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

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Abstract

I compute distances used in the gravity model of international trade that improve the existing measures along multiple lines and help remedy the border puzzle. I derive a trade cost aggregation that is agnostic to the underlying gravity framework while taking into account the economic geography of countries. The key parameter of the aggregation turns out to be the elasticity of trade to the respective trade cost, which, conveniently, can be estimated in the gravity model. Based on this method I then compute aggregate bilateral and internal country distances, making use of nightlight satellite imagery for information on the economic geography of countries. With around 60 million illuminated locations on earth, the data exhibits very fine detail on the location of economic activity and is available annually since 1992, allowing me to take into account changes over time. Employing these computed distances in a standard gravity equation yields a number of noteworthy results. Exploiting the time-variation of the distances, I can estimate the distance coefficient while controlling for unobserved country-pair characteristics. Trade elasticity estimates are in the vicinity of -1. Further, their use yields important consequences for 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 and support the magnitude of the estimated effects.

Keywords: Gravity equation, trade costs, distances, border puzzle, satellite imagery
JEL Classification: F10, F14

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1 Introduction

When concerned with the determinants of the volume of flows of goods, trade economists often have to resort to aggregate trade figures, by country, or sometimes state and province. This makes an aggregation of its determinants equally necessary. This article, building on earlier work by Head and Mayer (2009), sets out to provide an aggregation of trade costs that is derived from a very general representation of the gravity equation, while remaining agnostic to its micro-foundation. I apply the method to compute time-varying distances using nighttime satellite imagery. Using these theory-consistent distances, the elasticity of trade with respect to distance can be estimated in the within-dimension of a panel, allowing to control for time-invariant unobserved country pair characteristics. Further, the use of these distances produces the noteworthy results of significantly lower estimates of coefficients for variables that are correlated with distance. Most notable is an up to 50 % decrease in the estimated effect of borders on trade, i.e. the net cost of crossing a border.

In its earliest and simplest form, Tinbergen et al. (1962) described the volume of trade flows between countries as a function of the size of the two economies and their distance, borrowing an analogy from physics that has since named the relation: gravity. While the theoretical underpinnings of gravity of international trade have since received drastic improvements with Anderson (1979), Anderson and van Wincoop (2003) and others, the employed distance measures have seen 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. The contribution of this present paper is to improve the existing measures along multiple lines. First, I derive a trade cost aggregation that is agnostic to the underlying gravity framework, but yields concrete instructions on the method of computation and data to be used; Second, I turn to satellite imagery that provides information on 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 it moves away from a population-weighted measure towards a GDP-based measure, which is more consistent with the theoretical gravity frameworks. Third, the used data has an annual periodicity, allowing me to compute a time series of distances for each country pair and year since 1992.

The paper yields two important results. In the theoretical part I show that the estimated trade cost coefficient from a gravity equation serves also as a parameter in the respective trade cost aggregation itself. In the empirical part I then estimate the distance coefficient iteratively while, exploiting the data's time-variation, controlling for unobserved country-pair characteristics. The preferred distance elasticity estimate is in the vicinity of -1, in line with traditional results found in the gravity model 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 yields the second important, empirical, result of the paper. Using harmonic mean distances has consequences on 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 %. Additionally the coefficient on trade with a directly adjacent country is affected by a similar reduction, depending on the estimation method.

The paper is structured as follows: section 2 reviews the existing literature on distances and border effects in the gravity model. In section 3 I turn to theory to derive a simple trade cost aggregation that is agnostic to the underlying gravity framework. In section 4 I describe the data and computation method, and discuss some features of the distances. Section 5 then introduces a simple framework for evaluating the results. Finally in section 6 I estimate the distance coefficient and evaluate the border effect and that of other common gravity co-variates using the newly computed distance measure. Section 7 concludes.

2 Distances and borders in the literature

The present paper is of course related to a long literature on the effect of distance on trade, arguably one of the most persistent relations in economics (Head and Mayer, 2014). 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 indeed is "alive and well" (Disdier and Head, 2008). Distance itself is however only the proxy for various trade barriers: transportation costs, language barriers that tend to be correlated with distance, 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". Head and Mayer (2013) develop a helpful framework to conceptualize these trade barriers and facilitators as *light* and *dark matter* of trade costs.[2]

[1] See Disdier and Head (2008) and Head and Mayer (2014) for a survey.
[2] See also section 5.

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".[3] 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 due to exogenous events. This strategy allows them 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 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 -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

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

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 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 (2013) 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.[4] Coughlin and Novy (2016) also investigate the effects of spatial aggregation on the estimation of the border effect, arguing with the help of a model that larger countries mechanically report lower border effects than smaller countries.

[4]Interestingly, perhaps ironically, they do find a zip code-level border effect that 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 said zip code-level border effect.

In the following section I turn to theory and build on earlier work from Head and Mayer (2009) to derive a theory-based trade cost aggregation.

3 Theory-based trade cost aggregation

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

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

where x_{kl} are exports from a location k to another location l, s_k are exporter-specific terms, m_l importer-specific terms.[5] ϕ_{kl} is the bilateral resistance term, trade barriers and facilitators, between the two locations, θ being the trade elasticity. G can be thought of as a "gravitational constant".[6]

Bringing the model to the data can be considered very easy, but bears one caveat. Unfortunately most available trade data is aggregated to some degree and usually unavailable at fine-grained geographic detail.[7] Instead it is usually aggregated to geographic entities like 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 trade costs 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

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

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

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

[5] See appendix A.1 for the following derivation with a more explicit *structural gravity* setup. The resulting aggregation is isomorphic to the one below.

[6] See Head and Mayer (2014) for a detailed survey over the different underlying micro foundations. s_k and m_l usually embody a term that has been coined multilateral resistance term, accounting for country-specific factors determining its trade with all other locations. Similarly, the parameter θ has a range of different of interpretations, as briefly outlined in section 5.

[7] There are some notable exceptions in recent years, using micro-level data, as briefly discussed in section 2.

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 trade costs 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 trade costs have been generic. Let now ϕ be described by the function

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

where ϕ consists of a *location-specific* component χ_{kl}, like 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 trade costs to the location-specific trade costs and ϵ the elasticity to entity-specific ones. Following (1), country-level trade costs can then be rewritten as

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

where location-specific trade costs 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 exports of a geographic entity i to an entity j are therefore governed by the exporter- and importer specific terms s_i and m_j, entity-specific trade costs $\psi_{ij}^{\theta\epsilon}$, and the weighted *generalized mean* of location-specific trade costs $\chi_{ij}^{\theta\delta}$.

As Head and Mayer (2009) point out, the generalized mean has the convenient properties of reducing 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 $\theta\delta = 0$.

Importantly though, equation (2) asserts that the elasticity of trade with respect to location-specific trade costs $\theta\delta$ is also the exponent in this generalized mean.

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

Equations (2) and (3) however yield specific instructions on how to compute distances between trading entities consistently with theory. The weights in the general mean should incorporate information for *all* exporting and importing 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. In the following section I describe the data and process used to compute the distances.

