Estimating Border Effects: The Impact of Spatial Aggregation

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Abstract

Trade data are typically aggregated across space. In this paper, we investigate the sensitivity of gravity estimation to spatial aggregation. We build a model in which micro regions are aggregated into macro regions. We then apply the model to the large literature on border effects in domestic and international trade. Our theory shows that aggregation leads to border effect heterogeneity. Larger regions and countries are systematically associated with smaller border effects. We test our theory with aggregate and industry-level trade flows for U.S. states. Our results confirm the model's predictions, with strong heterogeneity patterns.

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1 Introduction

By how much do borders impede international trade? It has been a major objective of research in international trade to identify the frictions that hinder the international integration of markets, and many policy makers across the globe are keen on reducing them.

Ever since the seminal paper by McCallum (1995), many researchers have used the gravity equation as a workhorse model to estimate so-called border effects. The aim is to estimate by how much borders reduce international trade. In their simplest form, gravity equations with border dummies are estimated based on aggregate bilateral trade data. As aggregates, these data combine the trade flows of spatial subunits (such as boroughs, municipalities and counties) into trade flows at higher levels of spatial aggregation (such as regions, states and countries). The question we address in this paper is how this process of aggregation affects the estimation of border effects. How do border effects depend on the spatial units we find in any given data set? Put differently, how do border effects depend on the way we slice up the map?

To understand the effects of spatial aggregation, we build a theoretical framework based on a large number of 'micro' regions that trade with each other subject to spatial frictions. We then aggregate these regions into larger 'macro' regions. Due to the spatial frictions, the more micro regions we combine, the more we increase the cost of trading within the newly aggregated macro regions. As a result, aggregation increases the relative cost of trading within borders as opposed to across borders.

Our theory shows how this shift in relative cost leads to heterogeneous border effect estimates: smaller regions are associated with relatively strong border effects, and larger regions are associated with relatively weak border effects. We call this the *spatial attenuation effect*. It represents an important testable implication for the estimation of border effects. A second implication is that since standard border effects are averages of the underlying individual border effects, sample composition effects occur. That is, samples which happen to include many large regions (or countries) tend to have moderate border effects, and vice versa. A third implication is that when regions are combined into larger aggregates, their associated estimated border effects should weaken in magnitude.

In the empirical part of the paper, we test these theoretical implications with domestic and international trade flows at the level of U.S. states, both for aggregate data and at the industry level. Our results confirm the model's predictions, in particular the systematic heterogeneity of border effects across states. For example, we find that for a large state like California, removing the U.S. international border would lead to an increase of bilateral trade on average by only 13 percent, whereas for a small state like Wyoming trade would go up over four times as much (61 percent). We also find evidence of systematic sample composition effects. This means that border effects are typically not directly comparable across studies since samples inevitably vary as they contain different sets of spatial units. We also carry out a hypothetical scenario of aggregating U.S. states into larger spatial units such as the nine Census divisions defined by the U.S. Census Bureau. Consistent with our model, we obtain smaller estimated border effects at the level of Census divisions. Overall, we find that spatial aggregation has a strong, first-order quantitative impact on border effects.

The estimated border effects represent the direct impact of border frictions on trade flows. But in general equilibrium there are also indirect effects that operate through price indices. In the trade literature these are typically referred to as multilateral resistance effects, as highlighted by Anderson and van Wincoop (2003). We demonstrate that our mechanism of spatial aggregation is separate from such price index effects. In our model, due to the symmetric location of micro regions, every location faces the same price index, and aggregation does not affect this equilibrium structure. We therefore obtain border effect heterogeneity that is not related to price index effects. In the data, when we have to keep track of varying price indices across space, we find that the heterogeneity of border effects stemming from spatial aggregation clearly dominates the heterogeneity coming from general equilibrium effects. Moreover, we use our model to numerically simulate border effects. This further illustrates the spatial attenuation effect in operation. Finally, we explore potential determinants of border effects, namely transport infrastructure.

