The view from space: Theory-based time-varying distances in the gravity model*

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November 2019

Abstract

In this paper I use a general representation of the gravity model in international economics to derive a theory-consistent spatial aggregation of bilateral frictions. I apply the method to compute *time-varying* country-to-country distances, used in estimations of the gravity model in fields ranging from international trade, to foreign direct investment and migration. The aggregation takes the form of a weighted generalized mean, where the weights reflect the spatial distribution of economic activity in a country and the elasticity of the bilateral friction in question is a key parameter. I use annually available satellite imagery on nighttime light emissions for highly-detailed information on the economic geography of countries, capturing urban and rural areas and reflecting changes over time. Employing the computed distances in an application to the gravity equation of international trade yields a number of noteworthy results. Exploiting the time variation, I can estimate the distance elasticity while controlling for unobserved country-pair characteristics. Estimates for the distance coefficient are in the range of -0.5 and -1. Furthermore, the distances' use yields important consequences for estimates of other gravity variables: the border coefficient, i.e. the often puzzlingly large relative difference between internal and external trade, is reduced by between 30% and 50%. Regressions using simulated data confirm the theoretical and empirical findings.

Keywords: Gravity equation, bilateral frictions, distances, border puzzle, satellite imagery
JEL Classification: F10, F14

* *Acknowledgements*: Will be added later.

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1 Introduction

The gravity model in international economics is one of the most versatile and empirically robust frameworks in economics. It is found in fields ranging from international trade, to foreign direct investment and migration, relating bilateral flows or stocks to economic masses and frictions, in analogy to Newtonian gravity in physics. In empirical applications of the framework, these flows and stocks in question are often aggregated to country, state or province level. This makes an aggregation of their determinants equally necessary.

Building on earlier work by Head and Mayer (2009), this paper sets out to provide a theory-consistent spatial aggregation of bilateral frictions that is derived from a general representation of a gravity equation. It is written with a trade application in mind, but the results are generally applicable wherever a gravity relation is assumed. I apply the aggregation method to the arguably most prominent spatial friction, bilateral distances. Using satellite imagery on nighttime light emissions with annual periodicity, I compute time-varying country-to-country distances that improve customary measures along multiple lines, incorporating economic activity in urban and rural areas and reflecting changes in the economic geography of countries over time. I then demonstrate the implications of employing these distances in estimations of the gravity equation of international trade.

The first use of a gravity-like relation in social sciences is attributed to Ravenstein (1885, 1889), in a description of migration patterns in the United Kingdom. The gravity model was then popularized, primarily in the context of international trade, by Tinbergen et al. (1962), who described the volume of trade flows between countries as a function of the size of the two economies and their distance. While the theoretical underpinnings of the gravity model of international trade, in particular the structural form of the economic masses, have seen drastic improvements with Anderson (1979), Anderson and van Wincoop (2003) and others, bilateral frictions, including employed distance measures, have received surprisingly little attention.

The initial ad-hoc choice for bilateral country distances was the so-called *great circle* distance between the capitals or large cities of the respective countries. Helliwell and Verdier (2001) and Head and Mayer (2009) first noted the choice's possible influence on other gravity variables, showing that a mismeasurement, particularly that of the internal distance of a country, could have an impact on the estimated border effect. Mayer and Zignago (2011) then computed and made publicly available the current de-facto standard of bilateral and internal country distances, an arithmetic mean of great circle distances between population centers, weighted by time-invariant data on city sizes.

Nighttime lights have recently seen other intriguing uses in economic research. Most prominent is Henderson et al. (2011)'s paper on the estimation of growth rates, comparing year-on-year changes of light intensities. Others, like Alesina et al. (2012) and Hodler and Raschky (2014) investigate economic inequality and favoritism, by delineating changes in light intensity along ethnic and regional lines. Donaldson and Storeygard (2016) provide an overview of the use of satellite data on nighttime light emission and other satellite imagery in economic research. To my knowledge, this paper is the first to make use of this data in the context of gravity equations.

The contribution of this paper is threefold. First, I derive a spatial aggregation of bilateral frictions that is agnostic to the underlying gravity framework, but yields concrete instructions on the method of computation and data to be used. I show that the aggregation takes the form of a weighted generalized mean, where the key parameter is the elasticity of the bilateral friction in question. The data used for the weights should reflect the distribution of economic activity across space. Second, I use this aggregation method to compute theory-consistent distances between countries, making use of satellite imagery for information on the economic geography of countries. The data has several advantages over commonly used population data. It provides information on the exact location and intensity of economic activity, whether urban or rural region. This eliminates the possibility of measurement error in human-collected population figures and drastically increases the coverage to virtually all inhabited and economically active areas in very fine detail. Furthermore, the data has an annual periodicity, allowing me to compute a time series of distances for each country pair and year since 1992, reflecting changes in countries' economic geographies. This is particularly important in developing countries and emerging economies. Third, in an application to the gravity model of international trade, I estimate the distance elasticity of international trade exploiting the data's time-variation, controlling for unobserved country-pair characteristics. The coefficient is estimated in the range of -0.5 and -1, in line with traditional results found in the related literature.[1] The estimated coefficient calls for the use of harmonic mean distances, as opposed to the customary use of arithmetic mean distances. This in turn has important consequences for the estimated coefficients of other distance-correlated gravity variables. The border effect, i.e. the often puzzlingly large relative difference between internal and external trade, is reduced by up to 63 %. The distances computed as part of this paper are made available to other researchers online[2] and with the R package "gravity.distances".

The remainder of the paper is structured as follows: section 2 reviews the existing literature on distances and border effects in the gravity model in international trade. In section 3 I turn to theory to derive a spatial aggregation of bilateral frictions that is agnostic to the underlying gravity framework. In sections 4 and 5 I describe the data and computation method, and discuss the key features of the distances. Finally, in section 6 I estimate the distance elasticity of international trade and evaluate the border effect and that of other common gravity covariates using the newly computed distance measure. Section 7 concludes.

[1] See Disdier and Head (2008) and Head and Mayer (2014) for a survey.

[2] http://julianhinz.com/resources/#gravity.distances

2 Distances and borders in the gravity literature

The present paper is related to an extensive literature on the effect of distance on the flow of goods.[3] While it has been somewhat fashioned to declare it "dead" as the result of globalization, trade economists have come to the rescue and shown that it is indeed "alive and well" (Disdier and Head, 2008). Distance itself, however, is only a proxy for various frictions that are more difficult to measure: transportation costs, language barriers, cultural, informational and even genetic distance. Some of these can be accounted for in estimations of the gravity equation with control variables, while others are more difficult to identify or yet "unexplored".[4]

Disdier and Head (2008) and Head and Mayer (2014) provide a meta analysis for the effect of distance on trade and its somewhat puzzling persistence. The effect is pronounced puzzling, because the estimated coefficient has been shown to increase over time, depending on regression technique and data used. Conventional wisdom, on the other hand, has it that the world is currently experiencing a "Death of Distance".[5] A number of approaches have aimed to reconcile the believe that in "our time of globalization" the effect of distance on the volume of traded goods should decrease rather than increase. First, as Head and Mayer (2014) show, the puzzle is prevalent mostly when using an OLS estimator. Using Santos Silva and Tenreyro (2006)'s proposed PPML estimator leads to much lower and mostly non-rising coefficients. Additionally Head and Mayer show that the increase in the coefficient is largely due to new entrants to the trade matrix. This result is confirmed by Larch et al. (2015) who show that the presence of zeros leads the OLS estimator to be biased, unlike the estimation technique proposed by Helpman et al. (2008) that explicitly accounts for zeros. Others emphasize that we may be asking the wrong questions: Yotov (2012) e.g. argues that the distance puzzle of international trade can be explained by comparing the distance coefficient of international to intranational trade and shows that this has been indeed the case.

One difficulty in properly estimating the "true" effect of distance is that it is likely correlated with unobserved bilateral country pair characteristics. To isolate the unbiased effect of distance on trade, two recent papers exploit the variation of maritime distances in quasi-natural experiments as a result of exogenous events. This strategy allows the authors to include country-pair fixed effects that capture these correlated and unobserved characteristics. Feyrer (2009) uses the closing of the Suez canal, starting in 1967 with the Six Day War and ending with the Yom Kippur War eight years later, as the treatment. He estimates a coefficient between -0.15 and -0.5. These estimates however suffer from what Baldwin and Taglioni (2006) term the gold medal mistake, omitting multilateral resistance terms. Hugot and Umana Dajud (2014) perform a similar analysis, estimating the effect of the initial openings of the Suez canal in 1869 as well as that of the Panama canal in 1914 in a structural gravity model. Their estimates range between

[3] Head and Mayer (2014) give an in-depth overview of the gravity model of international trade, but also provide a brief summary of gravity models in other fields of international economics. Beine et al. (2015) provide an overview of the state-of-the-art on the gravity of migration.

[4] Head and Mayer (2013) develop a helpful framework to conceptualize these trade barriers and facilitators as *light* and *dark matter* of trade costs.

[5] See e.g. Friedman (2005)'s book "The World is Flat".

-0.38 and -0.54 for the Suez canal and -1.23 and -2.33 for the Panama canal. Both papers assume that the economic geography of the trading countries is static, but that optimal routes between countries change due to the exogenous event.

The present paper also contributes to the literature concerned with the effect of borders on trade. As will be shown below, the choice of the distance measure is consequential for estimates of the effect on a trade flow of crossing the origin country's border to another country. The border effect first received widespread attention after McCallum (1995), who noticed an apparent puzzle: average trade flows between Canadian provinces were a staggering 22 times larger than the average trade flow from a Canadian province to a US state. The sheer magnitude of the effect attracted further scrutiny. A big piece to resolve the puzzle was contributed by Anderson and van Wincoop (2003). The paper provided the micro-foundations to the previous *naive* specification that related trade flows to the two countries' GDPs, various trade barriers and, importantly, physical distance. Anderson and van Wincoop showed that the omittance of what they coined the multilateral resistance term, the barriers to trade affecting all trading partners equally, resulted in a bias of the estimation of gravity. Accounting for these multilateral resistance terms brought down the factor of internal over external trade flows to a factor of about 5.

The literature has since further evolved and investigated the issue at different levels of aggregation of the data and on numerous geographical entities. Chen (2004) shows the existence of a strong border effect for one of the most integrated regions in the world, the European Union. Even intranational subdivisions appear to result in border effects: Ishise and Matsuo (2015) find an effect along Democratic and Republican-leaning states in the US, Felbermayr and Gröschl (2014) along the former US American South and North, while Wolf (2009) and Nitsch and Wolf (2013) find a persistent border effect along Germany's former East-West divide. Coughlin and Novy (2012) combine data on trade flows between and within individual US states from the Commodity Flow Survey with state-level export and import data and find that, surprisingly, the intranational border effect appears to be even larger than the international border effect. Poncet (2003) finds a similar pattern for China.

A number of authors have linked the puzzlingly large border effect with the choice of the distance measure. Helliwell and Verdier (2001) first noted the importance of measuring internal distance correctly for the estimation of the border effect. In an endeavour most related to this present paper, Head and Mayer (2009) suggest the harmonic mean as an "effective" measure of distance and are the first to show the potential bias of using other measures on the estimated border effect in simulations. Hillberry and Hummels (2008), using micro-data from the Commodity Flow Survey, show that approximated distances within states and between neighboring states are often far overstated. Using accurate distances at the 5-digit zip code level reveals that the state-level border effect is in fact an artifact of geographic aggregation.[6] Coughlin and Novy (2016) also investigate the effects of spatial aggregation on the estimation of

[6]Interestingly, perhaps ironically, they do find a zip code-level border effect they consider a "reductio ad absurdum". They compute the distance between two 3-digit zip code regions as the arithmetic mean distance between all the 5-digit pairs within those 3-digit zip code regions. As will be seen below, this may be the culprit of the said zip code-level border effect.

the border effect, arguing with the help of a modified gravity model of micro and macro regions that larger countries mechanically report lower border effects than smaller countries.