4 Accurate distances using satellite imagery

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 as the weights for their distance aggregation, so that (2) becomes:

$$d_{ij} = \left(\sum_{k \in i} (\text{pop}_k / \text{pop}_i) \sum_{l \in j} (\text{pop}_l / \text{pop}_j) \, d_{kl}^{\theta\delta} \right)^{1/\theta\delta} \tag{4}$$

where d_{kl} is the great-circle distance between the geographic centers of two cities k and l, and pop_k/pop_i the share of city k's population in the total population of all cities in country i. Their population data comes originally from UN statistics. Aside from usual data collection issues that may lead to inaccuracies, there are three important caveats. First, the

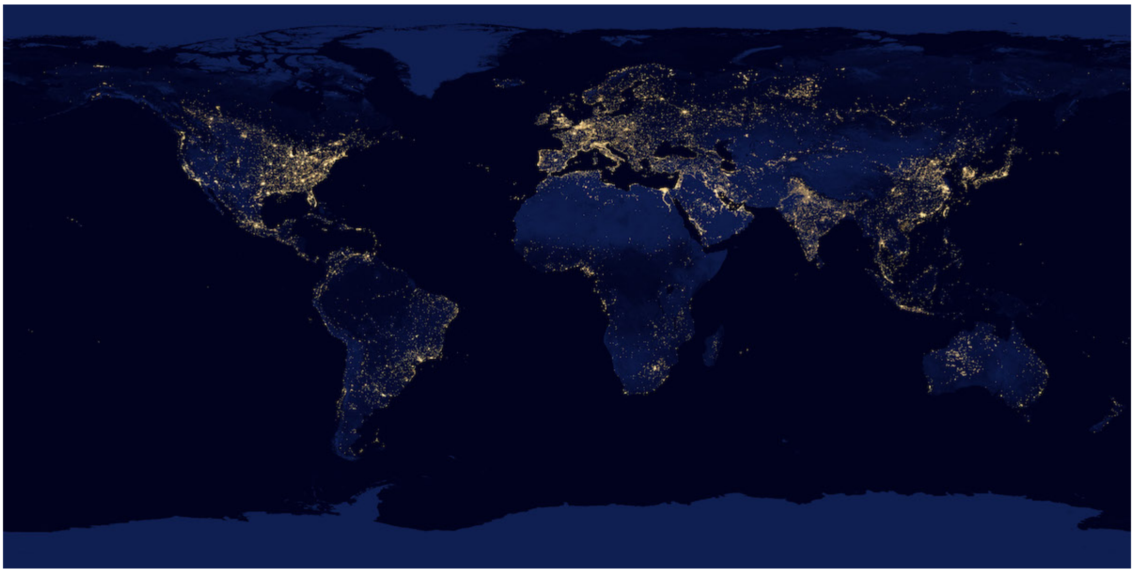


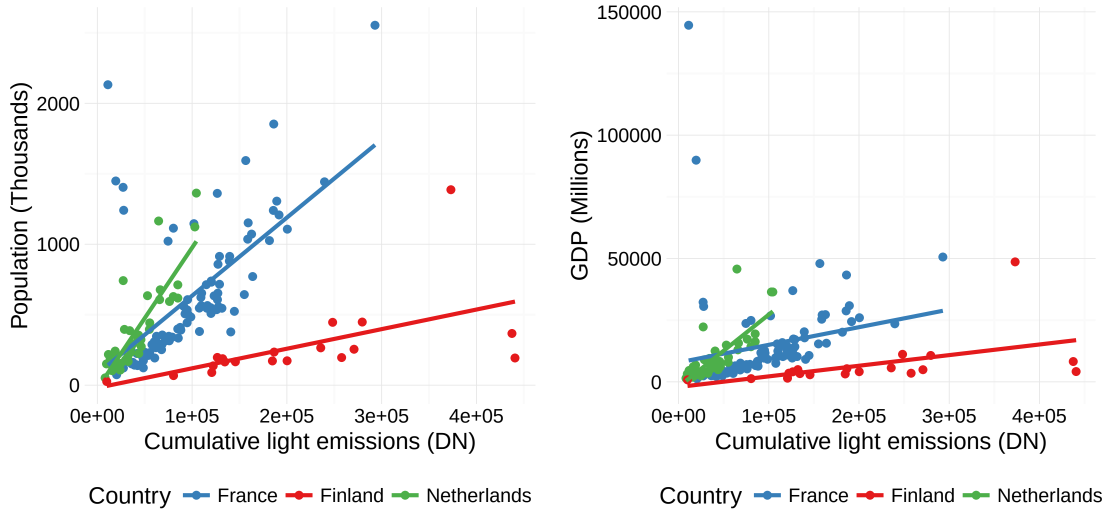
Figure 1: Nighttime light emissions in 2012 (Source: NOAA)

data is limited to a maximum of 25 cities, while economic activity is likely not limited to only those. 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. Here the authors resort to previously discredited area-based measures. Third, the data is only available for the year 2004. This assumes a static economic geography. This may be particularly questionable in developing and emerging economies.

4.1 Nighttime light emissions data

In trying to improve upon the existing measure, I am opting to use a different source of information on the sprawl of economic activity: nighttime satellite imagery. Figure 1 shows the fascinating picture of light visible from space, displaying the extent of human activity – and their 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 emission 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 yearly image then has a total of 725,820,001 pixels. Of these, roughly 60 million are on land and illuminated at some point in the time span between 1992 and 2012.

Using this data has a number of advantages. First, not only urban centers but also



(a) **(b)**

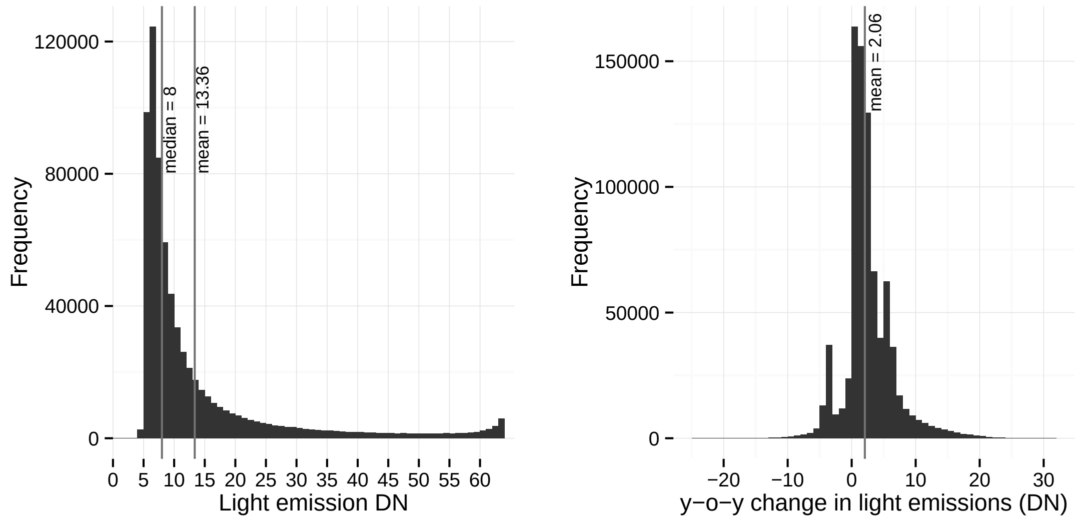
Figure 2: Light emissions and GDP or population by NUTS3 region.

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, as shown below in section 5.

Nighttime satellite imagery has been discovered as intriguing data for economic research before. 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. To my knowledge, I am the first to explicitly make use of the geographic information embedded in the data for economic research.

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 about $3.6 \cdot 10^{12}$. Next to managing these computational limitations and other technical issues such as the comparability of radiance figures over time,[8] a

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



(a) **(b)**

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

number of issues warrant attention. First, do light emission proxy well for the share of importer and exporter-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 total light emissions of each region with statistics that are usually assumed to have a close connection to importer- and exporter specific terms: economic output as measure by GDP and total population. Figures 2a and 2b show that total light emissions and these measures appear to be highly correlated *within* each country. Second, light emissions 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 light emissions are of low intensity and the year-on-year variation is very limited, signaling no drastic movements.