Our theory and empirical results on spatial aggregation apply to both branches of the border effects literature: the international border effect and the domestic border effect. McCallum (1995) found that Canadian provinces trade up to 22 times more with each other than with U.S. states. This astounding result has led to a large literature on the trade impediments associated with international borders. Anderson and van Wincoop (2003) famously revisit the U.S.-Canadian border effect with new theory-consistent estimates. Although they are able to reduce the border effect considerably, the international border remains a large impediment to trade. Havránek and Iršová (2017) provide an overview of this extensive literature.[1]

A parallel and somewhat smaller literature has explored the existence of border effects within a country, known as the domestic border effect or intranational home bias.

[1] Anderson and van Wincoop (2004) report 74 percent as an estimate of representative international trade costs for industrialized countries (expressed as a tariff equivalent). Hillberry (2002) and Chen (2004) document significant but varying border effects at the industry level. Anderson and van Wincoop (2004, section 3.8) provide guidance and intuition for border effects in the case of aggregation across industries with industry-specific elasticities of substitution and possibly also industry-specific border barriers. We provide industry-level evidence in section 4.9.

For example, Wolf (2000) and Millimet and Osang (2007) find that after controlling for economic size, distance and a number of additional determinants, trade within individual U.S. states is significantly larger than trade between U.S. states. Similarly, Nitsch (2000) finds that domestic trade within the average European Union country is about ten times larger than trade with another EU country. Nitsch and Wolf (2013) find a persistent domestic border effect between East and West Germany that has declined only slowly after reunification. Wrona (2018) documents an east-west border effect within Japan.

Our approach is inspired by Hillberry and Hummels (2008) who find empirically that border effects at the ZIP code level within the United States would be enormous, by far eclipsing the magnitude of traditional border effects typically found in the literature. Havránek and Iršová's (2017) meta-analysis of border effects highlights a related pattern, i.e., smaller economies tend to have stronger estimated international border effects than larger economies. To the best of our knowledge, our paper is the first in the literature to provide a formal explanation of these patterns. We show that the underlying mechanism operating through spatial aggregation applies to both domestic and international border effects.

Our results on heterogeneous border effects and spatial attenuation illustrate a more general issue known in the geography literature as the Modifiable Areal Unit Problem.[2] Briant, Combes, and Lafourcade (2010) systematically highlight this problem for empirical work in economic geography. In the context of Canadian provincial border effects, Bemrose, Brown and Tweedle (2020) find that these border effects decline when geographic units become more similar in size and shape. Our contribution is to provide a theoretical foundation for spatial aggregation that allows us to obtain precise analytical results for the size of estimated border effects. Our paper can thus be seen as an attempt to apply the general notion of the Modifiable Areal Unit Problem to the specific context of gravity estimation of border effects.

Our results highlight theoretically and empirically that border effect coefficients capture a relative cost, i.e., the cost of trading across relative to within borders (also see Agnosteva, Anderson and Yotov 2019), and that this relative cost systematically shifts with the size of spatial units. More generally, our paper is also related to the recent literature in international trade that explicitly models internal trade costs (Ramondo, Rodríguez-Clare and Saborío-Rodríguez 2016), or models space as a continuum (Allen and Arkolakis 2014). Ramondo et al. (2016) are concerned with endogenous growth models and thus, they address a distinct set of questions. However, in their framework as in ours, it is key to move away from the crude assumption of zero internal trade costs. As

[2] See Fotheringham and Wong (1991).

do they, we depart from the assumption that a country is fully integrated domestically with zero trade costs, in which case it can no longer be treated as a single dot.

The paper is organized as follows. In section 2 we briefly describe the typical estimation of border effects in the literature. In section 3 we use the theoretical gravity framework to outline the general problem of spatial aggregation. We then present a formal model of spatial aggregation with a closed-form solution for the international border effect. In section 4 we take the theory to the data and explore the testable implications, using domestic and international trade flows for U.S. states. We also discuss multilateral resistance effects in general equilibrium and explore transport infrastructure as a potential determinant of border effects. In section 5 we discuss the implications of our analysis for the interpretation of border effects, in particular to what extent they could be seen as statistical artefacts. We conclude in section 6 by providing practical recommendations for border effect estimation. In the appendix we provide further details on the theory including a separate model of spatial aggregation for the domestic border effect, and we also describe our data and provide numerical simulations.