In the following section I turn to theory and build on earlier work of Head and Mayer (2009) to derive a theory-based spatial aggregation of bilateral frictions.

3 Theory-consistent aggregation of bilateral frictions

The gravity equation is one of the most robust empirical relationships in economics, amounting to what Krugman (1997) coins "social physics". As Head and Mayer (2014) and Anderson (2011) describe, next to its usual trade context, gravity is also observed in migration, foreign direct investment, and other related fields. As such, the proper specification of bilateral frictions — distances in particular — is of general importance.

Following Head and Mayer (2014), the gravity equation usually comes in a form that can be reduced to

$$x_{kl} = G s_k m_l \phi_{kl}^{\theta}$$

where x_{kl} is a flow from a location k to another location l.[7] s_k are origin-specific terms, m_l destination-specific terms. ϕ_{kl} is the bilateral resistance term, i.e. barriers and facilitators of the flow between the two locations, θ being the elasticity. G is a "gravitational constant".[8]

In most cases, researchers perform analyses where x_{kl} is aggregated to some geographic entity, like a country, state or region. This aggregation of the left-hand side variable makes an aggregation for right-hand side variables necessary as well. In the following I derive an aggregation of bilateral frictions that builds on Head and Mayer (2009)'s "effective", yet rarely used, distance measure. Let k now be a location inside the geographic entity i and l inside j. Then

$$\begin{aligned} x_{ij} &= \sum_{k \in i} \sum_{l \in j} x_{kl} \\ &= G \sum_{k \in i} s_k \sum_{l \in j} m_l \phi_{kl}^{\theta} \end{aligned}$$

[7]Alternatively, x_{kl} could also be a stock originating from location k in location l, such as a stock of migrants or amount of FDI.

[8]See appendix A.1 for the following derivation with a more specific *structural gravity* setup often encountered in international trade. The resulting aggregation is isomorphic to the one below. See Head and Mayer (2014) for a detailed survey over the different underlying micro foundations in international trade. s_k and m_l usually embody a term that has been coined multilateral resistance term, accounting for country-specific factors determining its exchange with all other locations. Similarly, the parameter θ has a range of different of interpretations.

Calling $m_j = \sum_{l \in j} m_l$,

$$x_{ij} = G \sum_{k \in i} s_k m_j \sum_{l \in j} \frac{m_l}{m_j} \phi_{kl}^{\theta}$$

Further calling $\phi_{kj} = \left(\sum_{l \in j} \frac{m_l}{m_j} \phi_{kl}^{\theta} \right)^{1/\theta}$ and $s_i = \sum_{k \in i} s_k$,

$$x_{ij} = G s_i m_j \sum_{k \in i} \frac{s_k}{s_i} \phi_{kj}^{\theta}$$

Again, calling $\phi_{ij} = \left(\sum_{k \in i} \frac{s_k}{s_i} \phi_{kj}^{\theta} \right)^{1/\theta}$ finally yields the gravity equation for geographic entities:

$$x_{ij} = G s_i m_j \phi_{ij}^{\theta}$$

where bilateral frictions are aggregated as

$$\phi_{ij} = \left(\sum_{k \in i} \sum_{l \in j} \frac{s_k}{s_i} \frac{m_l}{m_j} \phi_{kl}^{\theta} \right)^{1/\theta} \tag{1}$$

So far these frictions have been generic. Let ϕ now be described by the function

$$\phi_{kl} = \psi_{ij}^{\epsilon} \chi_{kl}^{\delta}$$

where ϕ consists of a *location-specific* component χ_{kl}, e.g., the distance between the two locations, and an *entity-specific* component $\psi_{kl} = \psi_{ij} \; \forall \; k \in i, \; l \in j$, such as a common legal system or official language of the two entities. δ is then the elasticity of bilateral frictions to the location-specific frictions and ϵ the elasticity to entity-specific ones. Following (1), country-level frictions can then be rewritten as

$$\phi_{ij} = \psi_{ij}^{\epsilon} \chi_{ij}^{\delta}$$

where location-specific frictions are aggregated as

$$\chi_{ij} = \left(\sum_{k \in i} \sum_{l \in j} \frac{s_k}{s_i} \frac{m_l}{m_j} \chi_{kl}^{\theta\delta} \right)^{1/\theta\delta} \tag{2}$$

so that finally

$$x_{ij} = G s_i m_j \psi_{ij}^{\theta\epsilon} \chi_{ij}^{\theta\delta} \tag{3}$$

The flow from a geographic entity i to an entity j is therefore governed by the origin- and destination-specific terms s_i and m_j, entity-specific bilateral frictions $\psi_{ij}^{\theta\epsilon}$, and the weighted *generalized mean* of location-specific frictions $\chi_{ij}^{\theta\delta}$.[9] Importantly, equation (2) asserts that the elasticity of the flow with respect to location-specific frictions $\theta\delta$ is also the exponent in this generalized mean.

In the discussion below I focus on distance as a generally acknowledged proxy for location-specific frictions. Other common frictions, in particular in the field of international trade, include the existence of an RTA, a common currency, as well as a shared language, common legal system, or colonial legacy. It is safe to assume that under most circumstances these can be classified as country-specific. For most gravity aficionados the weighted arithmetic mean of great circle distances between the two countries' largest cities has been the go-to choice of a distance measure, readily provided by Mayer and Zignago (2011) as *distw*. Using these distances implicitly sets $\theta\delta = 1$. Although rarely used, Mayer and Zignago also provide the harmonic mean of city distances, which they call *distwces*.

Equations (2) and (3) yield specific instructions on how to compute distances between entities consistently with theory. The weights in the general mean should incorporate information for *all* origin and destination locations. Most importantly, the coefficient $\theta\delta$ should equal the (estimated) distance coefficient in the gravity equation. The remainder of the paper is concerned with calculating distances following these instructions and its implications for estimations of the gravity equation, with an application to international trade. In the following section I describe the data and process used to compute the distances.

4 Nighttime lights data

The great circle distance — "as the crow flies" — between two locations is generally assumed to be a good proxy for transport costs, but also for cultural and informational separation. Citing concerns with previous ad-hoc measures, such as the distance between capitals or largest cities for international distances and area-based measures for internal distances, Head and Mayer (2009) propose to use population data from UN statistics as weights for their average country-to-country distances. Aside from data collection issues that may lead to inaccuracies, there are three important caveats. First, the data is limited to a maximum of 25 cities, while economic activity is likely not limited to those alone. This is a particular limitation for geographically large and populous countries like the US or China. Second, there exists only one data point for several geographically small countries, like Luxembourg and Singapore, or developing countries, like Mongolia and Zimbabwe. Here the authors resort to previously discredited area-based measures. Third, the data is available only for the year 2004. This assumes a static economic geography, which may be particularly questionable in developing and emerging economies.

I am opting to use a different source of information on the sprawl of economic activity:

[9] The generalized mean reduces to the arithmetic mean for $\theta\delta = 1$ and the harmonic mean for $\theta\delta = -1$. It can be shown that it also nests the geometric mean for $\theta\delta = 0$.

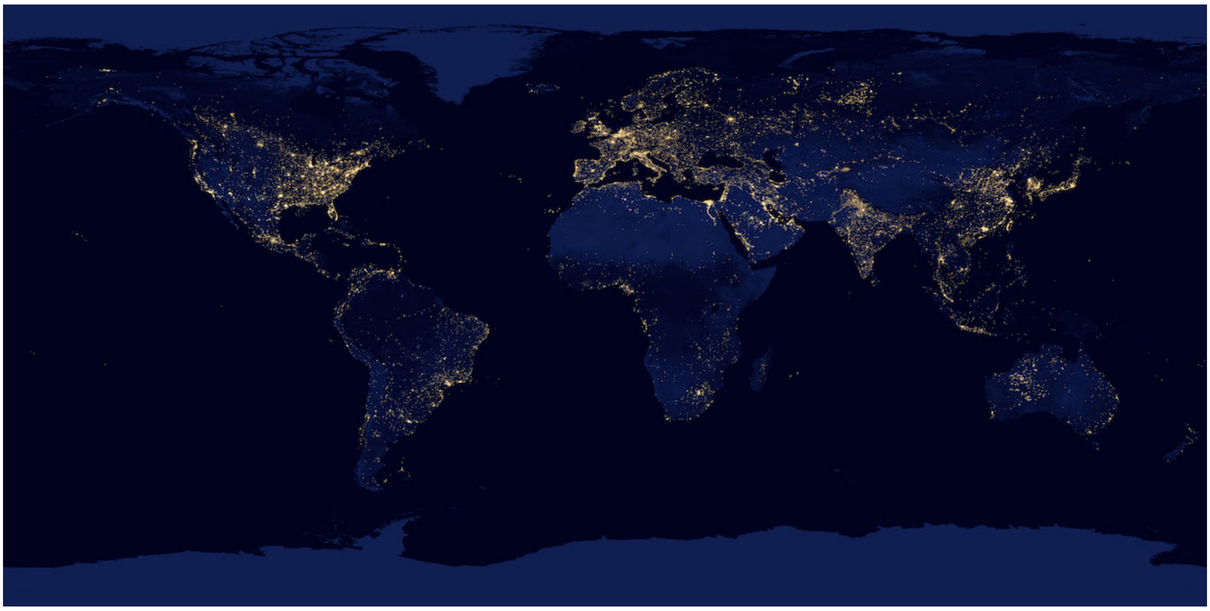
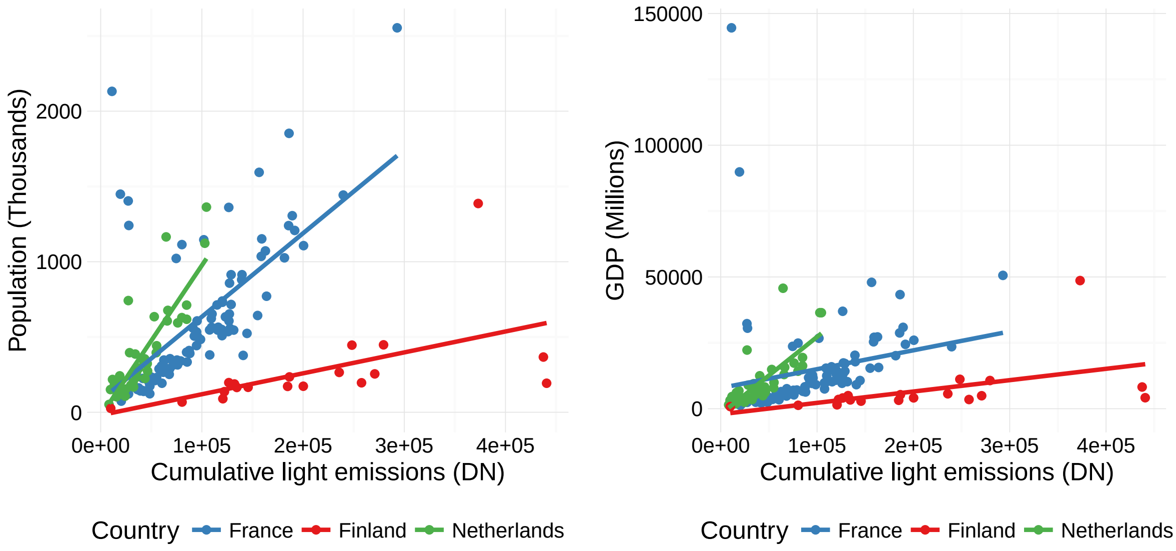


Figure 1: Nighttime lights in 2012 (Source: NOAA)

nighttime satellite imagery. Figure 1 shows the fascinating picture of light visible from space, displaying the extent of human activity — and its exact geographic location. The National Oceanic and Atmospheric Administration (NOAA) provides the imagery since 1992 on a yearly basis. Each image is a composite of average light emissions over the course of the year. The image is recorded on cloud-free evenings between 8:30pm and 10pm local time by the United States Air Force Defense Meteorological Satellite Program. The satellite's sensor's received radiance is coded as a so-called digital number (DN) on a scale from 0 to 63. The resolution is 30 arc-seconds, which translates into about 860m at the equator. Each annual image then has a total of 725,820,001 pixels. Of those, roughly 60 million are on land and illuminated at some point in the time span between 1992 and 2012.

