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 the same country but less so for 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 weight.

JEL classification: C21, F14, R14

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1 Introduction

We introduce the use of spatial lags to estimate the effect of externalities generated by neighbor's exports in gravity models, using the physical distance to those neighboring exporters. We test for an externality effect of neighbors' exports to the same country and neighbors' exports in general. We find evidence of a statistically significant positive effect of neighbors' exports to the same country that is many times larger than the positive effect of neighbors' exports in general. We also find that using the physical distance to neighbors in the spatial weight outperforms models that uses a binary metric for neighbors within some boundary.

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 (2014) 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 their workings. That is, because of the relatively blunt methods of modeling space in the literature, there is neither a consensus of their importance 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, inconsistent estimates, and erroneous conclusions about the economic impacts of international trade policy. Hence we conduct a formal analysis of the spatial relationship between exporter locations, destination countries, and export externalities.

After converting firm-level data to the level of highly disaggregated places in space, we estimate the significance of neighbors' exports to the same country as well as 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-dependence variable. This advances the literature as previous work considered exporters within some large politically-defined region such as a state.[1] Using such a zero-one weighting scheme (1 if in state/region, 0 otherwise) has been shown to bias location quotients and 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 a spatially lagged dependent variable, find foreign direct investment in U.S. states generates Marshallian externalities that positively affect productivity elsewhere.

We start exploring the nature of destination-specific externalities by assuming their strength decreases with the physical distance to other potential exporters. Kerr, and Kominers (2012) argue that 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 spatially-lagged dependent variable terms. Furthermore, because Cassey and Schmeiser (2013a) *do not* find empirical evidence that the export-destination externality is due to firms exporting the same or similar products, we focus on testing for the importance of spatial terms with respect to destinations and not products.

There are, potentially, 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 neighboring ℓ to that country c.

[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.

First, exports from neighbors to c may cause the exporters in location ℓ to choose some otherwise less desirable market where they 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. Blonigen, Davies, Naughton, and Waddell (2008) document this effect for inbound FDI into the United States from the European Union.

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 for foreign direct investment by Baltagi, Egger, and Pfaffermayr (2007) and Blonigen, Davies, Waddell, and Naughton (2007). 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 statistically significant positive effect from third country exports, though that effect is much smaller in magnitude. Because we have positive signs on both externalities, we can rule out that the larger economic force is of neighbors' exports causing firms to choose different export destinations. Instead, we find exporting activity nearby creates a conducive exporting environment on net.

That spatial externalities exist around exporting has only recently begun to be understood with empirical trade studies because traditionally gravity regressions were based on two-country models. 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 may contain one or more exporters. Exporters may sell to any one, or more, of the C foreign destinations. 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. 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 underlying firm-level structure of the economy, their main theorem shows that 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 their theory to the data, 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 index within the product operator 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, $b_0 = \ln(\alpha) + \ln(\beta)$, $W x_{mc}$ is the vector of log exports from all $L - 1$ other individual exporting locations 1 through L to the same country c except for location ℓ, and $\epsilon_{\ell c} = b_6 \ln F_{\ell c}$. Exports from neighbors of the exporting location to the same country x_{mc} is on the right hand side as the spatial lag of the dependent variable $x_{\ell c}$. The spatial weight matrix is W. Lower-case letters denote natural logs. Despite omitting the own-location from the spatial lag term, endogeneity concerns may remain. We discuss how we address these in section 4.

We test whether 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 to exports from the same geographic or political structure to the same destination as the ex-

[2]Technically we set $w_{\ell\ell} = 0$ for all locations, which is the standard method described in LeSage, and Fischer (2010) and Fischer, and Wang (2011) so that no location is a neighbor to itself and thus avoids a problem with joint and simultaneous determination of the spatially-lagged variable.

porter 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 Simple Spatial Lag.

In the third specification, we 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. 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. Fischer and Wang (2011), LeSage and Fischer (2010), and LeSage, and Pace (2008) advocate this stacking procedure in order to decrease the computational 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 (LeSage and Pace 2008). Using the method of Blonigen et al., 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 distance from every other country to the importing country under observation. Then we interact that with the weight based on the the distance from every other location to the exporting location under observation. Therefore this second weight matrix $\overline{W}$ is applied to the vector of exports from all *other* locations to all *other* countries $x_{m,-c}$. We have:

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

[3]Though we can do the stacking procedure, 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.

where the fourth specification only includes the third-country spatially-lagged term $\overline{W}x_{m,-c}$ 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 $m \neq \ell$.