4.2 Computing theory-consistent distances

After some initial pre-processing of the data, I can proceed to computing the aggregate distance between each country pair for all years between 1992 and 2012. As Head and Mayer (2009), I assume that importer and exporter-specific terms in a location have the same share in their entity-aggregated importer and exporter-specific terms. Calling this share $w_k = \frac{s_k}{s_i} = \frac{m_k}{m_i}$, equation (2) can be rewritten in matrix form as:

$$d_{ij} = \left(\mathbf{w}_i^T \mathbf{D}_{ij}^{\theta\delta} \mathbf{w}_j\right)^{1/\theta\delta} \tag{5}$$

where

$$\mathbf{w}_i = \frac{1}{\sum_{k \in i} w_k} \begin{pmatrix} w_1 \\ \vdots \\ w_k \end{pmatrix} \tag{6}$$

and w_j accordingly, and

$$\mathbf{D}_{ij} = \begin{pmatrix} d_{1,1} & \cdots & d_{1,l} \\ \vdots & \ddots & \vdots \\ d_{k,1} & \cdots & d_{k,l} \end{pmatrix} \quad k \in i,\ l \in j \tag{7}$$

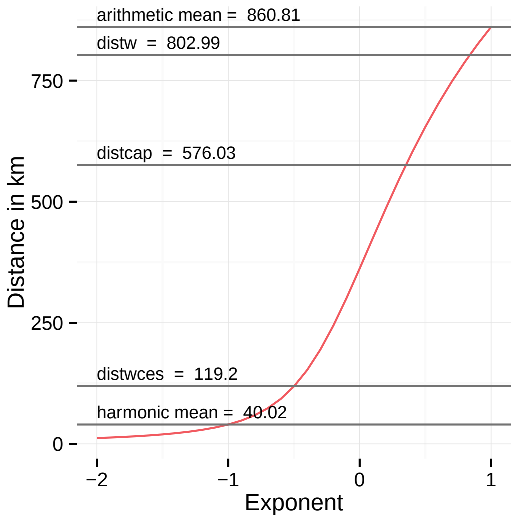
where $d_{k,l}$ is the great circle distance between locations k and l. The great circle distance between any two points is approximated by the spherical law of cosines. Using the described nighttime light emissions data, $\mathbf{w}_i$ is then proxied by the vector of each location k's share in the total light emissions of country i.

4.3 Distance variation over time and by exponent

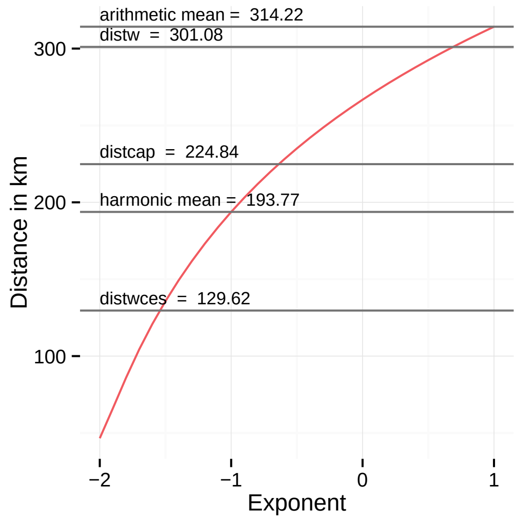
As derived above, the exponent in the generalized mean is supposed to be equal to the elasticity of trade with respect to distance.

In the literature the exponent $\theta\delta$ is usually implicitly set at 1 by the use of arithmetic mean distances, although traditionally estimation place the distance elasticity somewhere in the broader neighborhood of -1, calling for the use of harmonic mean distances.

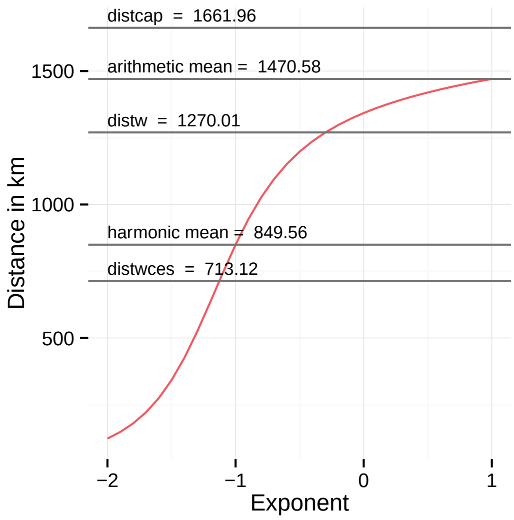
Figure 4 displays the computed bilateral distances as a function of the exponent $\theta\delta$ for four exemplary country pairs, including the distances provided by Mayer and Zignago (2011) for comparison. The results highlight the importance of picking the correct exponent. The difference between commonly 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 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.