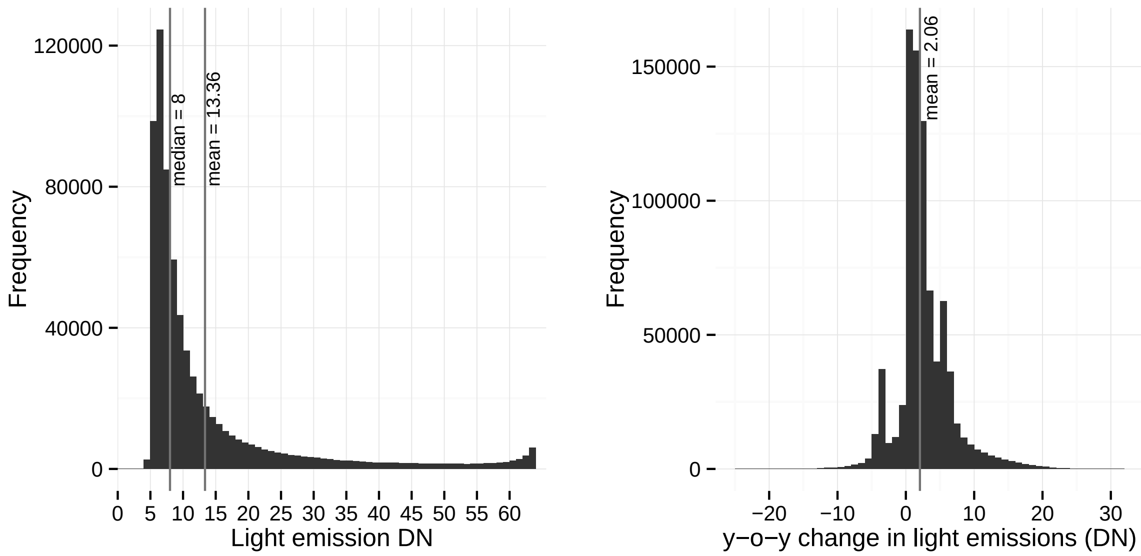
Using this data for location-specific weights in the computation of distances between countries — or other geographic entities like states, provinces and counties — has a number of advantages. First, not only large urban centers but also rural areas are present in the data. Second, even the smallest countries cover at least hundreds of pixels. Luxembourg has around 4800 illuminated pixels and even the city-state Singapore has around 900. Third, the annual periodicity of the data allows me to calculate distances for each year, reflecting changes in the economic geography of countries. As an additional bonus, data collection issues that are likely to affect city population figures are sidestepped. All of these features significantly improve upon existing data.

The use of light emissions data however also presents some challenges. To handle the size of the matrix of distances between all illuminated locations on Earth while maintaining general validity, I compute a reduced matrix composed of data from a sample of illuminated cells. The sample is constructed by drawing randomly 100 times 1 % and a minimum of 1000 from each country's illuminated cells. This reduces the total number of elements in the distance matrix to



(a) **(b)**

Figure 2: Light emissions and GDP or population by NUTS3 region.



(a) **(b)**

Figure 3: Distribution of (a) light emissions in France in 2000 and (b) its year on year changes.

about 3.6×10^{12}.

Next to managing these computational limitations and other technical issues, such as the comparability of radiance figures over time,[10] a number of questions warrant attention. First, do light emissions proxy well for the share of origin and destination-specific terms, as required by equation (1)? In order to validate this, I aggregate light emission of European countries to NUTS3 region level. This allows me to compare cumulative light emissions of each region

[10]See appendix B.1 for a description of the data processing.

with statistics that are usually assumed to have a close connection to origin- and destination specific terms in the gravity equation: economic output as measured by GDP and total population. Figures 2a and 2b show that cumulative light emissions and these measures appear to be highly correlated *within* each country. Second, nighttime lights maybe be erratic over time and not reflect true changes in the economic geography of a country. Figures 3a shows the distribution of light emissions in France, a country where little variation over time can be expected, in 2000 and figure 3b its year-on-year changes. The bulk of nighttime lights are of low intensity and the year-on-year variation is very limited, signaling no drastic changes.

5 Theory-consistent country-to-country distances

I now proceed to compute the aggregate distance between all country pairs years between 1992 and 2012. Countries are defined geographically following Weidmann et al. (2010a), yielding between 177 countries in 1992 and 195 countries in 2012. As in Head and Mayer (2009), I assume that origin and destination-specific terms in a location have the same share in their entity-aggregated origin and destination-specific terms, i.e.

$$\frac{s_k}{s_i} = \frac{m_k}{m_i} = w_k.$$

Equation (2) can then be rewritten in matrix form as

$$d_{ij} = \left(\mathbf{w}_i^T \mathbf{D}_{ij}^{\theta\delta} \mathbf{w}_j\right)^{1/\theta\delta} \tag{4}$$

where

$$\mathbf{w}_i = \frac{1}{\sum_{k\in i} w_k} \begin{pmatrix} w_1 \\ \vdots \\ w_k \end{pmatrix} \tag{5}$$

and w_j accordingly, and

$$\mathbf{D}_{ij} = \begin{pmatrix} d_{1,1} & \cdots & d_{1,l} \\ \vdots & \ddots & \vdots \\ d_{k,1} & \cdots & d_{k,l} \end{pmatrix} \quad k \in i,\ l \in j \tag{6}$$

where $d_{k,l}$ is the great circle distance between locations k and l. The great circle distance between any two points is approximated by the spherical law of cosines.[11] The distance *within* a given

[11]This approximation of the distance, computed as $d_{ij} = 6378.388 \cdot \arccos\big(\sin \mathrm{lat}_i \cdot \sin \mathrm{lat}_j + \cos \mathrm{lat}_i \cdot \cos \mathrm{lat}_j \cdot \cos(|\mathrm{lon}_i - \mathrm{lon}_j|)\big)$ with latitude and longitude converted into radians, creates a minor measurement error, as it assumes the Earth to be a perfect sphere. Its magnitude, however, is negligible being "not more than 0.5% for latitude, 0.2% for longitude" (p. 10, Admiralty, 1987).

location is computed assuming a uniform distribution of activity.[12] Using the described nighttime lights data, $\mathbf{w}_i$ is then proxied by the vector of each location k's share in the total light emissions of country i.

5.1 Distance variation over time and by exponent

As derived above, the exponent in the generalized mean is supposed to be equal to the elasticity of the flow with respect to distance. In the gravity literature the exponent $\theta\delta$ is usually implicitly set at 1 by the use of arithmetic mean distances, although traditionally estimations place the distance elasticity somewhere in the broader neighborhood of -1, calling for the use of harmonic mean distances.

Figure 4 displays the computed bilateral distances as a function of the exponent $\theta\delta$ for four exemplary pairs of origin and destination countries, including the distances provided by Mayer and Zignago (2011) for comparison. The results highlight the importance of picking the correct exponent. The difference between commonly used arithmetic distances and harmonic distances is particularly large for developing countries and internal distances. Figure 4a shows a difference for the internal distance of the Democratic Republic of Congo between harmonic and arithmetic mean of factor 21. Yet even for a developed economy such as Germany the factor remains at 1.6. Figure 4c shows the schedule for the country pair of the Democratic Republic of Congo and Rwanda. The ratio between arithmetic and harmonic mean stands at 1.7. For the distance between Germany and France the ratio is lower but still at 1.2.

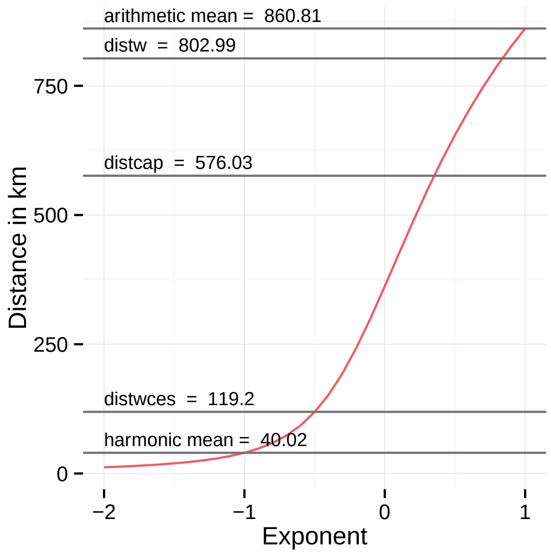
With respect to estimations of the gravity equation this entails an important effect that will be shown empirically in section 6: Assuming the true aggregate distance is captured by a harmonic mean, using arithmetic mean distances biases the estimation, as short distances are overstated. Figure 5a plots the ratio of arithmetic over harmonic mean distances against harmonic mean distances. Again it becomes clear that internal distances are more affected than external distances, as shorter distances are generally more affected than larger ones. In an estimation of the gravity equation of international trade this effect will be picked up mainly by the border coefficient. As internal distances are overestimated relative to external distances, the border effect is artificially inflated as there is "too little" trade externally.[13] The effect could also partially be picked up by any variable that is correlated with shorter distances, as the effect itself decreases with distance.[14]

Figure 5b highlights the issue of mismeasurement when using human-collected data and

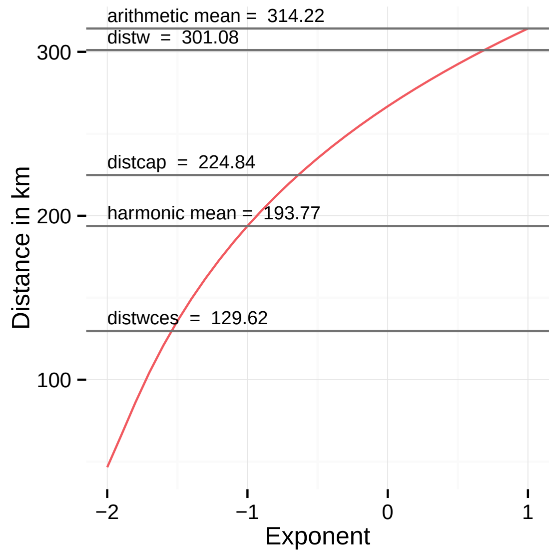
[12] See appendix A.2 for the derivation of within-location distances assuming a uniform distribution of activity that varies by degree of latitude.

[13] It can be shown that in a hypothetical setting in which distance were the only bilateral friction, this ratio of arithmetic to harmonic mean is equal to the bias of the border effect, i.e. the exponent of the border coefficient, in an OLS estimation.

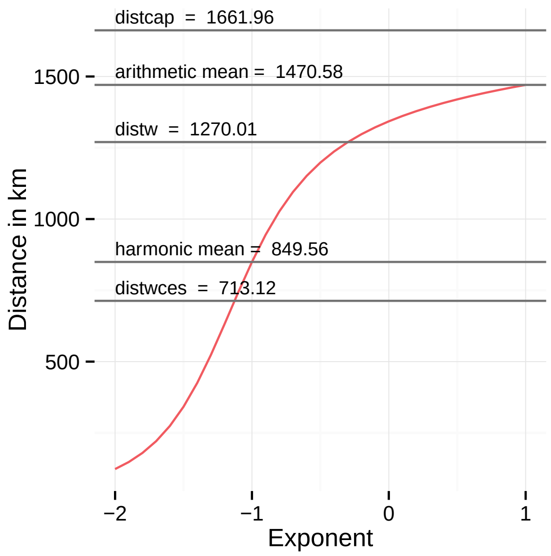
[14] Due to the saturation of the sensor of the satellite the radiance data is top-coded at DN 63, i.e. all values larger than 63 are coded as 63. This obviously biases the measurement: the computed harmonic mean might still be *overstating* the distance, so that the difference to the arithmetic mean could be even larger. See the discussion below.