2 Border effects in gravity estimation

The seminal contribution of McCallum (1995) has led to a large number of papers that estimate border effects based on a gravity framework. For both the theoretical and empirical analysis of border effects in this paper, we follow the canonical structural gravity model by Anderson and van Wincoop (2003). They derive their model from an endowment economy under the Armington assumption of goods differentiated by country of origin. It is well-known that a near-isomorphic gravity structure can be derived from different types of trade models.[3] We first briefly review how domestic and international border effects are typically defined in the literature.

2.1 The structural gravity framework

We adopt the widely used structural gravity framework by Anderson and van Wincoop (2003). They derive the following gravity equation for the value of exports x_{ij} from region i to region j:

$$x_{ij} = \frac{y_i y_j}{y^W} \left(\frac{t_{ij}}{P_i P_j} \right)^{1-\sigma}, \tag{1}$$

[3] Head and Mayer (2014) state the structural gravity framework more generally. Arkolakis, Costinot and Rodríguez-Clare (2012) analyze the properties of the underlying Armington model in more detail. In addition, they demonstrate under which conditions near-isomorphic gravity equations hold for Ricardian trade models such as Eaton and Kortum (2002) and trade models with heterogeneous firms such as Melitz (2003) and Chaney (2008).

where y_i and y_j denote nominal income of regions i and j, and y^W denotes world income. The bilateral trade cost factor is given by $t_{ij} \geq 1$ (one plus the tariff equivalent). It is assumed symmetric for any given pair (i.e., $t_{ij} = t_{ji}$). P_i and P_j are the multilateral resistance terms, which can be interpreted as average trade barriers of regions i and j.[4] The parameter $\sigma > 1$ is the elasticity of substitution across goods from different countries. There are N regions in the sample.

In the theory and the data, we will deal with three different tiers of trade flows: *international* trade flows that cross an international border, *domestic* bilateral trade flows between different regions of the same country, and *internal* trade flows within regions.[5]

2.2 The trade cost function

We follow McCallum (1995) and other authors by hypothesizing that trade costs t_{ij} are a log-linear function of bilateral geographic distance $dist_{ij}$, and an international border barrier represented by the dummy INT_{ij} that takes on the value 1 whenever regions i and j are located in different countries, and 0 otherwise. The INT_{ij} variable is therefore an *international border dummy.* We also include a dummy variable DOM_{ij} for bilateral domestic trade flows that takes on the value 1 whenever regions i and j are in the same country but distinct ($i \neq j$), and 0 otherwise. In a sample without international flows, we therefore refer to the DOM_{ij} dummy as the *domestic border dummy* since the case of $DOM_{ij} = 1$ implies that a domestic border has been crossed.[6]

We can express our trade cost function as

$$\ln\left(t_{ij}^{1-\sigma}\right) = \beta INT_{ij} + \gamma DOM_{ij} + \rho \ln\left(dist_{ij}\right), \tag{2}$$

where β and γ are dummy coefficients, and ρ is the distance elasticity of trade. We log-linearize gravity equation (1) and insert the trade cost function (2) to obtain

$$\ln\left(x_{ij}\right) = \ln\left(y_i\right) + \ln\left(y_j\right) - \ln\left(y^W\right) + \ln\left(P_i^{\sigma-1}\right) + \ln\left(P_j^{\sigma-1}\right) + \beta INT_{ij} + \gamma DOM_{ij} + \rho \ln\left(dist_{ij}\right), \tag{3}$$

where β and γ are the coefficients of interest used to compute border effects.[7] Both coef-

[4]As explained by Anderson and van Wincoop (2003, footnote 12), symmetry between outward and inward multilateral resistance price indices implies a particular normalization. Alternative normalizations are possible such that outward and inward multilateral resistance terms differ but they would differ by a factor of proportionality that is constant across countries.

[5]Some authors use *domestic* to describe trade flows within a region. We stick to *internal* here.