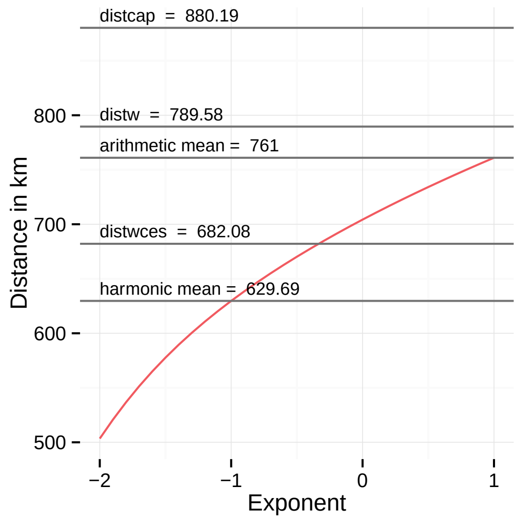
(a) Distance COD - COD



(b) Distance DEU - DEU



(c) Distance COD - RWA

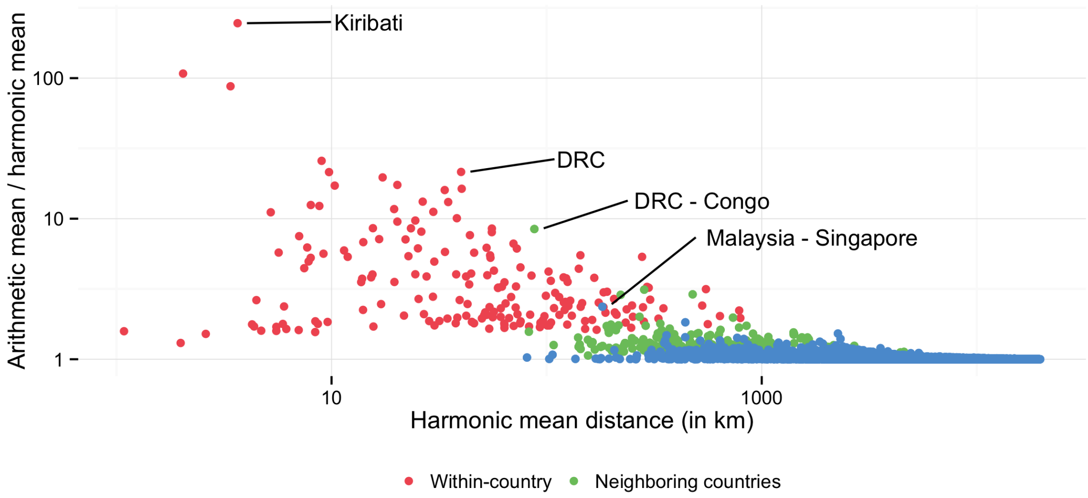


(d) Distance DEU - FRA

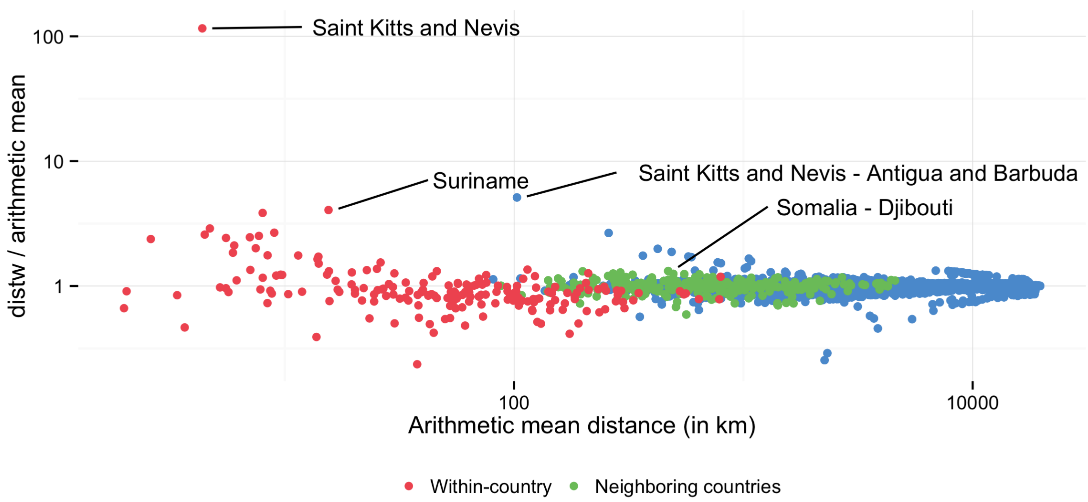
Figure 4: Aggregate distances depending on the exponent in generalized mean in 2000. Commonly used distances from Mayer and Zignago (2011) for comparison.

With respect to estimations of the gravity equation this entails an important effect that will be shown empirically in section 6: Assuming that the true aggregate distance is 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.[9] Again it becomes clear that internal distances are more affected than external distances and shorter distances are more affected than larger ones. In a gravity estimation this effect will be mainly picked up by the border coefficient. As

[9]It can be shown that in a hypothetical setting in which distance were the only trade cost, 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.



(a)



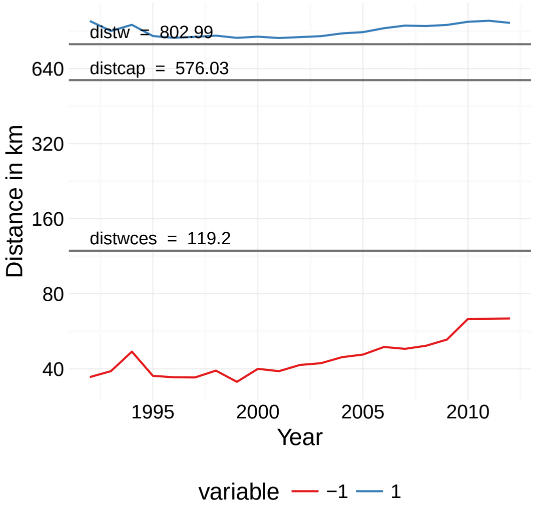
(b)

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

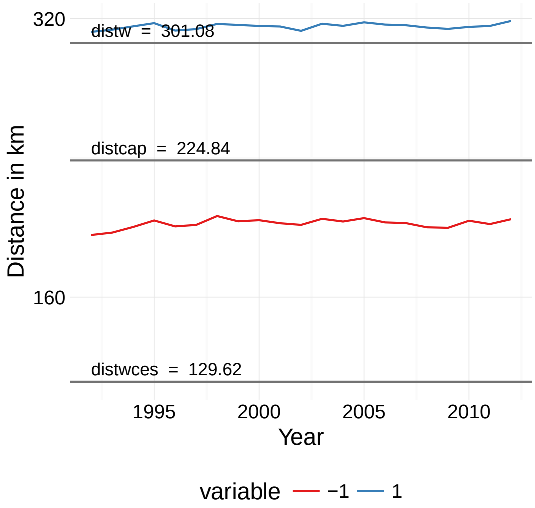
internal distances are overestimated relative to external distances, the border effect is artificially inflated as there is "too little" trade externally. [10] The effect could also partially be picked up by any variable that is correlated with shorter distances, as the effect itself decreases with distance.

Figure 5b highlights the issue of mismeasurement when using human-collected data and displays the aforementioned advantage of using satellite imagery for the weighting of

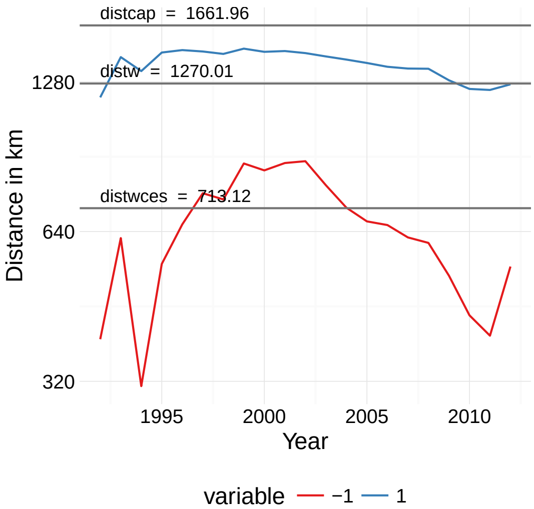
[10]Due to the saturation of the sensor of the satellite the radiance data is top-coded at DN 63, i.e. all values larger than 63 are coded as 63. This obviously biases the measurement: the computed harmonic mean might be still *overstating* the distance, so that the difference to the arithmetic mean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



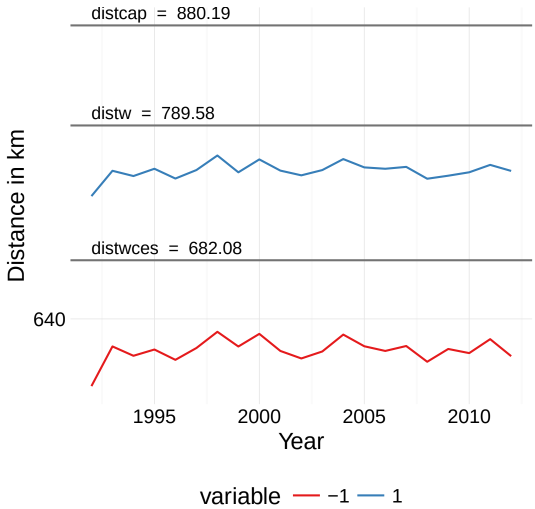
(a) Distance COD - COD



(b) Distance DEU - DEU



(c) Distance COD - RWA



(d) Distance DEU - FRA

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 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 much higher detail of information is available than through figures manually collected.