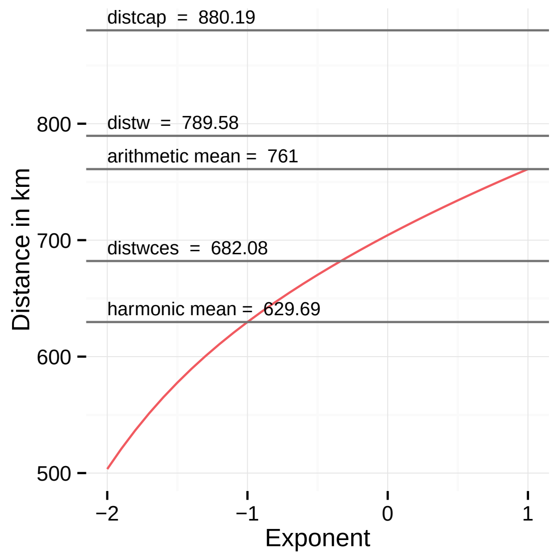
(a) Distance DRC - DRC



(b) Distance Germany - Germany



(c) Distance DRC - Rwanda



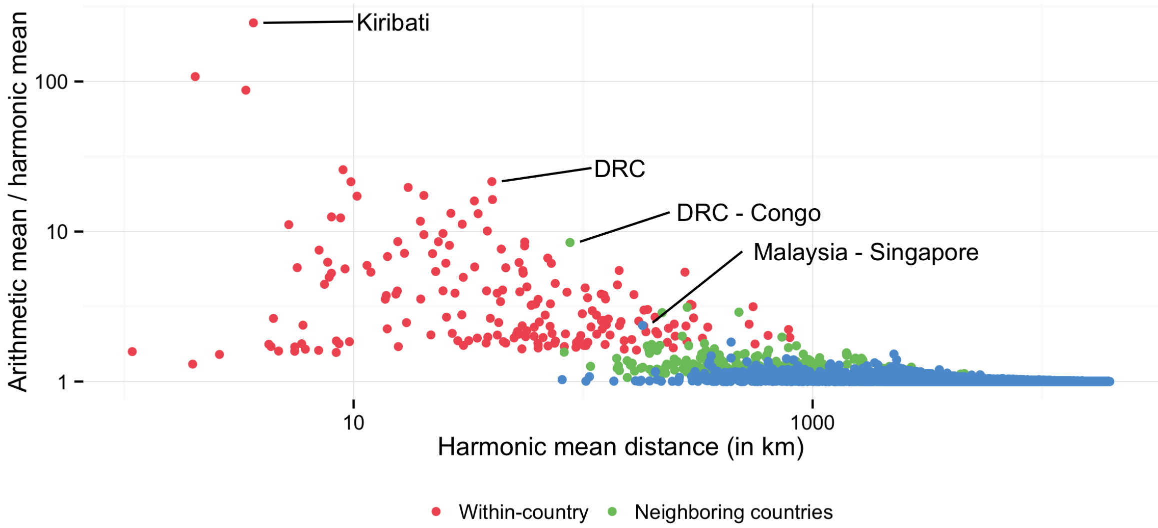
(d) Distance Germany - France

Figure 4: Aggregate distances conditional on the exponent in the generalized mean in the year 2000. Commonly used distances from Mayer and Zignago (2011) for comparison.

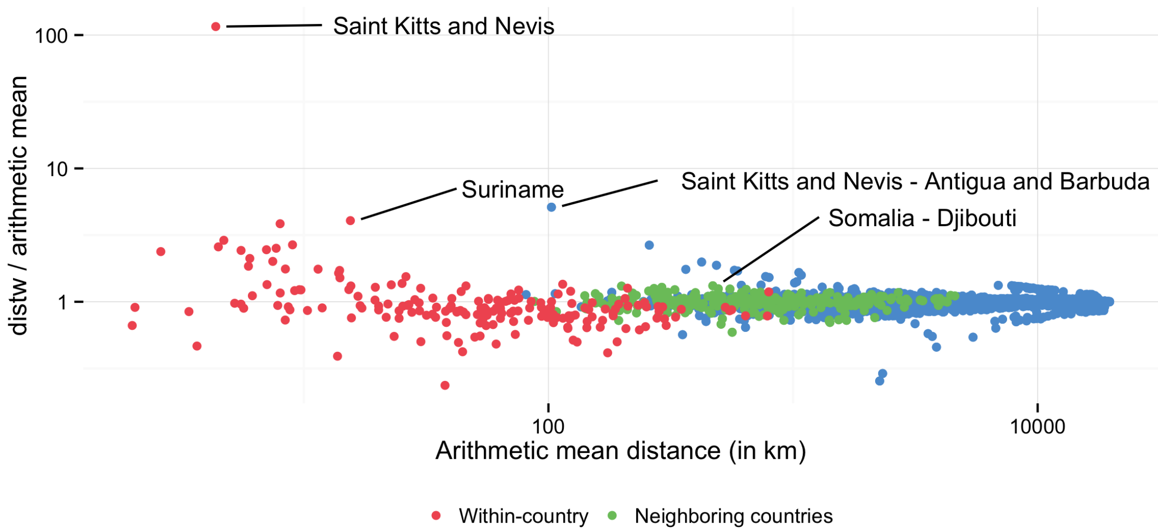
displays the aforementioned advantage of using satellite imagery for the weighting of the mean. Arithmetic mean distances calculated with satellite images, i.e. $\theta\delta = 1$, vary significantly from Mayer and Zignago (2011)'s *distw*, calculated with city-level population data. For geographically smaller countries and developing and emerging economies a far greater detail of information is available than through figures collected manually.

Another benefit of using light emissions data from satellite imagery as weights for the distance calculation is, as discussed above, its annual periodicity. This allows me to calculate distances between all country pairs for each year since 1992.[15] Figure 6 shows the variation

[15]That is, given they existed at that point in time. There are a number of new countries in the data in the wake of



(a)

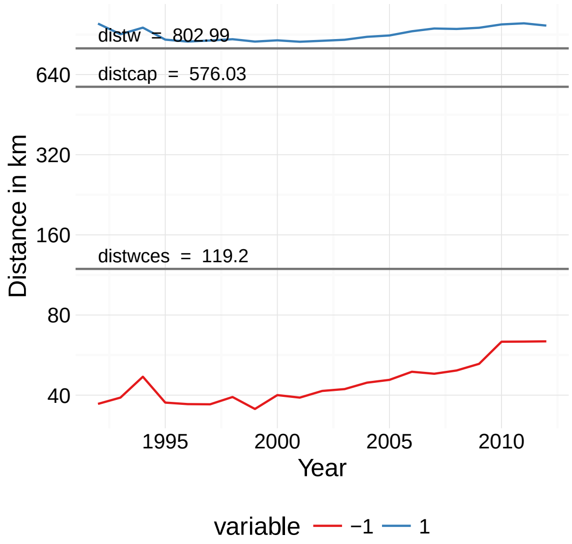


(b)

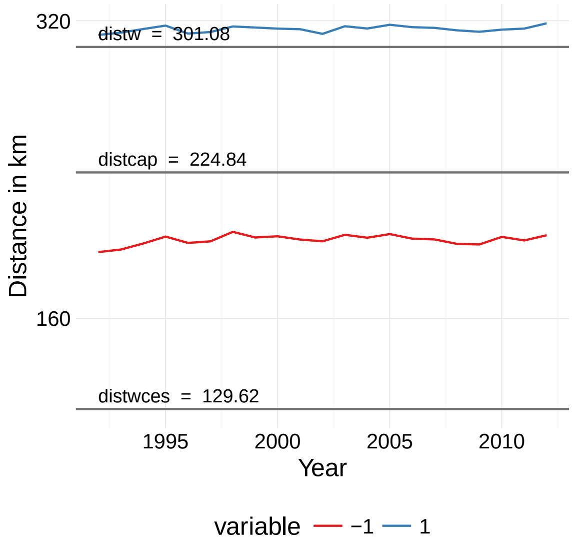
Figure 5: (a) bias of arithmetic over harmonic distances and (b) measurement error of Mayer and Zignago (2011)'s *distw* over arithmetic distances.

over time of the previously discussed arithmetic and harmonic mean distances for the same country pairs as in figure 4. The variation is again noticeably larger for developing countries. The internal distance of the Democratic Republic of Congo varies over the range of 35 to 63 kilometers when measured as a harmonic mean and 850 to 997 kilometers for the arithmetic mean. For a high income country like Germany, this variation is, as would be expected, much lower and lies between 187 and 195 kilometers for the harmonic mean and 309 and 318 for

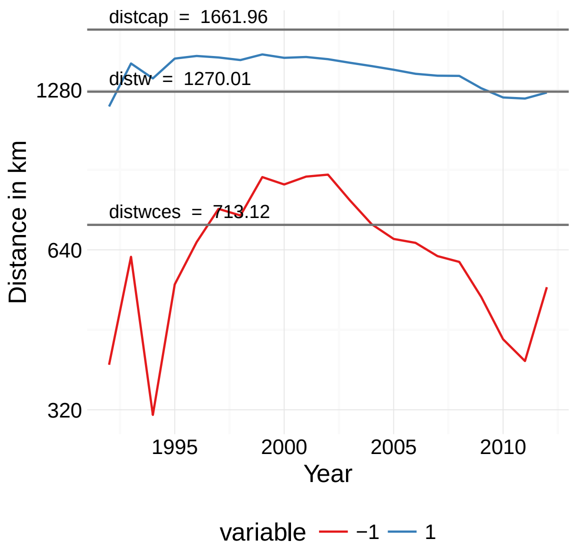
the disintegration of former Yugoslavia, as well as territorial changes in other parts of the world. I use data on border locations from Weidmann et al. (2010b). This provides an additional source of time variation that is not the result of changes in economic geography.



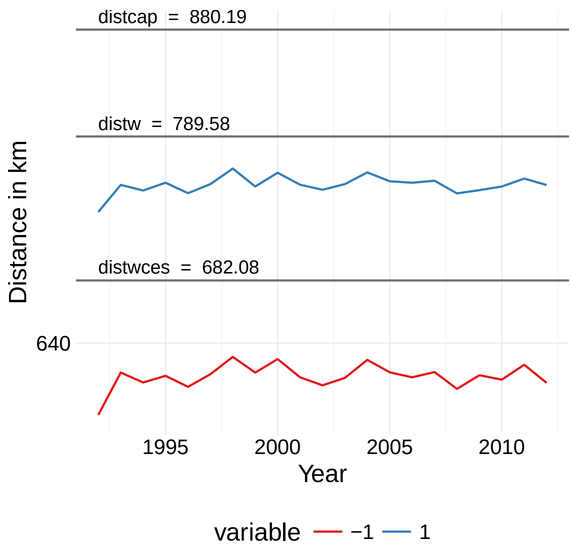
(a) Distance DRC - DRC



(b) Distance Germany - Germany



(c) Distance DRC - Rwanda



(d) Distance Germany - France

Figure 6: Aggregate distances over time (Exponents in generalized mean of -1 and 1). Commonly used time-invariant distances from Mayer and Zignago (2011) for comparison.

the arithmetic mean. Variation is also observed for between-country distances. The aggregate distance between the Democratic Republic of Congo and Rwanda varies between 313 and 886 kilometers (1191 to 1492 for the arithmetic mean) with a staggering drop of almost 50 % from 1993 to 1994 — the year of the Rwandan genocide. The distance between Germany and France, on the other hand, exhibits much less variation and ranges between 594 and 631 kilometers for the harmonic mean (731 to 764 for the arithmetic mean). Overall, the variation over time is not negligible, especially for internal distances and distances between geographically close countries.