[6]The DOM_{ij} dummy corresponds to the 'ownstate' dummy in Hillberry and Hummels (2003) and the 'home' dummy in Nitsch (2000), with the 0 and 1 coding swapped.

[7]For instance, suppose $\beta = -0.5$. As a back-of-the-envelope calculation ignoring price index effects, all else equal international trade flows would only be 61 percent as large as other trade flows since $\exp(-0.5) = 0.61$. In partial equilibrium, this would typically be interpreted as a border effect equivalent

ficients are typically found to be negative, and we will reproduce such standard estimates in the empirical section 4. The distance elasticity is typically estimated around $\rho \approx -1$ based on OLS estimation and closer to $\rho \approx -0.7$ with PPML estimation.

Expression (2) nests the most common trade cost functions in the literature. Wolf (2000) and Hillberry and Hummels (2003) only consider trade flows within the United States so that an international border effect cannot be estimated. This corresponds to $\beta = 0$ in trade cost function (2). Conversely, Anderson and van Wincoop (2003) follow McCallum's (1995) specification that does not allow for a domestic border effect ($\gamma = 0$).

3 A theory of spatial aggregation

We now explore formally how border dummy coefficients are affected when regions are spatially aggregated. We first describe the problem of spatial aggregation in general terms before turning to a more specific model.

3.1 The general problem of spatial aggregation

Our modeling strategy is to imagine a world of many 'micro' regions as the basic spatial unit. We then aggregate these micro regions into larger 'macro' regions that more closely resemble those we observe in the data. We can think of large regions as a cluster of many micro regions combined. For example, we can imagine California as a cluster of a fairly large number of micro regions, but in comparison Vermont is a cluster of only a few micro regions.

3.1.1 The basic framework

We model the world as consisting of an arbitrary number of small micro regions denoted by the subscripts k and l. Each region is endowed with a differentiated good as in the Armington framework of Anderson and van Wincoop (2003). As in expression (1), the standard gravity equation for trade flows x_{kl} holds:

$$x_{kl} = \frac{y_k y_l}{y^W} \left(\frac{t_{kl}}{P_k P_l} \right)^{1-\sigma}, \tag{4}$$

where bilateral trade costs are assumed symmetric (i.e., $t_{kl} = t_{lk}$). We assume the same trade cost function as in expression (2):

$$t_{kl}^{1-\sigma} = \exp\left(\zeta BORDER_{kl}\right) \; dist_{kl}^{\rho}, \tag{5}$$

to a reduction of international trade by 39 percent.

where $\zeta BORDER_{kl}$ is a stand-in that could equal either βINT_{kl} for the international border effect or γDOM_{kl} for the domestic border effect.

How can we measure a border effect? It is implied by the comparison of a trade flow across the border relative to a trade flow within the border. For example, we can compare $x_{kl'}/x_{kl}$ where trade of region k with region l' crosses the border and trade with region l does not.[8] Using equations (4) and (5) we can solve for the implied border dummy coefficient as

$$\exp(\zeta) = \frac{x_{kl'}}{x_{kl}} \frac{y_l/P_l^{1-\sigma}}{y_{l'}/P_{l'}^{1-\sigma}} \frac{dist_{kl}^{\rho}}{dist_{kl'}^{\rho}}. \tag{6}$$

That is, the border barrier coefficient ζ is a function of relative trade flows, other relative trade cost components (represented by distance) and region-specific factors (income and multilateral resistance price indices). The implied border coefficient is by construction the same for all possible pairings of trade flows across and within the border, and equivalent versions of expression (6) would hold for all these pairings, not just for the particular pairing $x_{kl'}/x_{kl}$. In other words, the gravity system (4) and (5) implies a common border coefficient that can be identified with standard regression methods.[9] We will now see how spatial aggregation changes this conclusion.