Another benefit of using light emissions data from satellite imagery as weights for the distance calculation is, as discussed above, its yearly availability. This allows me to calculate distances between all country pairs for each year since 1992.[11] Figure 6 shows the variation

[11]That is, given they existed at that point in time. There are a number of new countries in the data in the wake of the disintegration of former Yugoslavia, as well as territorial changes in other parts of the world. I use

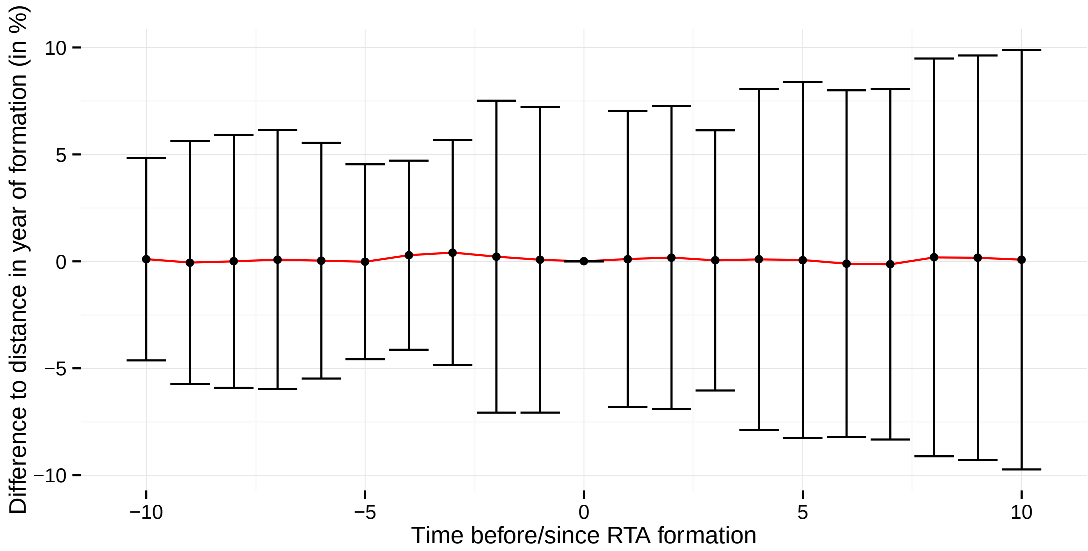


Figure 7: Mean change of distance for neighboring countries in RTAs in 10 years prior and after the formation. Bars display the 95% confidence interval.

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 expectedly much lower and lies between 187 and 195 kilometers for the harmonic mean and 309 and 318 for the arithmetic mean. Variation is also observed for between-country distances, although the effect itself is again a decreasing function of distance. The country pair of 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 country pair Germany - France exhibits muss 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 country pair distances for geographically close countries.

As noted in section 2, other research endeavours have estimated the effect of distance on trade in the within dimension of a panel. Feyrer (2009) and Hugot and Dajud (2014) 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

data on border locations from Weidmann et al. (2010). This provides an additional source of time variation that is not due to changes in economic geography.

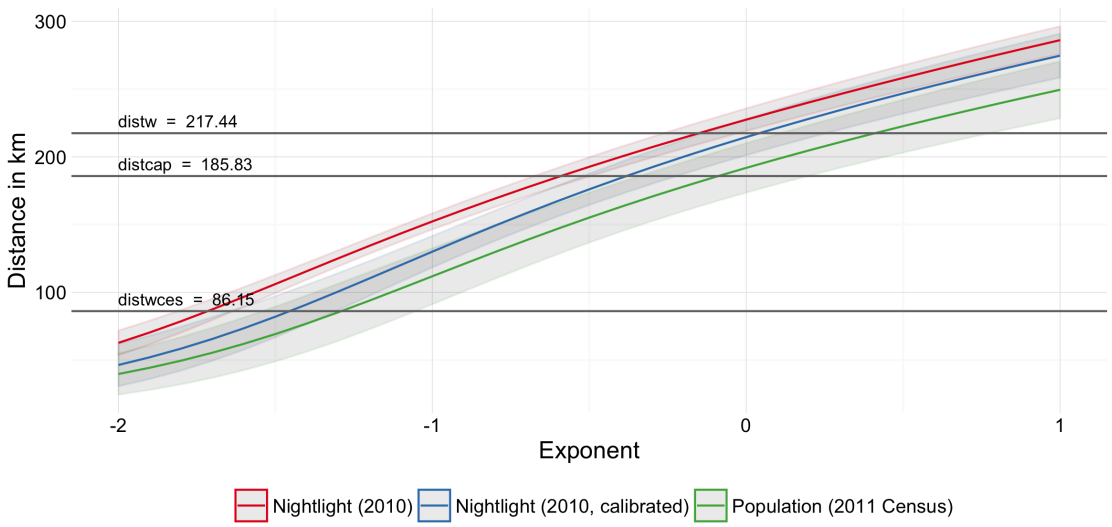


Figure 8: Distance for the UK with different source for weights (95 % confidence interval)

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. An example could be the car industry in southern Ontario, Canada: Due to 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 due to the relocation of economic activity. While this mechanism cannot be entirely ruled out, figure 7 suggests that a reduction in trade barriers (the formation of an RTA), or anticipation thereof, has no significant influence on the distance between neighboring countries. The mean percentage difference of the distance in the ten years around the formation of a RTA to the year of its formation is never significantly different from 0.[12]

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 for the weights *calibrated* nightlight data (blue line) made available by Hsu et al. (2015) and gridded 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-light urban areas. This in turn could yield consistently lower distances as a smaller

[12]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.

share of emitted light comes from non-urban areas. 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. Due to technical limitations of the sensor on the satellites this data is only available for select years (Hsu et al., 2015). 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.

5 Evaluating the new distance measure

Before running gravity equations with the computed distances in section 6, it is useful to construct a framework against which to evaluate the results. In their research program on gravity equations, Head and Mayer (2013) borrow another analogy from physics to describe the *known unknowns*[13] of trade barriers: dark trade costs. In physics, dark matter describes the seemingly immeasurable mass that leads to measurable outcomes that can otherwise not be reconciled with orthodox theories. In the present context of international trade, dark trade costs describe the fraction of trade costs that is observed but not quantifiable in usual terms of tariffs, transportation costs or other trade barriers and facilitators such as a common language spoken in two trading countries.

In section 3 trade costs ϕ_{ij} were assumed to have the form of

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

where ψ_{ij} is an *entity-specific* trade cost and χ_{ij} the aggregate of *location-specific* ones. ψ_{ij} can equivalently be thought of as capturing any type of border effects, while χ_{ij} captures distance effects. ϵ and δ are then the elasticities of trade costs to border and distance, respectively. When estimating a gravity equation, one usually estimates the elasticities of *trade* to these specific trade costs, that is to say $\theta\delta$ and $\theta\epsilon$.[14] The elasticity of trade to trade costs, θ, is a standard parameter in most theoretical models that yield a gravity-type expression. As Head and Mayer (2013) explain in further detail, it is $\sigma - 1$, i.e. the elasticity of substitution less 1, in Anderson and van Wincoop (2003)-type models; in Ricardian models à la Eaton and Kortum (2002) the parameter governs the distribution of labor

[13]Hat tip to former US Secretary of Defense Donald Rumsfeld, who popularized this term. However, it seems to originally have been coined by Nassim Nicholas Talib and/or NASA administrator William Graham.

[14]See Head and Mayer (2013) for a survey of studies that aim to estimate ϵ and δ directly.

requirements across countries; and in Chaney (2008), θ determines firm heterogeneity. In most cases, Head and Mayer (2014) report in a meta analysis, θ is in the range between 3 and 9, with a median of 5.