As noted in section 1, other research endeavours have estimated the effect of distance on trade in the within dimension of a panel. Feyrer (2009) and Hugot and Umana Dajud (2014)

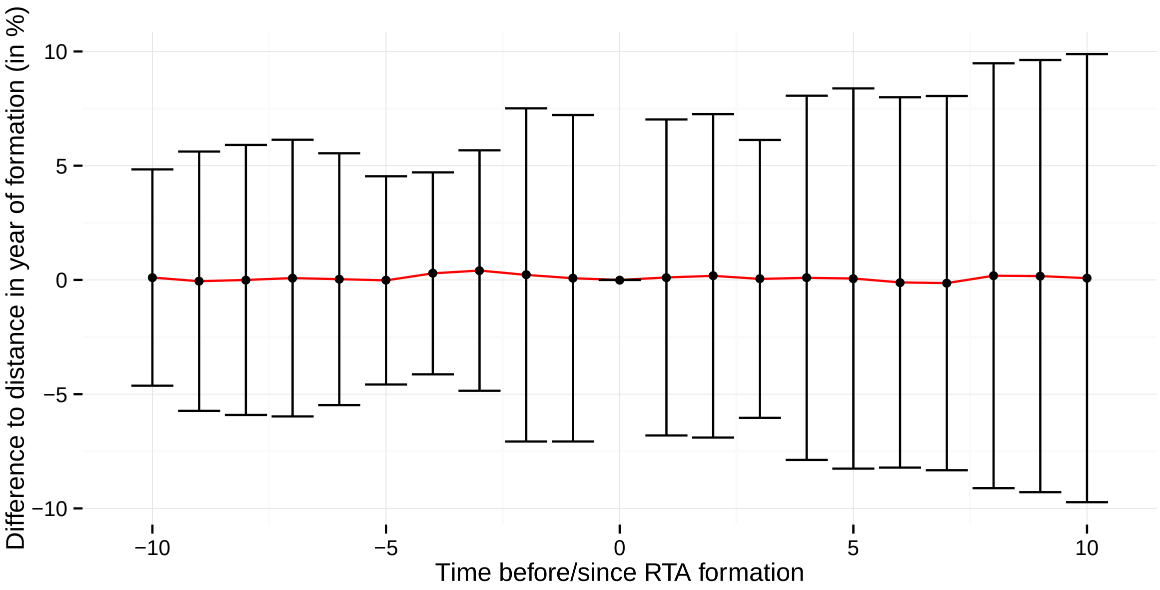


Figure 7: Mean change of distance for neighboring countries in RTAs in 10 years before and after the formation. Bars display the 95% confidence interval.

exploit an exogenous shock to maritime shipping distances in order to assess the effect. While, as will be seen below, their estimates are comparable, their approach exhibits one noticeable difference. In their case, the locations of economic activity are assumed to be static, but the optimal route connecting the importing and exporting entity changes. In the present case, I assume the inverse: the geography of economic activity is changing over time, but optimal routes are static. This in turn means that there is the possibility that the change in distances over time is actually driven or influenced by an endogenous process: economic activity could move closer to the border with another country in anticipation of more trade with said country. The result would be observed as a shorter aggregate distance and more trade. The car industry in southern Ontario, Canada could be taken as a potential example for this mechanism: Because of the automobile production on the American side of the border, Canadian manufacturing companies might move closer to the border to reduce transportation costs. One would then observe higher cross-border activity as well as shorter distances resulting from the relocation of economic activity. While this mechanism cannot be entirely ruled out, figure 7 suggests that a reduction in other trade barriers, in this case the formation of an RTA, or anticipation thereof, has no significant influence on the distance between two neighboring countries. The mean percentage difference of the distance in the ten years around the formation of an RTA to the year of its formation is never significantly different from 0.[16]

Figure 8 displays a further test for the validity of the use of nightlight data for the weights. I recompute the aggregate internal distance for the United Kingdom, however now using as weights *calibrated* nightlight data (blue line) made available by Hsu et al. (2015) and gridded

[16]See also figure 11 in the appendix that shows the change of distances between Mexico and the bordering US States of Texas, New Mexico, Arizona and California relative to 1994, the year NAFTA came into force. No clear pattern is visible with respect to smaller distances in the aftermath of the trade agreement.

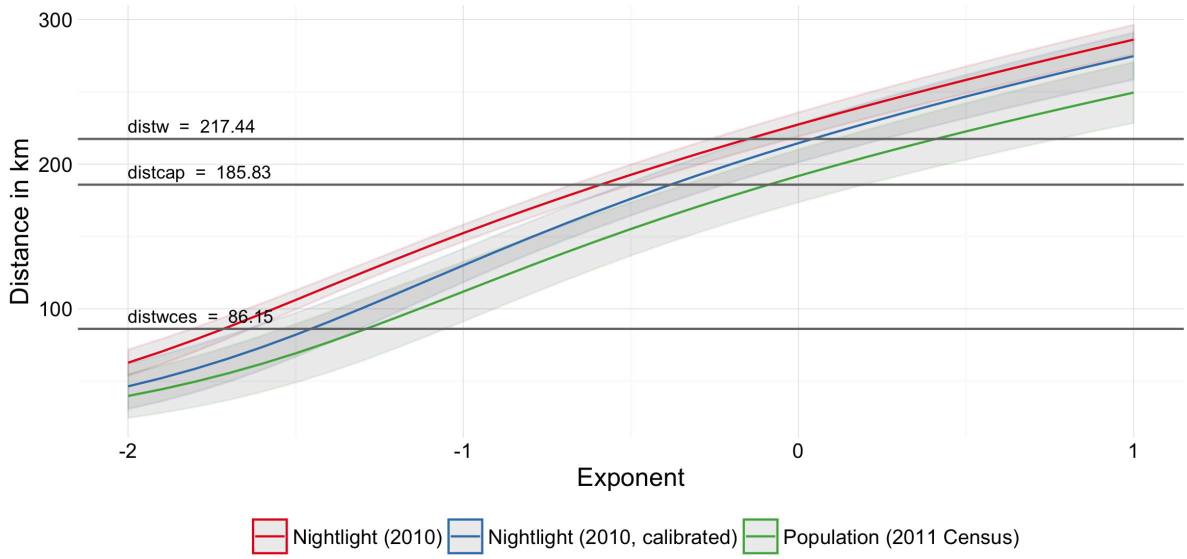


Figure 8: Distance for the UK with different source for weights (95 % confidence interval)

population data from the 2011 UK census (green line) made available by Reis (2016). The red line denotes the distance computed using the "regular" nightlight data used for the computations above. The difference between the regular nightlight data and calibrated nightlight data is the absence of top-coding of radiance, likely giving more weight to well-lit urban areas. This in turn could yield consistently lower distances as a smaller share of emitted light comes from non-urban areas. Bluhm and Krause (2018) report that on average about 3.7% of all locations are top-coded across satellites and years. Due to technical limitations of the sensor on the satellites this data is available only for select years (Hsu et al., 2015). The population-weighted distance in turn could give even more weight to densely populated areas—e.g. through multi-story buildings—resulting in even smaller (although not always significantly) distances. For reference, the customary measures from Mayer and Zignago (2011) are again displayed as horizontal bars. The computed distances all display the same pattern and are significantly lower than *distw* for the standard distance elasticity as exponent at -1. In fact, it appears as if distances computed using the uncalibrated nightlight data could still slightly overstate actual distance, although for almost all exponents the three distance measures are not statistically different at the 5 % significance level.

6 Iterative estimation of the gravity equation

I now turn to the estimation of the gravity equation of international trade using the distances computed above. When estimating a gravity equation in the cross section, the estimated coefficient for distance also captures other entity-specific effects that are correlated with distance, such as cultural similarity. Traditionally, the elasticity of trade to distance has been estimated to be in the neighborhood of -1. In a meta survey Disdier and Head (2008) find the mean of estimates to be -0.9 (with 90% of estimates between -0.28 and -1.55). Head and Mayer (2014) update this survey and report for structural estimations a mean of -1.1 (standard deviation of 0.41) and for all estimations including naive gravity, a mean of -0.93 (standard deviation of 0.4). The time-variation of the data allows me to exploit the within-dimension of the data to estimate the distance coefficient.

As laid out in the previous section, the choice of the exponent in the generalized mean makes a significant difference in the computed aggregate distance. Recall that

$$\chi_{ij} = \left(\sum_{k \in i} \sum_{l \in j} \frac{s_k}{s_i} \frac{m_l}{m_j} \chi_{kl}^{\theta\delta} \right)^{1/\theta\delta}$$

where the exponent $\theta\delta$ is a parameter in the gravity equation

$$x_{ij} = G s_i m_j \psi_{ij}^{\theta\epsilon} \chi_{ij}^{\theta\delta}.$$

Hence, I use an iterative estimation procedure that yields the parameter used in the distance aggregation itself as the estimated distance coefficient. The gravity equation is estimated with an OLS estimator in its log-linearized form as

$$\log X_{ij} = S_i + M_j + \beta_0 \cdot \log \text{Distance}_{ij} + \beta_1 \cdot \text{Border}_{ij} + \alpha \cdot \text{Controls}_{ij} + \epsilon_{ij} \tag{7}$$

or using the PPML estimator as suggested by Santos Silva and Tenreyro (2006) as

$$X_{ij} = \exp\left(S_i + M_j + \beta_0 \cdot \text{Distance}_{ij} + \beta_1 \cdot \text{Border}_{ij} + \alpha \cdot \text{Controls}_{ij}\right) + \epsilon_{ij}. \tag{8}$$

The variables of interest are primarily the estimated coefficients β_0 for the distance measure and later β_1 for the border effect. S_i is an exporter fixed effect and M_j an importer fixed effect that capture everything that is country-specific. Controls_{ij} is a vector of usual bilateral gravity control variables such as contiguity, common language, historical colonial ties, a common currency and the existence of an economic integration agreement, with α being the vector of respective coefficients.

The iterative estimation procedure is as follows: Using an arbitrary initial value,[17] I estimate the gravity equation, retrieve the distance coefficient β_0 and then use it as the parameter $\theta\delta$ in the calculation of the aggregate distance in equation (4). This new distance is then used for the next iteration. I repeat this process until the coefficient β_0 remains unchanged in its 5th digit.

I estimate equations (7) and (8) in multiple specifications. In section 6.1 I add country-pair fixed effects and exploit the within-dimension of the panel in order to identify the distance coefficient. The added fixed effect captures all bilateral time-invariant characteristics that may be

[17] I choose the value 0, i.e. the assumed absence of an effect of distance on trade. The choice has no influence on the end result, it influences only the number of iterations to reach convergence.

Table 1: Estimation in pooled panel and within-dimension of panel

(a) OLS estimator

	Dependent variable: log(flow)					
	(1)	(2)	(3)	(4)	(5)	(6)
log(Distance)	-1.282^{***}	-1.264^{***}	-1.260^{***}	-0.407^{***}	-0.950^{***}	-0.927^{***}
	(0.007)	(0.006)	(0.006)	(0.125)	(0.100)	(0.100)
Distance	arithmetic	harmonic	iterate	arithmetic	harmonic	iterate
Pair FE	No	No	No	Yes	Yes	Yes
No. of Iterations	-	-	4	-	-	12
Observations	177,996	177,996	177,996	177,996	177,996	177,996
R^2	0.785	0.787	0.787	0.925	0.925	0.925

Notes: All regression include exporter × year and importer × year fixed effects. Significance levels: *: p<0.1, **: p<0.05, ***: p<0.01.