The spatial weights that make up the elements of W and $\overline{W}$ must be defined. Based on Kerr and Kominers (2012), we assume the spatial weights in the location-to-location weight matrix, W, decrease with distance so that neighboring exporters that are further away from the exporting location under observation have decreased impact. Similarly, we assume the weights in the third countries weight matrix, $\overline{W}$, decrease with the distance as well. We define the spatial weights to be inverse exponential distances, $w_{\ell m} = e^{-\tau d_{\ell m}}$ as in Bode et al. (2013). 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 $\tau = 0.02$. For robustness, we also use inverse distance, squared inverse distance, and inverse square roots of distance as weights.

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 one otherwise. As is common in the literature, we row-standardize W. The row-standardized matrix captures the relative distance between locations rather than absolute distances.

We choose to model the spatial process by including a lagged dependent variable as an explanatory variable instead of in the error term. We do this because if the spatial effect is in the error term the partial derivative impacts are the same as in a model where spatial dependence is not considered (LeSage and Fischer 2010). Our goal is to explicitly perform statistical inference on the spatial weight coefficient and thus we need to include a spatial lag as an explanatory variable.

LeSage and Pace (2008) show there are three possible spatial dependence structures. The first is the exports-of-neighbors-to-the-same-country effect. The second is the exports-of-neighbors-to-neighbors-of-destination third country effect. These two effects are the ones we are interested in in order to better understand export-by-destination externalities. The third effect is an exports-from-location-to-neighbors-of-country effect. We do not consider that spatial dependence because it represents the effect of a firm learning how to export and choose destinations and not the effect of spillovers from others, common resources, or economies of scale in transportation. Furthermore that effect has been shown to be "weak" by Lawless (2013), who does not consider the same-country and third-country effects. LeSage and Pace also argue a properly specified model includes a spatial lag for the independent destination and location-specific variables. In our estimation, we control for destination and location-specific features, including spatially-lagged independent features, with destination and location fixed effects.

Finally we do not explicitly consider the products being exported. We do not include products in our specification because Cassey and Schmeiser (2013a) find little empirical evidence that product mix could account for export externalities. Furthermore the inclusion of products would make the spatial weights matrix, even in its stackable form, too computationally burdensome for effective identification.

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).[4] 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

[4] 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
Simple lag	38.113	11.585	78.948	0	780.004
Same country lag	1.889	0.522	3.768	0	34.224
Third country lag	0.085	0.004	0.255	0	9.460
GDP of 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.

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. Though places-in-space are our level of observation, the data are the most disaggregated possible in order to calculate the distance to neighbors and thus represent a significant upgrade over the literature that uses the equivalent of U.S. states.

The data we have are the location of the exporting firm, not the port of exit. For our purposes, we want the location of the agent making the decision of where and how much to sell as they are the one to be affected by the actions of others. That agent is not likely to be a freight-forwarder. Therefore it makes sense to use the address of the exporter and not the port of exit.

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 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, which is too big for computation. 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 or that it is computational feasible to try. 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 computation burden and the difficulty of identification. 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

We wish to test if same and third-country effects exist for exports and if so, what sign in order to better understand how these externalities behave. Hence our emphasis will be statistical inference of the coefficients. If the coefficient on the spatial lag term for the same country is positive then it suggests there is a beneficial externality from neighbors exporting to the same destination. If, in addition, the coefficient on the spatial lag term for third countries is positive then it 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 some 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 as well as any spatially-lagged location or destination-specific variables. 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.[5] 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 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 simple 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

[5] 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.

neighbors or economies of scale in transportation to the same country.

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. It is common for the point estimate on distance to decrease in importance when spatially lagged variables are included in a gravity model as distance acts as a proxy for spatial dependence when it is not included (LeSage and Fischer 2010; Sellner, Fischer, and Koch 2013). Thus we are neither surprised nor concerned by the result on distance.