Following the analogy from physics, the observed distance coefficient can be broken down into

$$\theta\delta_g = \theta\left(\delta_l + \delta_d\right) \tag{8}$$

and analogously the border coefficient into

$$\theta\epsilon_g = \theta\left(\epsilon_l + \epsilon_d\right) \tag{9}$$

where the subscript g denotes the *gross* coefficient, l denotes *light* trade costs, i.e. known impediments or facilitators to trade, and the subscript d the above-mentioned *dark*, or unknown trade costs. In the exercise below, I exploit the time-variation that is present in the computed distances in order to estimate both $\theta\delta_g$, the gross effect of distance on trade, and $\theta\delta_l$, the measurable and unbiased direct effect of distance on trade. The difference between the two, $\theta\delta_d$, is the dark part.

6 Iterative estimation of Gravity equation

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 is has been estimated to be in the neighborhood of -1, relating nicely to the original analogy from physics. 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).

As noted above, the time-variation of the data allows me to exploit the within-dimension of the data to estimate the distance coefficient. The choice of the exponent in the generalized mean, as laid out in the previous section, makes a significant difference in the computed aggregate distance. In the following I use results from section 3 to aggregate distances using an iterative approach to find the *unbiased* exponent $\theta\delta_l$. 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

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

The equation can easily estimated with an OLS estimator in its log-linearized form as

$$\log X_{ij} = \alpha_0 + S_i + M_j + \alpha_1 \cdot \text{Controls}_{ij} + \beta_0 \cdot \text{Border}_{ij} + \beta_1 \cdot \log \text{Distance}_{ij} + \epsilon_{ij} \quad (10)$$

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

$$X_{ij} = \exp\left(\alpha_0 + S_i + M_j + \alpha_1 \cdot \text{Controls}_{ij} + \beta_0 \cdot \text{Border}_{ij} + \beta_1 \cdot \text{Distance}_{ij}\right) + \epsilon_{ij}. \quad (11)$$

The variables of interest are the estimated coefficients $\beta_1 = \theta\delta$ for the distance measure and later $\beta_0 = \theta\epsilon$ 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.

I estimate equations (10) and (11) in multiple specifications: first in section 6.1 in a panel, exploiting the within-dimension in order to obtain the unbiased effect of distance on trade. The addition of a country-pair fixed effect FE$_{ij}$ in the panel estimation captures all bilateral time-invariant characteristics. While this eliminates unobserved time-invariant country-pair features, it also captures the border coefficient β_0. In a second step in section 6.2 I estimate equations (10) and (11) in the cross section annually. This allows me to estimate the border effect using those distances computed with the distance coefficient from the panel estimation.

The iterative estimation procedure is as follows: Using an arbitrary initial value,[15] I estimate the gravity equation, retrieve the distance coefficient β_1 and then use it as the $\theta\delta$ in the calculation of the aggregate distance in equation (5). This new distance is then used for the next iteration. I repeat this process until the coefficient β_1 remains unchanged in its 5th digit.

In order to ensure robustness of the results I use multiple trade data sources and estimate on several different samples. For the panel estimation trade data comes primarily 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 robustness checks I use UN COMTRADE data (United Nations Statistics Division, 2015). For estimations where

[15] 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 only influences the number of iterations to get there.

Table 1: OLS estimation - pooled and within-dimension

	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
Adjusted R^2	0.776	0.778	0.778	0.918	0.918	0.918

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

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). It has the advantage of having consistent figures for internal and external trade. For the other two data sources, I calculate internal trade as the difference between GDP and total exports, per usual following Wei (1996).

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 equation (10) in a balanced 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.[16] Columns (1) to (3) of table 1 report the results for the benchmark pooled panel with different distance measures, arithmetic and harmonic mean distances as well as those from the generalized mean through iteration. 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.

All coefficients are highly significant. The results strongly suggest that the unbiased

[16]Coefficients are suppressed here but are almost identical to usual within-estimations of RTA and common currency coefficients.

Table 2: Robustness checks - different samples and datasets

	Dependent variable: log(flow)					
	(1)	(2)	(3)	(4)	(5)	(6)
log(Distance)	-1.019^{***}	-1.177^{***}	-0.615^{*}	-0.860^{***}	-1.399^{***}	-0.771^{**}
	(0.098)	(0.208)	(0.322)	(0.282)	(0.288)	(0.323)
Distance	iterate	iterate	iterate	iterate	iterate	iterate
Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Dataset	DOTS	DOTS	DOTS	DOTS	COMTRADE	TradeProd
Sample	Neighbors	External	High inc.	Low inc.	all	all
No. of Iterations	14	6	21	13	6	27
Observations	30,429	175,140	31,395	2,646	87,969	132,795
R^2	0.971	0.919	0.959	0.967	0.929	0.927
Adjusted R^2	0.961	0.911	0.954	0.934	0.921	0.918

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

distance coefficient is close to -1. 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 use the generalized mean with a coefficient of -1, i.e. the harmonic mean. Arithmetic mean distances strongly overstate short distances, as shown in section 4.3.

In order to ensure the robustness of the results I estimate the same equation on different samples and datasets. Table 2 column (1) reports the coefficient on neighboring country pairs, countries that directly share a border or are within a 2000km distance. Section 4.3 suggested that here the highest variation would be found. Again the distance coefficient is very close to -1. Column (2) reports the coefficient of -1.18 when restricting the sample to external trade. This suggests that the average effect of distance on *internal* trade is lower relative to that than on external trade, which appears reasonable and is in line with results from Yotov (2012). Columns (3) and (4) 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 columns (5) and (6) report the coefficient when using UN COMTRADE and TradeProd data. Both datasets have much lower numbers of observations than IMF DOTS, which might explain the difference in the estimated coefficients. However both coefficients, -1.4 for COMTRADE and -0.77 for TradeProd, are well in the range of reasonable results.

The results are appealing: the coefficient estimated in the preferred specification is highly significant and closely resembles the traditional estimate of the distance coefficient of around -1. Estimates from the other specifications are all well in the range of traditional estimates surveyed by Disdier and Head (2008) and Head and Mayer (2014).

Judging the results in terms of the framework setup in section 5, the estimated coefficient from the pooled panel regression can be thought of as the gross distance effect $\theta\delta_g$ from equation (8), while $\theta\delta_l$ is the coefficient estimated in the within dimension.

Differentiating then between the light and dark shares of the distance effect in terms of equation, I find that

$$\theta\delta_g = \theta\left(\delta_l + \delta_d\right)$$
$$-1.26 = -0.927 + \theta\delta_d$$

so that dark trade costs make up a share of $\delta_d/\delta_g = 0.264$. About one quarter of the traditionally measured distance effect is *dark*, i.e. due to trade costs that are merely correlated with distance.

The estimated coefficients for distance elasticity being very close to the customary estimate of -1, the results call for generally using harmonic mean distances in estimations of the gravity equation, as opposed to the traditionally used arithmetic mean distances. In the following, I analyze the effect using the former as opposed to the latter on various standard gravity controls variables.

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 resort to estimating it in the cross section annually. To ensure comparability, I use the same balanced panel as before and stratify by year, while bearing in mind that the bilateral coefficients might pick up other effects, as they cannot be controlled for with a country-pair dummy.