(b) PPML estimator

	Dependent variable: flow					
	(1)	(2)	(3)	(4)	(5)	(6)
log(Distance)	-1.026^{***}	-0.932^{***}	-0.938^{***}	-0.52^{***}	-0.55^{***}	-0.527^{***}
	(0.007)	(0.006)	(0.006)	(0.164)	(0.138)	(0.146)
Distance	arithmetic	harmonic	iterate	arithmetic	harmonic	iterate
Pair FE	No	No	No	Yes	Yes	Yes
No. of Iterations	-	-	5	-	-	8
Observations	530,913	530,913	530,913	492,295	492,295	492,295

Notes: All regression include exporter × year and importer × year fixed effects. Significance levels: *: p<0.1, **: p<0.05, ***: p<0.01.

correlated with distance, while also absorbing the border coefficient β_1. In section 6.2 I estimate equations (7) and (8) in the cross section. This allows me to estimate the border effect using those distances computed with the distance coefficient from the within-panel estimation. Unless otherwise specified, for the panel estimations trade data is taken from the IMF DOTS dataset (International Monetary Fund, 2015), as it provides wide and continuous coverage over the whole time period from 1992 to 2012. For estimations where external and internal flows are separated, in particular in the cross section estimations in section 6.2, I use the TradeProd dataset (De Sousa et al., 2012). While encompassing fewer countries, it has the advantage of having consistent figures for internal and external trade. Data on RTAs and currency unions come from De Sousa (2012), other time-invariant variables come from CEPII (Mayer and Zignago, 2011).

6.1 Distance effect

As a benchmark I estimate equations (7) and (8) in a pooled panel. Then I re-estimate controlling for unobserved country-pair characteristics with country-pair fixed effects FE_{ij}. I further control for time-varying bilateral variables, RTA and common currency.[18] Columns (1) to (3) of table

[18]Coefficients are suppressed here.

1a and 1b report the results for the benchmark pooled panel with an OLS and PPML with different distance measures, arithmetic and harmonic mean distances as well as those from the generalized mean through iteration. For the OLS estimator the coefficients on distances do not vary much between the measures. This changes drastically when introducing the country-pair fixed effects, wiping out all distance-correlated but time-invariant characteristics. Columns (4) to (6) report those coefficients for the same distances measures. The distance coefficient drops markedly to -0.41 for the arithmetic mean, while the coefficients with harmonic mean and iterated general mean with -0.95 and -0.93 are in the close vicinity of -1, in line with customary cross-section estimations in the related literature. The results for the PPML estimator are in almost all instances lower than those for the OLS estimator, mirroring the results obtained by Head and Mayer (2013). Controlling for time-invariant characteristics using fixed effects (columns 4–6) yields estimates around -0.5. While the estimator has the advantage of taking zero flows into account, it also grants large flows more influence on the coefficient (Head and Mayer, 2014).

All coefficients are highly significant. The results strongly suggest that the unbiased distance coefficient is rather between to -0.5 and -1, than 1, as implied by using arithmetic mean distances. The important take-away for estimations of the gravity equation is that, as laid out in section 3, this result calls for using aggregate distances that adopt the generalized mean with a negative coefficient in this range. Arithmetic mean distances then strongly overstate short distances, as shown in section 5.1.

In order to ensure the robustness of the results, I estimate the same equation on different samples and datasets. Table 6 in appendix D replicates table 1 using UN Comtrade data (United Nations Statistics Division, 2015). Table 7 column (1) reports the coefficient on neighboring country pairs, countries that directly share a border or are within a 2000km distance. Section 5.1 suggested that here the highest variation would be found. Again the distance coefficient is very close to -1. Columns (2) and (3) report the coefficient for what the World Bank classifies as high income and low income countries. The coefficient for high income countries is about 30% lower than for low income countries, which again appears reasonable. Finally column (5) reports the coefficient when using TradeProd data. The dataset has a lower number of observations than IMF DOTS, but includes *internal* trade figures. All estimated coefficients are statistically significant and well in the range of traditional estimates surveyed by Disdier and Head (2008) and Head and Mayer (2014).

While the aggregation in section 3 yields specific instructions on the use of the estimated coefficient as the parameter in the generalized mean, oftentimes an involved iterative estimation procedure may not be feasible or beyond the scope of an analysis. In most of those cases then, using harmonic mean distances, i.e. implying an estimated distances of -1, as opposed to the customary arithmetic mean distances, is a reasonable choice. In the following, I will therefore focus on the effects of using the former as opposed to the latter in the estimation of other standard gravity controls variables.

Table 2: Border coefficient estimation with TradeProd data

	Dependent variable:			
	log(flow)		flow	
	(1)	(2)	(3)	(4)
log(distance)	-1.530^{***}	-1.464^{***}	-0.886^{***}	-0.813^{***}
	(0.033)	(0.031)	(0.025)	(0.018)
border	1.959^{***}	0.956^{***}	2.091^{***}	1.728^{***}
	(0.202)	(0.212)	(0.053)	(0.050)
Estimator	OLS	OLS	PPML	PPML
Distance	arithmetic	harmonic	arithmetic	harmonic
Observations	4,220	4,220	4,220	4,220
R^2	0.856	0.856		

Notes: All regression include exporter and importer fixed effects. Significance levels: *: p<0.1, **: p<0.05, ***: p<0.01.

6.2 Border effect

As the border effect is captured by the country-pair fixed effect in the within-dimension of the panel estimation, I re-estimate equations (7) and (8) in the cross section annually. As in table 7 column (4), I use the TradeProd dataset and stratify by year, bearing in mind that the coefficients might now pick up other effects, as they cannot be controlled for with country-pair fixed effects.

There is some disagreement as to how to estimate and interpret the border effect. This often makes a comparison of the estimated coefficients difficult, if not impossible. Different studies set other gravity controls, such as a dummy for RTA, neighboring country, or historical colonial linkages, to either 0 or 1 for internal flows. The choice indeed makes a large difference on the estimates border coefficient. Suppose a setting as in De Sousa et al. (2012) in which the border dummy takes 1 for internal flows. All other variables take 1 only if they apply for the external flow, e.g. for the US and UK the dummies for common language and former colonial relation are set to 1. For internal flows, the dummy is set to 0. With this setting, the border coefficient, i.e. the coefficient for *internal* flows, increases ceteris paribus with any added dummy variable for a trade facilitator and decreases with any additional trade barrier that is controlled for. The benchmark, against which to evaluate the border effect, thus depends on the nature and number of added control variables. What is then measured is therefore *not* the average effect of a border on trade, but the effect of crossing the border to a country for which none of the bilateral dummies is set 1. More importantly though, and present whenever including *any other* covariates next to a border dummy and distance measure, the setting entails interpreting internal flows as subject to directly comparable trade barriers and facilitators as external trade flows. This may be plausible for common language, but fails at the colony dummy.[19]

I therefore estimate the border coefficient, the gross effect of crossing a border, by exclusively including the border dummy next to distance, at the expense of having the distance coefficient

[19] Compare also Coughlin and Novy (2012) who argue along similar lines.

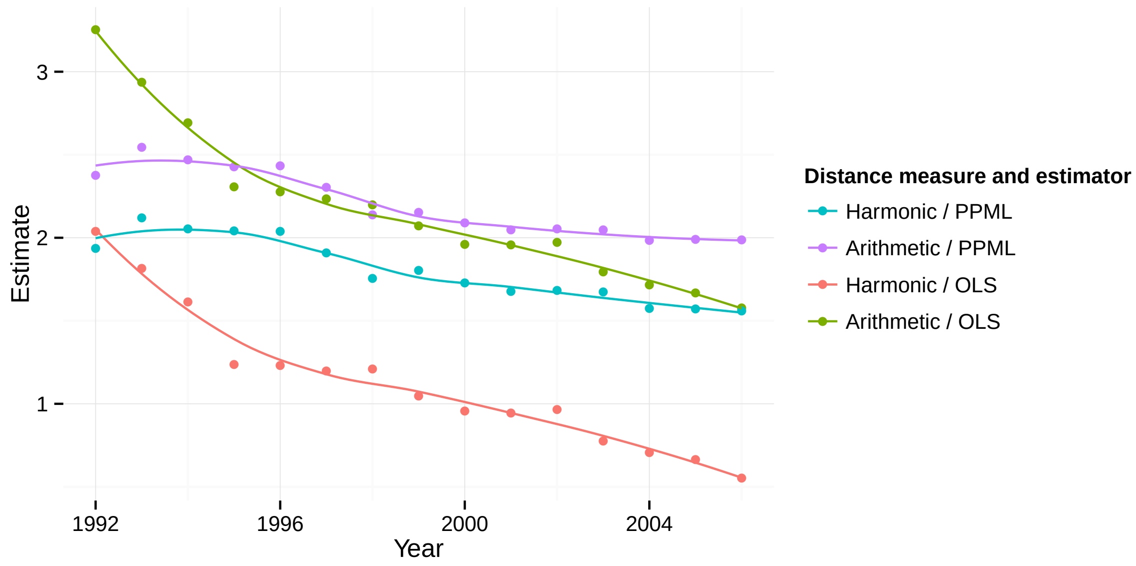


Figure 9: Border coefficients from cross section estimations using OLS and PPML estimators with TradeProd data.

capture (part) of those trade costs that are correlated with distance. Table 2 reports the coefficients for the estimations for the year 2000. As noted above, the advantage of the data is, as De Sousa et al. (2012) point out, that internal and external flows are consistently comparable, as internal flows are represented by actual production data.[20] Columns (2) and (4) show the estimates when using harmonic mean distances as suggested above. For comparison, columns (1) and (3) report the coefficient when estimated with arithmetic mean distances.

Using the OLS estimator, harmonic mean distances reduce the border coefficient from 1.96 to 0.956 in 2000, which translates into a reduction of the border effect from a factor of about $\exp(1.96) \approx 7.1$ to $\exp(0.958) \approx 2.6$ for internal trade over external trade. When assuming a trade elasticity θ of -4, as suggested by Head and Mayer (2013), the tariff-equivalent reduces from $\epsilon = \exp(1.96/4) - 1 = 63\%$ to 27%. For the PPML estimator the effect is smaller, with a tariff-equivalent reduction from 68% to 54%, but significant nevertheless. Figure 9 displays the variation of the coefficient over time. The magnitude of the difference between using arithmetic and harmonic distances stays roughly the same for each estimator.

Table 3 shows the change in the estimated border coefficient, conditional on the size of the bias in terms of the ratio of arithmetic over harmonic mean, as in figure 5a. Columns (1) and (2) show the coefficients for the same specification as above, but restricting the sample on those exporting countries, whose bias is above the median, i.e. those countries with a strongly overstated internal distance. Conversely, columns (3) and (4) display those coefficients for the group with a bias lower than the median. The results confirm the intuition. The estimated border coefficient indeed drops by far more for the group with a higher bias (from 2.31 to 0.79) than

[20]See table 8 in appendix D for the estimations with IMF DOTS dataset with internal trade calculated as the difference between GDP and total exports following Wei (1996). The magnitude of the effects is similar.

Table 3: Change in border coefficient by group with TradeProd data

	Dependent variable:			
	log(flow)		flow	
	(1)	(2)	(3)	(4)
log(distance)	-1.755^{***}	-1.662^{***}	-1.350^{***}	-1.290^{***}
	(0.055)	(0.053)	(0.044)	(0.042)
border	2.311^{***}	0.793^{**}	1.553^{***}	0.982^{***}
	(0.337)	(0.363)	(0.255)	(0.263)
Estimator	OLS	OLS	OLS	OLS
Distance	arithmetic	harmonic	arithmetic	harmonic
Bias (AM/HM)	$\geq$ median	$\geq$ median	$<$ median	$<$ median
Observations	1,737	1,737	2,483	2,483
R^2	0.823	0.822	0.890	0.890
Adjusted R^2	0.801	0.800	0.881	0.881

Notes: All regression include exporter and importer fixed effects. Significance levels: *: p<0.1, **: p<0.05, ***: p<0.01.

with a lower bias (from 1.55 to 0.98).

