0.0735)
Spatial lag same country	0.526^{***}	0.608^{***}	0.164^{***}	0.117^{***}
	(0.013)	(0.018)	(0.017)	(0.004)
Spatial lag other countries	90.290^{***}	124.800^{***}	843.000	126.000^{***}
	(8.562)	(41.510)	(672.200)	(10.270)
Observations	55,360	55,280	55,360	55,280
Adjusted R-squared	0.374	0.426		
Location Fixed Effects	Yes	No	Yes	Yes
Country Fixed Effects	Yes	No	Yes	Yes
Clustering	No	Both	No	No
F(.)/Wald Chi2	61.52	5221	39407	718444
AIC	257802	270486	1.710e+10	200179
BIC	258533	270539	1.710e+10	207118

Standard errors in parentheses.

*** $p<0.01$.

Table A.3. Inverse Square Root of Distance Weights

Model	Fixed Effects	Cluster	Poisson	Zero-inflated Neg. Bin.
Distance	0.300^{***}	0.690^{***}	-0.305	-0.150^{**}
	(0.086)	(0.167)	(0.190)	(0.076)
Spatial lag same country	0.675^{***}	0.793^{***}	0.230^{***}	0.130^{***}
	(0.009)	(0.017)	(0.026)	(0.005)
Spatial lag other countries	10.370^{***}	0.847^{***}	1.509^{*}	4.121^{***}
	(0.757)	(0.198)	(0.849)	(0.472)
Observations	55,360	55,280	55,360	55,280
Adjusted R-squared	0.435	0.494		
Location Fixed Effects	Yes	No	Yes	Yes
Country Fixed Effects	Yes	No	Yes	Yes
Clustering	No	Yes	No	No
F(.)/Wald Chi2	379.7	8910	37133	2.373e+06
AIC	252092	263475	1.640e+10	200266
BIC	252824	263529	1.640e+10	207205

Standard errors in parentheses.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.