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. Some authors are arguing over whether other gravity controls, such as a dummy for RTA, neighboring country, or historical colonial linkages, should be set 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

Table 3: 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		
Adjusted R^2	0.848	0.849		

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

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* co-variates next to a border dummy and distance measure, the setting entails interpreting internal flows to be 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.[17]

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 capture (part) of those trade costs that are correlated with distance. Thinking in terms of dark and light parts of trade costs from equation (9), the estimated coefficient is then $\theta\epsilon_g$. Table 3 reports the coefficients for the estimations using TradeProd data 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.[18] 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

[17] Compare also Coughlin and Novy (2013) who argue along similar lines.

[18] See appendix D for the estimations with IMF DOTS dataset. The magnitude of the effects is similar.

Table 4: Change in border coefficient by group with TradeProd data

	Dependent variable:			
	log(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.

nevertheless.

Table 4 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 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. Indeed, the estimated border coefficient drops by far more for the group with a higher bias (from 2.31 to 0.79) than with a lower bias (from 1.55 to 0.98).

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.

Judging the results again by the framework set up in section 5, the applied tariff can be thought of as $\theta\epsilon_l$, so that in 1992 for the OLS estimator and harmonic mean distances

$$\theta\epsilon_g = \theta\left(\epsilon_l + \epsilon d\right)$$
$$exp(2.01/4) = 1.1189 + \epsilon_d$$

and hence the share of unknown border impediments expressed in a tariff equivalent is equal to $(\epsilon_d - 1)/(\epsilon_g - 1) = 0.82$. In 2006 this has dropped to about 0.33.

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

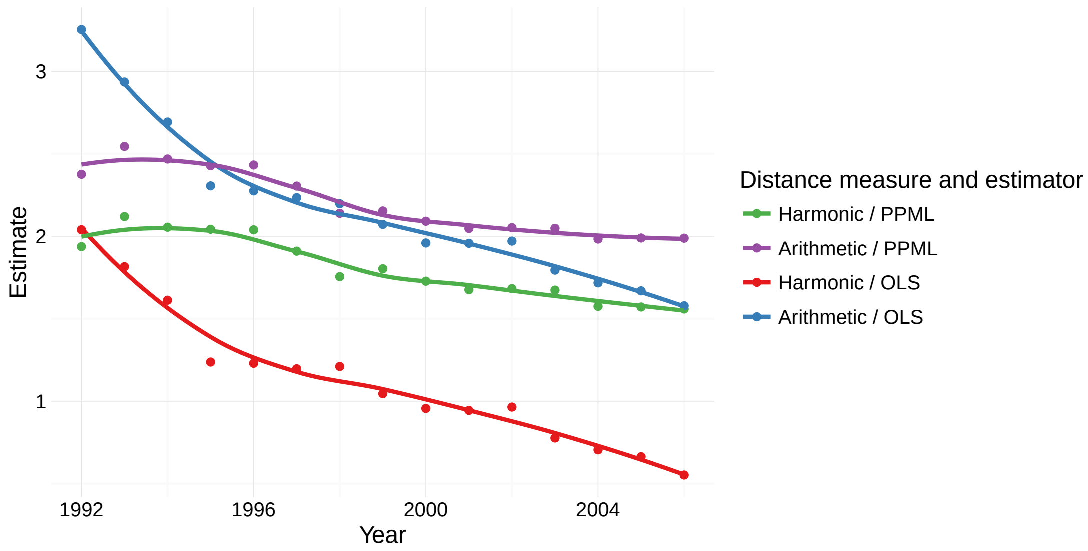


Figure 9: Gross border coefficients from cross section estimations using OLS and PPML estimators with TradeProd data.

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 suggest much shorter distances for internal trade flows than 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 and reduces the share of dark costs down to 33 %, conditional on the estimation technique employed.

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 (10) and (11) 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. To mind comes here 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 in greater distance.

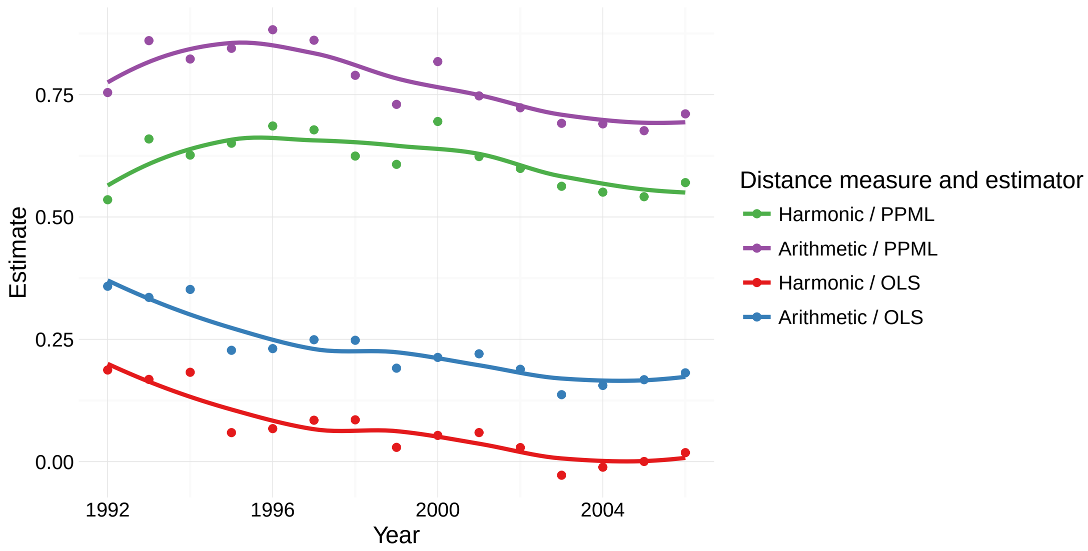


Figure 10: Neighbor coefficient over time by estimation method

Table 5: Gravity co-variates 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		
Adjusted R^2	0.797	0.797		
Residual Std. Error (df = 8471)	1.308	1.310		

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

Table 5 shows the estimates for the year 2000 and the TradeProd data for the most commonly used co-variates in the gravity equation: A dummy for trade between directly neighboring countries, the existance of a 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.

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 very simple structural gravity model à la Head and Mayer (2014) in which I explicitly set the bilateral trade costs, in this case solely 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 case 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

$$X_{ij} = \frac{Y_i}{\Omega_i} \cdot \frac{X_j}{\Phi_j} \cdot \phi_{ij} \tag{12}$$

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 Fally (2015) notes, 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 6: Gravity co-variates estimation with simulated data

	Dependent variable:					
	log(trade_flow)				trade_flow	
	(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		
Adjusted R^2	1.000	0.999	1.000	1.000		
Note:					*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

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

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

Conveniently equation (12) can be estimated as

$$\log(X_{ij}) = F_i + F_j + \hat{\delta} \cdot \ln(\text{Dist}_{ij}(\delta)) + \hat{\gamma} \cdot z_{ij} + \epsilon_{ij}$$

where F_i and F_j are fixed effects capturing all exporter and importer characteristics and z_{ij} is an additional bilateral variable. The coefficients of interest are $\hat{\delta}$, the estimated distance elasticity which is supposed to be equal to δ when estimated with the correct distance measure, and $\hat{\gamma}$, which is supposed to be zero, as ϕ_{ij} is only governed by distance. In case of a mismeasurement of the distance, $\hat{\gamma}$ could be non-zero, in which case z_{ij} were to 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 6 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 trade cost aggregation from a very general representation of structural gravity that takes into account location- and entity-specific trade costs. 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 most importantly, it yields an aggregation in the form of a generalized mean of location-specific trade costs where the exponent is equal to the elasticity of trade to these trade costs in the gravity model.