In the fourth column, we include the spatial lag for the third-country effect. The resulting coefficient is 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. It should be mentioned that though the statistical inference is correct, there is no easy interpretation of the coefficients on the spatial lags because they are not simple partial derivatives (LeSage, and Thomas-Agnan 2015). We will discuss interpretation of the point estimates below, but no comparative interpretation should be made between the spatial lag coefficient on the same-country term in column 3 and third-country term in column 4.

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.

A direct interpretation of the coefficients on the spatial lags is difficult because of how all of the exporting neighbors relate to each other. The method described in LeSage and Thomas-Agnan (2015) to ease interpretation does not apply in our case because we have a different number of exporters than importers. Thus to give a meaningful and comparable interpretation, we multiply the estimated coefficients for the simple 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

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)
Simple 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 simple 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

0.008, respectively.[6] Thus, evaluated at the median, the spatial lag of exports to the same country accounts for far more of the exports data than the simple 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 export externalities exist has been established in the literature using the simple weight. Thus we want to know if the results using the inverse exponential weights offer improvement. 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 simple spatial lag in addition to distance and the 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. This means the "simple"

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

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)
Same country lag	0.599^{***}		0.572^{***}
	(0.004)		(0.0039)
Third country lag		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.

spatial indicator that has been used in the literature does not adequately account for the significant externalities generated by other exporters and thus underestimates their complementarity. Even entering the spatial lag to other countries raises the R-squared by much more than the simple 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 simple weight based on large but 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 check our results using a panel instrumental variable specification. The results are shown in table 3.

We use the weight of exports in kg as an instrument, as in Cassey and Schmeiser (2013a), and create the spatial lags from that instrument.[7] Though it is true for a specific exporter that more export value would increase export weight, it is not necessarily true that an increase in the neighbor's export value would increase the exporter's weight that is under observation. This is because the neighbor could be exporting a bulky item like steel whereas the first exporter may

[7] We assign 0 kg to observations on exports that do not have a corresponding export weight.

be shipping a high-value item like pharmaceuticals. The first-stage F-statistics are very large, so these spatially lagged export weights appear to be good instruments. The IV-results provide very similar statistical inferences for the coefficients of the spatial lag terms. Using the same procedure as before, 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 has a 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), results may change when large changes are made to the distance decay function. To make sure our results do not depend on a specific distance decay function, 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 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

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)
Simple spatial lag		0.00816***			
		(0.00262)			
Same country lag			0.658***		0.633***
			(0.0232)		(0.0251)
Third country lag				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 simple 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.

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 simple 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

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)
Simple spatial lag		0.003^{***}			
		(0.001)			
Same country lag			0.183^{***}		0.179^{***}
			(0.018)		(0.018)
Third country lag				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 simple 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.

zero. Santos Silva and Tenreyro (2006) show that the use of a poisson estimator can eliminate the bias associated with these zeros. LeSage and Fischer (2010) argue the Poisson estimator is preferred to the Tobit when more than 50% of the dependent variables observations are zeros as in the data we use. Thus we repeat our fixed effects regressions using the Poisson estimator and robust standard errors following the set up of Sellner et al. (2013). Results are shown in Table 5. All spatial lag variables continue to have positive and highly statistically significant coefficients. Our estimated coefficients in Table 5 are attenuated compared to those in Table 2 by about one third, a result common in the literature and described by Sellner et al. As both the spatial lag of exports to the same and to other destinations attenuate, 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, and in the same relative strength.

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

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)
Simple spatial lag		$-1.57e{-}05$			
		(0.000)			
Same country lag			0.122^{***}		0.121^{***}
			(0.004)		(0.004)
Third country lag				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 simple 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.