3.1.2 Aggregation

We aggregate micro regions into macro regions. Micro regions with a k subscript are aggregated into a macro region denoted with an i subscript, and micro regions with an l subscript are aggregated into a macro region with a j subscript. The resulting aggregate trade flow between macro region i and macro region j follows as the sum of all underlying micro flows, given by

$$x_{ij} = \sum_{k \epsilon i} \sum_{l \epsilon j} x_{kl} = \sum_{k \epsilon i} \sum_{l \epsilon j} \frac{y_k y_l}{y^W} \left(\frac{t_{kl}}{P_k P_l} \right)^{1-\sigma}. \tag{7}$$

If i and j are made up of exactly the same set of micro regions, then $x_{ii} = x_{jj}$ is an internal flow. If i and j are disjoint sets, then x_{ij} represents a bilateral flow with $x_{ij} = x_{ji}$. We assume there is no aggregation of micro regions across countries. That is, all micro regions aggregated into i belong to the same country, and the same holds for the micro regions subsumed into j.

To simplify equation (7) we define the weight parameter $\theta_{k,i} \equiv (y_k/P_k^{1-\sigma})/(y_i/P_i^{1-\sigma})$

[8] In case of the domestic border effect, we would have $l = k$ such that the benchmark trade flow becomes x_{kk}.

[9] For example, a log-linearized gravity specification as in equation (3) can be estimated where region-specific factors are absorbed by fixed effects. See the empirical analysis in section 4.

so that we arrive at

$$x_{ij} = \frac{y_i y_j}{y^W} \frac{\sum_{k\epsilon i} \sum_{l\epsilon j} \theta_{k,i} \theta_{l,j} t_{kl}^{1-\sigma}}{(P_i P_j)^{1-\sigma}}.$$

When we further define aggregate trade costs t_{ij} as a weighted CES trade cost index with

$$t_{ij}^{1-\sigma} \equiv \sum_{k\epsilon i} \sum_{l\epsilon j} \theta_{k,i} \theta_{l,j} t_{kl}^{1-\sigma}, \tag{8}$$

we obtain

$$x_{ij} = \frac{y_i y_j}{y^W} \left(\frac{t_{ij}}{P_i P_j} \right)^{1-\sigma}.$$

This equation looks the same as the standard gravity equation (1). But the key difference is that aggregate trade costs t_{ij} are endogenous. They contain the weight parameters $\theta_{k,i}$ and $\theta_{l,j}$ that are functions of endogenous income and price index terms. Inserting trade cost function (5) into the trade cost index, we further find

$$t_{ij}^{1-\sigma} = \exp\left(\zeta BORDER_{ij}\right) \; \widetilde{dist}_{ij}^{\rho} \tag{9}$$

with

$$\widetilde{dist}_{ij}^{\rho} \equiv \sum_{k\epsilon i} \sum_{l\epsilon j} \theta_{k,i} \theta_{l,j} dist_{kl}^{\rho}, \tag{10}$$

where $\widetilde{dist}_{ij}$ is a CES distance index with endogenous weight parameters.[10]

To measure the border effect with spatially aggregated data, we perform the same type of comparison as in equation (6). We obtain

$$\exp\left(\zeta\right) = \frac{x_{ij'}}{x_{ij}} \frac{y_j / P_j^{1-\sigma}}{y_{j'} / P_{j'}^{1-\sigma}} \frac{\widetilde{dist}_{ij}^{\rho}}{\widetilde{dist}_{ij'}^{\rho}}, \tag{11}$$

where $x_{ij'}$ is an aggregate cross-border trade flow and x_{ij} is an aggregate within-border flow. As with micro regions, this type of comparison yields the same common border coefficient for all possible pairings but only if we use the theoretically consistent distance index correctly constructed as indicated by equation (10). If researchers use alternative distance measures – perhaps because the relevant micro-level distances and the corresponding weights in equation (10) are not observable – then the implied border coefficients will generally deviate from the true underlying micro friction ζ.