The results are consistent with the literature on border effects that use disaggregated shipment data, like Hillberry and Hummels (2008). Their results suggest the border puzzle largely to be a statistical artifact due to aggregation. Hillberry and Hummels show that trade within a single 3-digit ZIP code region is on average three times higher than trade with partners outside the ZIP code. This suggests much shorter distances for internal trade flows than are usually assumed with arithmetic mean distances. This statistical observation however is reflected in the use of the harmonic mean that gives short distances a proportionally larger weight than long distances. As shown above, using harmonic mean distances remedies the border puzzle to a large extent.

6.3 Effect on other variables

The effect on other gravity variables is estimated separately from the border coefficient, as discussed above. Again estimating equations (7) and (8) in the cross section, but restricting to external trade, the difference between using arithmetic or harmonic distances is most visible in those variables that are correlated with distance. The first standard gravity covariate that comes to mind is the dummy variable for neighboring countries. As seen above in section 5a, the bias of using arithmetic distances is particularly pronounced for those within countries or with neighboring countries, as the bias is itself a function of distance. Arithmetic distances are biased upwards, so that a dummy variable for trade with a neighboring country picks up the ceteris paribus too large trade flows. The use of harmonic distances corrects this: giving more weight to short distances reduces the mean and accounts for the larger cross-border trade with neighbors compared to those at a greater distance.

Table 4: Gravity covariates estimation with TradeProd data

	Dependent variable:			
	log(flow)		flow	
	(1)	(2)	(3)	(4)
log(distance)	-1.379^{***}	-1.338^{***}	-0.578^{***}	-0.521^{***}
	(0.028)	(0.027)	(0.015)	(0.013)
neighbor	0.266^{**}	0.099	0.372^{***}	0.355^{***}
	(0.103)	(0.105)	(0.024)	(0.024)
rta	0.539^{***}	0.550^{***}	0.871^{***}	0.903^{***}
	(0.063)	(0.063)	(0.033)	(0.033)
comcur	-0.061	-0.083	-0.088^{***}	-0.119^{***}
	(0.138)	(0.138)	(0.030)	(0.030)
colony	0.808^{***}	0.805^{***}	-0.018	0.004
	(0.093)	(0.093)	(0.027)	(0.027)
comlang off	0.485^{***}	0.488^{***}	0.143^{***}	0.115^{***}
	(0.054)	(0.054)	(0.027)	(0.027)
comleg	0.242^{***}	0.240^{***}	0.169^{***}	0.167^{***}
	(0.038)	(0.038)	(0.018)	(0.018)
Estimator	OLS	OLS	PPML	PPML
Distance	arithmetic	harmonic	arithmetic	harmonic
Observations	8,811	8,811	8,811	8,811
R^2	0.805	0.804		

Notes: All regression include exporter and importer fixed effects. Significance levels: *: p<0.1, **: p<0.05, ***: p<0.01.

Table 4 shows the estimates using TradeProd data for the year 2000 for the most commonly used covariates in the gravity equation: A dummy for trade between directly neighboring countries, the existance of an RTA, a common currency, historical colonial links, a common official language and the presence of a common legal system. Columns (1) and (3) show the coefficients for OLS and PPML estimates when using arithmetic mean distances, columns (2) and (4) those for the harmonic mean distances. The coefficient for trade with a neighboring country when using the latter over the former drops from 0.27, i.e. on average 30% more trade than with other countries, to an insignificant 0.1, or 10.5% more, when using the OLS estimator. When using the PPML estimator the coefficient drops from 45% to 42%, the decrease however is not significant.

Figure 10 shows the evolution of the coefficient from 1992 to 2006. Again, as in the case of the border coefficient, the difference between the estimated coefficient using the two distance measures remains relatively stable. Unsurprisingly the other variables are largely unaffected, as they tend to be less correlated with distance.

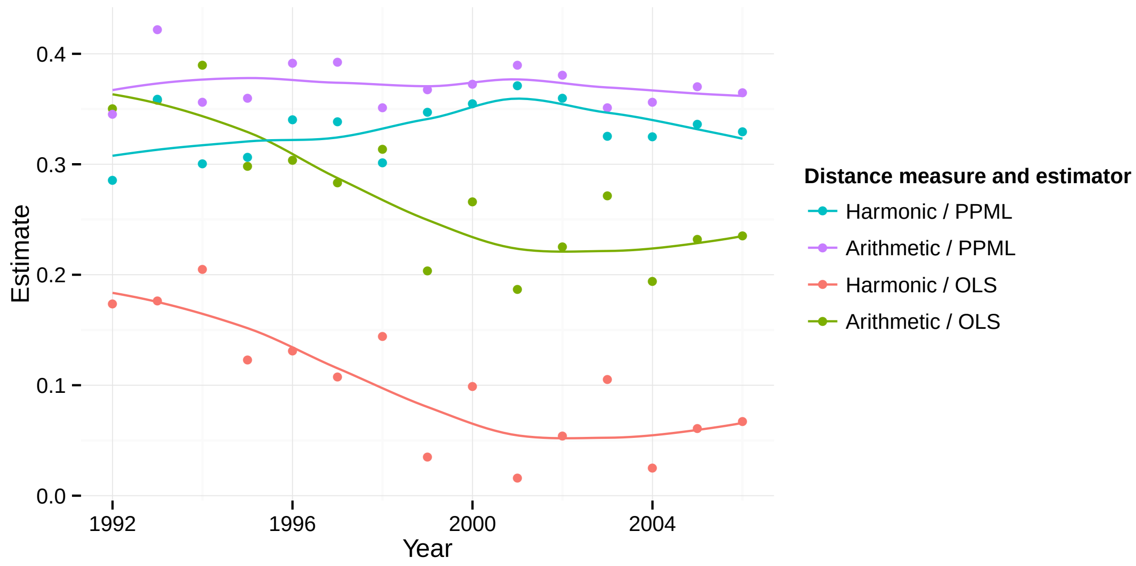


Figure 10: Neighbor coefficient over time by estimation method

6.4 Gauging the effects on simulated data

In order to further validate the theoretical and empirical findings as well as their magnitude, I perform a simulation exercise. I first generate data using a simple structural gravity model à la Head and Mayer (2014), in which I explicitly set the bilateral trade costs, in this case exclusively to be described by distance. Knowing the *true* distance elasticity, I estimate the distance coefficient using both *correct* and *mismeasured* distances. Furthermore I can introduce additional variables in the estimation that are orthogonal to the *true* distance, but may not be to the *mismeasured* ones, as is hypothesized above about the border and neighboring country dummies. In the case that the econometric results from above are correct, they should be replicable in this simulated environment.

Suppose now that bilateral trade flows X_{ij} are described by

$$X_{ij} = \frac{Y_i}{\Omega_i} \cdot \frac{X_j}{\Phi_j} \cdot \phi_{ij} \tag{9}$$

where $Y_i = \sum_j X_{ij}$ is the value of production in i, $X_j = \sum_i X_{ij}$ is the value of all imports in j, and

$$\Omega_i = \sum_k \frac{X_k \phi_{ik}}{\Phi_k} \quad \text{and} \quad \Phi_j = \sum_k \frac{Y_k \phi_{ik}}{\Omega_k}$$

are the multilateral resistance terms. As Anderson and Yotov (2010) note, these can be solved for a given set of trade costs ϕ_{ij}, production and expenditure figures. Assuming that both Y_k and X_k can be proxied for by data on GDP, I can easily simulate real-world trade data by specifying

Table 5: Gravity covariates estimation with simulated data

	Dependent variable:					
	$\log(X_{ij})$				X_{ij}	
	(1)	(2)	(3)	(4)	(5)	(6)
log(distance_harm)	-1.000^{***}				-1.000^{***}	
	(0.000)				(0.000)	
log(distance_arith)		-1.075^{***}	-1.028^{***}	-1.015^{***}		-1.077^{***}
		(0.001)	(0.001)	(0.001)		(0.001)
border	0.000^{***}		1.136^{***}	1.185^{***}	-0.000^{**}	0.541^{***}
	(0.000)		(0.006)	(0.006)	(0.000)	(0.003)
neighbor	0.000^{***}			0.171^{***}	0.000	0.108^{***}
	(0.000)			(0.003)	(0.000)	(0.002)
Estimator	OLS	OLS	OLS	OLS	PPML	PPML
Observations	32,041	32,041	32,041	32,041	32,041	32,041
R^2	1.000	0.999	1.000	1.000		

Note: Significance levels: *p<0.1; **p<0.05; ***p<0.01

trade costs ϕ_{ij}.

Suppose therefore, for the purpose of the argument, that bilateral trade costs ϕ_{ij} were to be governed exclusively by the bilateral geographic distance between i and j, such that

$$\phi_{ij} = \exp(\widetilde{\delta} \cdot \ln \text{Dist}_{ij}(\widetilde{\delta}))$$

where Dist_{ij} is the *harmonic mean* distance for $\widetilde{\delta} = -1$.

Similar to the above, equation (9) can be estimated using an OLS or PPML estimator as

$$\log(X_{ij}) = F_i + F_j + \delta \cdot \ln(\text{Dist}_{ij}(\widetilde{\delta})) + \Gamma \cdot \mathbf{z}_{ij} + \epsilon_{ij} \qquad \text{or}$$

$$X_{ij} = \exp\left(F_i + F_j + \delta \cdot \ln(\text{Dist}_{ij}(\widetilde{\delta})) + \Gamma \cdot \mathbf{z}_{ij}\right) + \epsilon_{ij}$$

where F_i and F_j are fixed effects capturing all exporter and importer characteristics and $\mathbf{z}_{ij}$ are additional bilateral variables. The coefficients of interest are δ, the estimated distance elasticity, which is supposed to be equal to $\widetilde{\delta}$ when estimated with the correct distance measure, and Γ, which is supposed to be zero, as ϕ_{ij} is only governed by distance. In case of a mismeasurement of the distance, Γ could be non-zero, in which case $\mathbf{z}_{ij}$ would capture some of the distance effect. As discussed above, of particular interest here are the variables capturing the border and neighboring country effect. Both variables are correlated with distance to some degree and therefore could capture distance effects.

Table 5 reports the estimated coefficients for a variety of specifications: Columns (1) and (5) show the benchmark result in which the *correct* harmonic mean distances are used, estimated using an OLS or PPML estimator respectively. The distance coefficient is, as expected, -1. The coefficients for the border and neighboring country variable are both 0. Columns (2) - (4) and (6) report the corresponding estimates when erroneously using the *mismeasured* arithmetic mean distances: in all cases the distance coefficient is biased upwards, i.e. away from zero. Remarkably, the estimated border coefficients stand at more than 1.1 for the OLS estimator and more than 0.5 using the PPML estimator, although its true value is 0. The neighboring country coefficient yields about 0.2 and 0.1, respectively.

The consequences of using mismeasured distances, i.e. a substantially inflated border coefficient as well as an overestimated neighboring country coefficient, are replicated by using simulated data. Moreover the magnitude of the effects are validated. The use of mismeasured distances leads to a severe overestimation of the border and neighboring country coefficients, or in other words, using the correct—harmonic mean—distances helps remedy the border puzzle of international trade.

7 Conclusion

In this paper I derive a spatial aggregation of bilateral frictions from a general representation of the gravity model in international economics. The method, building on earlier work from Head and Mayer (2009), is agnostic to the underlying micro-foundation of the gravity framework and yields specific instructions on data and computation. Specifically and importantly, it yields an aggregation in the form of a weighted generalized mean of location-specific frictions where the key parameter is the elasticity of this friction in the gravity equation itself.

I then apply the aggregation method to the arguably most acknowledged proxy for location-specific frictions, distances. Using annual high resolution satellite imagery on nighttime light emissions for the calculation of the weights, I compute bilateral distances for all country pairs (including within-country) and all years between 1992 and 2012. The data significantly improves upon previously used human-collected figures with much broader and finer coverage. Furthermore, the annual periodicity allows me to take into account changes in the economic geography of countries, which are particularly prevalent in developing and emerging economies. The time dimension of the computed distances then makes it possible to estimate the required distance elasticity from the gravity model in the within-dimension of the panel. This in turn ensures that time-invariant, potentially distance-correlated bilateral characteristics are controlled for. The estimated coefficient ranges close to traditional estimates, between -0.5 and -1.