*** $p<0.01$.

negative binomial estimator on export data with many zeros. The results, shown in Table 6, are again largely identical to those from before. 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 functions shows 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. As 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 the 80 export destinations. Each dot shows the point estimate for one country and the vertical line

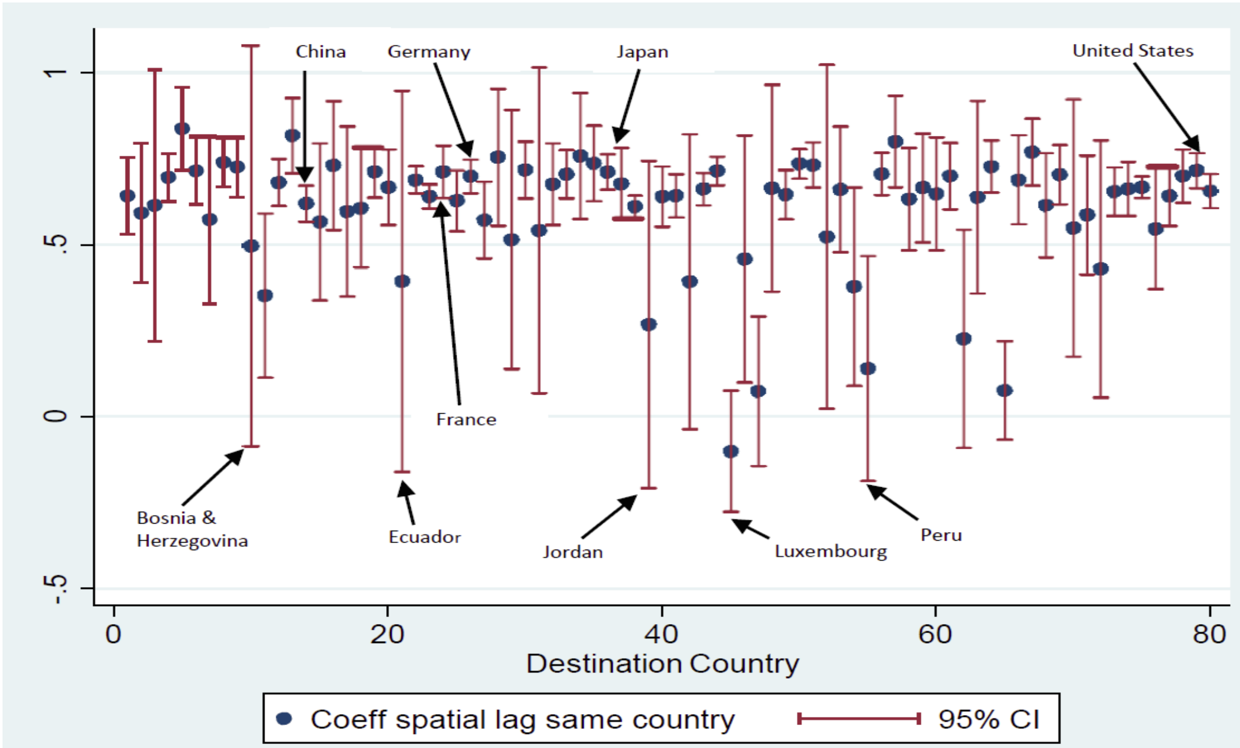

Figure 1. Destination Specific 'Same Country' Spatial Lag

is the 95 percent confidence interval. We see that there is only one country with a negative point estimate indicating dispersion (Luxembourg) and that there are only another 8 of 80 countries that are not statistically significant at the 5% level.[8] These nine countries are all small, have relatively large standard errors in the estimates, and are not among Russia's important trading partners. 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. 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.

[8]These countries are, in order from left to right in the figure, Bosnia & Herzegovina, Ecuador, Jordan, Lebanon, Malta, Peru, Slovenis, and Sudan.

5 Conclusion

Industrial localization is a well documented economic occurrence that is 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 the simple spatial weight matrix used previously may have been sufficient to document the existence of beneficial export externalities, but that it is too simple to fully capture the effects. Using spatial econometrics techniques on data of 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 using physical distances. Even though the literature has found similar variables to be important in analyzing FDI flows, the export literature has focused on political regions (such as states) as the boundary of exporting externalities.

Although 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.

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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)
Same country lag	0.618***	0.641***	0.211***	0.126***
	(0.007)	(0.020)	(0.024)	(0.005)
Third country lag	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

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)
Same country lag	0.526***	0.608***	0.164***	0.117***
	(0.013)	(0.018)	(0.017)	(0.004)
Third country lag	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)
Same country lag	0.675***	0.793***	0.230***	0.130***
	(0.009)	(0.017)	(0.026)	(0.005)
Third country lag	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.