I then apply the procedure to the arguably most acknowledged proxy for location-specific trade costs, distances. Using annual high resolution satellite nighttime imagery 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 and the absence of mismeasurement. Additionally, the annual periodicity allows 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 allows me 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 in the preferred estimation conveniently very close to the traditional estimate of -1, is then used for the aggregation.

I show that with these harmonic mean 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. This result is driven by the fact that arithmetic mean distances strongly overstate short distances relative to harmonic mean distances. It is consistent with the literature suggesting that the border puzzle generally disappears when using disaggregated data on volume and distance of shipment, such as in Hillberry and Hummels (2008). Regressions using simulated data confirm the theoretical and empirical findings and support the magnitude of the estimated effects.

The results strongly suggest the use these harmonic mean distance over the de-facto standard of arithmetic mean distances. The new distance measure also warrants an evaluation on the effect of national and subnational borders in the initial spirit of McCallum (1995) and recently Coughlin and Novy (2013), testing the results of this present paper on less aggregated flows.

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A Theoretical appendix

A.1 Aggregation for structural gravity

Following Head and Mayer (2014), structural gravity 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.[19]

Finally putting it all together yields

$$\begin{aligned}X_{ij}&=\frac{Y_i}{\Omega_i}\cdot\frac{X_j}{\Phi_j}\cdot\sum_{k\in i}\sum_{l\in j}\frac{Y_k/\Omega_k}{Y_i/\Omega_i}\frac{X_l/\Phi_l}{X_j/\Phi_j}\phi_{kl}^{\theta}\\&=\frac{Y_i}{\Omega_i}\cdot\frac{X_j}{\Phi_j}\cdot\phi_{ij}^{\theta}\quad\text{with}\quad\phi_{ij}=\left(\sum_{k\in i}\sum_{l\in j}\frac{Y_k/\Omega_k}{Y_i/\Omega_i}\frac{X_l/\Phi_l}{X_j/\Phi_j}\phi_{kl}^{\theta}\right)^{\frac{1}{\theta}}\end{aligned}\tag{13}$$

which is isomorphic to equation (1).

[19]See also Ramondo et al. (2012), whose aggregation over regions yields a similar country-level price index.

B 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 60,000,000 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. (2010). 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 Gravity results

D.1 Border effect

Table 7: 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		
Adjusted R^2	0.777	0.780		
Residual Std. Error (df = 7288)	1.450	1.439		

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

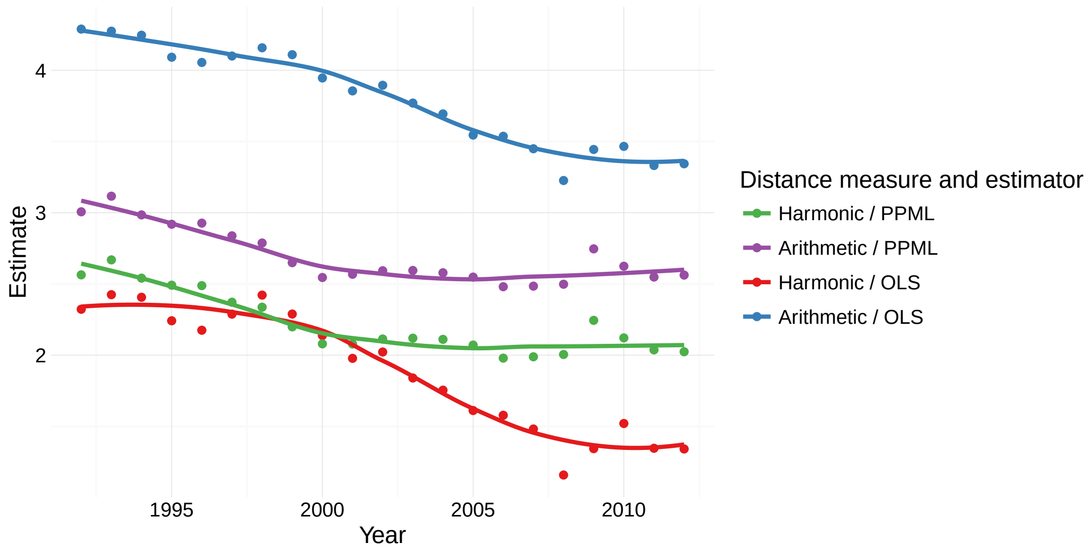

Figure 12: Gross border coefficients from cross section estimations using OLS and PPML estimators with IMF DOTS data.

D.2 Effect on other variables

Table 8: Gravity co-variates estimation with IMF DOTS data

	Dependent variable:			
	log(flow)		flow	
	(1)	(2)	(3)	(4)
log(distance)	−1.321***	−1.279***	−0.592***	−0.531***
	(0.031)	(0.030)	(0.017)	(0.015)
neighbor	0.359***	0.202**	0.367***	0.347***
	(0.095)	(0.097)	(0.027)	(0.027)
rta	0.532***	0.544***	0.855***	0.893***
	(0.065)	(0.065)	(0.038)	(0.038)
comcur	0.301**	0.299**	−0.029	−0.059*
	(0.131)	(0.131)	(0.035)	(0.036)
colony	1.049***	1.047***	0.048	0.073**
	(0.105)	(0.105)	(0.033)	(0.032)
comlang off	0.199***	0.200***	0.052*	0.019
	(0.059)	(0.059)	(0.031)	(0.031)
comleg	0.335***	0.334***	0.186***	0.186***
	(0.042)	(0.042)	(0.021)	(0.021)
Estimator	OLS	OLS	PPML	PPML
Distance	arithmetic	harmonic	arithmetic	harmonic
Observations	8,340	8,340	8,340	8,340
R^2	0.773	0.772		
Adjusted R^2	0.764	0.763		
Residual Std. Error (df = 8009)	1.440	1.441		

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

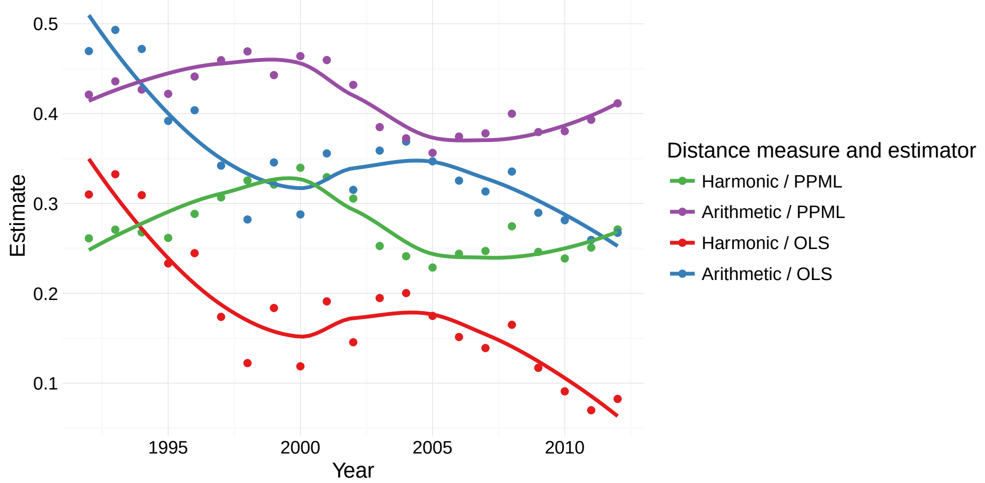

Figure 13: Neighbor coefficient over time by estimation method