In an application to the gravity model of international trade, I then show that with these distances, as opposed to the customary use of arithmetic mean distances, the border puzzle of international trade becomes much less severe or even disappears, depending on the data and estimation technique employed. The result is driven by the fact that arithmetic mean distances strongly overstate short distances relative to harmonic mean distances. The effect is consistent with the literature, suggesting that the border puzzle generally disappears when using disaggregated data on volume and distance of shipment. Regressions using simulated data confirm the theoretical and empirical findings. Overall, the results strongly suggest to moving away from the de-facto standard of using population-weighted arithmetic mean distances in estimations of the gravity model.

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A Theoretical appendix

A.1 Aggregation for structural gravity

Following Head and Mayer (2014), structural gravity in international trade is defined as

$$X_{kl} = \frac{Y_k}{\Omega_k} \cdot \frac{X_l}{\Phi_l} \cdot \phi_{kl}^{\theta}$$

where $Y_k = \sum_l X_{kl}$ is the value of production (i.e. exports) in k, $X_l = \sum_k X_{kl}$ is the value of all expenditure (i.e. imports) in l, and

$$\Omega_k = \sum_l \frac{X_l \phi_{kl}^{\theta}}{\Phi_l} \quad \text{and} \quad \Phi_l = \sum_k \frac{Y_k \phi_{kl}^{\theta}}{\Omega_k}$$

are the multilateral resistance terms. For all $k \in i$ and $l \in j$ call $Y_i = \sum_{k\in i} Y_k$ and $X_j = \sum_{l\in j} X_l$, the total value of production in i and expenditure in j respectively. Then

$$\begin{aligned} X_{ij} &= \sum_{k\in i}\sum_{l\in j} X_{kl} \\ &= \sum_{k\in i}\sum_{l\in j} \frac{Y_k}{\Omega_k} \cdot \frac{X_l}{\Phi_l} \cdot \phi_{kl}^{\theta} \end{aligned}$$

Multiply and divide by the sum of all exporter and importer-specific terms, such that

$$X_{ij} = \sum_{k\in i} Y_k/\Omega_k \cdot \sum_{l\in j} X_l/\Phi_l \cdot \sum_{k\in i}\sum_{l\in j} \frac{Y_k/\Omega_k}{\sum_{k\in i} Y_k/\Omega_k} \frac{X_l/\Phi_l}{\sum_{l\in j} X_l/\Phi_l} \phi_{kl}^{\theta}$$

The sum of importer and exporter-specific terms can be simplified further, as

$$\begin{aligned} \sum_{k\in i} \frac{Y_k}{\Omega_k} &= \frac{Y_i}{Y_i} \sum_{k\in i} \frac{Y_k}{\Omega_k} \\ &= Y_i \sum_{k\in i} \frac{Y_k}{Y_i} \Omega_k^{-1} \\ &= \frac{Y_i}{\Omega_i} \quad \text{with} \quad \Omega_i = \left(\sum_{k\in i} \frac{Y_k}{Y_i} \Omega_k^{-1} \right)^{-1} \end{aligned}$$

and accordingly

$$\sum_{k\in i} \frac{X_l}{\Phi_l} = \frac{X_j}{\Phi_j} \quad \text{with} \quad \Phi_j = \left(\sum_{l\in j} \frac{X_l}{X_j} \Phi_l^{-1} \right)^{-1}$$

The entity-level multilateral resistance terms are hence the harmonic mean of multilateral resistances of locations, weighted by their share in the value of production or expenditure, respectively. [21]

Finally putting it all together yields

$$X_{ij} = \frac{Y_i}{\Omega_i} \cdot \frac{X_j}{\Phi_j} \cdot \sum_{k \in i} \sum_{l \in j} \frac{Y_k/\Omega_k}{Y_i/\Omega_i} \frac{X_l/\Phi_l}{X_j/\Phi_j} \phi_{kl}^{\theta}$$

$$= \frac{Y_i}{\Omega_i} \cdot \frac{X_j}{\Phi_j} \cdot \phi_{ij}^{\theta} \quad \text{with} \quad \phi_{ij} = \left(\sum_{k \in i} \sum_{l \in j} \frac{Y_k/\Omega_k}{Y_i/\Omega_i} \frac{X_l/\Phi_l}{X_j/\Phi_j} \phi_{kl}^{\theta} \right)^{\frac{1}{\theta}} \tag{10}$$

which is isomorphic to equation (1).

A.2 Within-location distance

The density function $f(x)$ of distances x between uniformly distributed points within a rectangle with sides a and b, $a \leq b$ and $c = \sqrt{a^2 + b^2}$, can be shown to follow

$$f(x) = \frac{4x}{a^2 b^2} \phi(x) \tag{11}$$

where

$$\phi(x) = \begin{cases} \frac{ab\pi}{2} - (a+b)\,x + \frac{x^2}{2} & \text{for} \quad 0 \leq x < a \\ ab \arcsin\left(\frac{a}{x}\right) - \frac{a^2}{2} - bx + b\sqrt{x^2 - a^2} & \text{for} \quad a \leq x < b \\ ab \arcsin\left(\frac{a}{x}\right) - ab \arccos\left(\frac{b}{x}\right) - \frac{(a^2+b^2)}{2} - \frac{x^2}{2} + \\ \qquad a\sqrt{x^2 - b^2} + b\sqrt{x^2 - a^2} & \text{for} \quad b \leq x \leq c \\ 0 & \text{otherwise.} \end{cases} \tag{12}$$

As the generalized mean over a continuous function for the interval $[y, z]$ can be expressed as $\Upsilon(x) = \left[\int_y^z x^{\rho} f(x)\, dx\right]^{\frac{1}{\rho}}$ for $\rho \neq 0$ and $\Upsilon(x) = \exp\left[\int_y^z \log(x) f(x)\, dx\right]$ for $\rho = 0$, we have here

[21] See also Ramondo et al. (2016), whose aggregation over regions yields a similar country-level price index.

$$\Upsilon(x) = \Bigg[\int_0^a x^\rho \frac{4x}{a^2b^2}\left(\frac{ab\pi}{2} - (a+b)\,x + \frac{x^2}{2}\right)\,dx\,+$$
$$\int_a^b x^\rho \frac{4x}{a^2b^2}\left(ab\arcsin\left(\frac{a}{x}\right) - \frac{a^2}{2} - bx + b\sqrt{x^2-a^2}\right)\,dx\,+$$
$$\int_a^b x^\rho \frac{4x}{a^2b^2}\left(ab\arcsin\left(\frac{a}{x}\right) - ab\arccos\left(\frac{b}{x}\right) - \frac{(a^2+b^2)}{2} - \frac{x^2}{2} + \right.$$
$$\left. a\sqrt{x^2-b^2} + b\sqrt{x^2-a^2}\right)\,dx\,\Bigg]^{\frac{1}{\rho}} \tag{13}$$

for $\rho \neq 0$ and

$$\Upsilon(x) = \exp\Bigg[\int_0^a \log(x)\frac{4x}{a^2b^2}\left(\frac{ab\pi}{2} - (a+b)\,x + \frac{x^2}{2}\right)\,dx\,+$$
$$\int_a^b \log(x)\frac{4x}{a^2b^2}\left(ab\arcsin\left(\frac{a}{x}\right) - \frac{a^2}{2} - bx + b\sqrt{x^2-a^2}\right)\,dx\,+$$
$$\int_a^b \log(x)\frac{4x}{a^2b^2}\left(ab\arcsin\left(\frac{a}{x}\right) - ab\arccos\left(\frac{b}{x}\right) - \frac{(a^2+b^2)}{2} - \frac{x^2}{2} + \right.$$
$$\left. a\sqrt{x^2-b^2} + b\sqrt{x^2-a^2}\right)\,dx\,\Bigg] \tag{14}$$

for $\rho = 0$.

B Data appendix

B.1 Processing of satellite imagery

The United States Air Force Defense Meteorological Satellite Program (DMSP) has satellites circling the planet about 14 times in 24h, image captured between 8:30pm and 10pm local time. The results are digitally available since 1992, pre-processed by NOAA (cloud-free, no fires). The resolution is 30 arc-seconds or about 860m at the equator, where the recorded data is a so-called digital number (DN), an integer between 0 and 63. The number is not necessarily true radiance, it is what the sensor picks up. In total there are about 60 million illuminated cells, with variation over time.

I rasterize the raw satellite images and remove artefacts (gas flares and aurora borealis), boats, etc. I reduce the sample to illuminated landmasses by detecting borders with georeferenced border shapefiles from Weidmann et al. (2010b). In line with the literature I intercalibrate across years following Elvidge et al. (2014) with:

$$DN^{'} = c_0 + c_1 DN + c_2 DN^2$$

A number of years have observations from two satellites. For these years I average the intercalibrated data by cell. Using this processed data I calculate great circle distances between each illuminated cell and calculate the generalized mean as discussed above. To reduce the size of the distance matrix to be calculated while maintaining general validity, I randomly draw 100 times 1 percent and a minimum of 1000 from each country's illuminated cells.

C Validity checks for Distance Measure

Figure 11: Change of distance (1994 = 1) after NAFTA between Mexico and the US States of Texas, New Mexico, Arizona and California.

D Additional gravity results

Table 6: PPML estimation - pooled and within-dimension using UN Comtrade data

	Dependent variable: flow					
	(1)	(2)	(3)	(4)	(5)	(6)
log(Distance)	-1.003^{***}	-0.911^{***}	-0.918^{***}	-0.684^{***}	-0.495^{***}	-0.554^{***}
	(0.007)	(0.006)	(0.006)	(0.157)	(0.125)	(0.146)
Distance	arithmetic	harmonic	iterate	arithmetic	harmonic	iterate
Pair FE	No	No	No	Yes	Yes	Yes
No. of Iterations	-	-	5	-	-	8
Observations	361,634	361,634	361,634	361,634	361,634	361,634

Notes: All regression include exporter × year and importer × year fixed effects. Significance levels: *: p<0.1, **: p<0.05, ***: p<0.01.

Table 7: Robustness checks - different samples and datasets

	Dependent variable: log(flow)			
	(1)	(2)	(3)	(4)
log(Distance)	-1.019^{***}	-0.615^{*}	-0.860^{***}	-0.771^{**}
	(0.098)	(0.322)	(0.282)	(0.323)
Distance	iterate	iterate	iterate	iterate
Pair FE	Yes	Yes	Yes	Yes
Dataset	DOTS	DOTS	DOTS	TradeProd
Sample	Neighbors	High inc.	Low inc.	all
No. of Iterations	14	21	13	27
Observations	30,429	31,395	2,646	132,795
R^2	0.971	0.959	0.967	0.927

Notes: All regression include exporter × year and importer × year fixed effects. Significance levels: *: p<0.1, **: p<0.05, ***: p<0.01.

Table 8: Border coefficient estimation with IMF DOTS data

	Dependent variable:			
	log(flow)		flow	
	(1)	(2)	(3)	(4)
log(distance)	-1.544^{***}	-1.496^{***}	-1.143^{***}	-1.029^{***}
	(0.024)	(0.023)	(0.014)	(0.012)
border	3.926^{***}	2.332^{***}	2.563^{***}	2.076^{***}
	(0.147)	(0.159)	(0.028)	(0.031)
Estimator	OLS	OLS	PPML	PPML
Distance	arithmetic	harmonic	arithmetic	harmonic
Observations	7,584	7,584	7,584	7,584
R^2	0.786	0.789		

Notes: All regression include exporter and importer fixed effects. Significance levels: *: p<0.1, **: p<0.05, ***: p<0.01.