If we set equations (6) and (11) equal, we get a condition for obtaining the same common implied border coefficients from micro-level and macro-level data. This condition

[10] This distance index is similar to the one in Head and Mayer (2009) but it accounts for multilateral resistance terms.

is:

$$\frac{x_{kl'}}{x_{kl}} \frac{y_l/P_l^{1-\sigma}}{y_{l'}/P_{l'}^{1-\sigma}} \frac{dist_{kl}^{\rho}}{dist_{kl'}^{\rho}} = \frac{x_{ij'}}{x_{ij}} \frac{y_j/P_j^{1-\sigma}}{y_{j'}/P_{j'}^{1-\sigma}} \frac{\widetilde{dist}_{ij}^{\rho}}{\widetilde{dist}_{ij'}^{\rho}} \tag{12}$$

for all possible pairings as described above. This condition can be seen as a "neutrality result" in the sense that it would have to be met for aggregation not to affect estimated border dummy coefficients. But it is unlikely to hold in practice given that popular empirical distance measures such as distances between capital cities are not based on the theoretically consistent distance aggregator in equation (10).

We can build intuition by looking at a special case. Imagine all micro regions were of symmetric size and had symmetric price indices. Then all weight parameters would be equal (i.e., $\theta_{k,i} = \theta_{l,j} = 1$ for all k, l, i, j). If in addition all micro-level distances aggregated for a particular flow were equal (i.e., $dist_{kl} = dist_{ij}$), then the distance aggregator would be the same as the micro-level distances (i.e., $\widetilde{dist}_{ij} = dist_{kl}$). The neutrality result (12) would hold, and aggregation would have no impact on the implied border coefficient. The intuition is that aggregation makes no difference as long as the aggregated micro regions are economic "clones" with the same size and the same trade costs over all micro-level flows that need to be aggregated to obtain the macro-level flow. However, as we show in the remainder of section 3, the conditions for this special case are very restrictive and unrealistic, and they are inconsistent with the empirical evidence in section 4.[11]

For further intuition, let us assume we initially measure the border effect in equation (11) correctly by using the appropriate distance aggregator on the right-hand side. Then, all else being equal, suppose we mismeasure bilateral distance for the within-border flow by employing a measure $dist_{ij}$ that is shorter than suggested by the distance aggregator, i.e., $dist_{ij} < \widetilde{dist}_{ij}$. Due to the negative distance elasticity ($\rho < 0$) the smaller distance measure would lead to an increase in the implied border friction ζ. Given that ζ is typically negative (see section 2.2), the inferred border friction would seem less severe (i.e., less negative). Intuitively, if the distance for trade within borders is relatively short, then we would expect more trade within and less trade across borders. To reconcile this view with the observed trade ratio $x_{ij'}/x_{ij}$, we would conclude that the implied border friction cannot be as burdensome. Thus, underestimating within-border distances will lead us to underestimate the border friction. Vice versa, underestimating cross-border distances will lead us to overestimate the border friction.

[11] It is important to note how restrictive this special case is. For example, for an aggregated internal trade flow x_{ii} the special case would imply that the internal friction of a micro region, t_{kk}, is the same as the bilateral friction between micro regions, $t_{kk'}$, with $k, k' \epsilon i$. For more details see our analytical results in the remainder of section 3.

3.1.3 The aggregate trade cost function

To summarize the effect of trade cost mismeasurement on border effects, we can write the distance employed by the researcher as a function of the theoretically consistent distance aggregator and a residual:

$$dist_{ij} = \widetilde{dist}_{ij} \ e_{ij}^{-\frac{1}{\rho}},$$

where e_{ij} captures the difference between the two distance measures. Substituting this expression into trade cost function (9) we obtain

$$t_{ij}^{1-\sigma} = \exp\left(\zeta BORDER_{ij}\right) \ dist_{ij}^{\rho} \ e_{ij} \tag{13}$$

as the aggregate trade cost function. We stress that for purposes of interpretation, distance should be seen as representing all potential trade cost components apart from the border barrier itself. In our theoretical setting, we use distance as the only other trade cost component, and trade cost mismeasurement is therefore by construction focused on distance. But as the empirical gravity literature has demonstrated, in practice there are likely additional trade cost components.

Overall, if trade cost mismeasurement as captured by e_{ij} is random, then using observed distances instead of the theoretical distance measure should not matter for border effect estimation. However, as we will show below based on a theoretical model with an analytical closed-form solution for aggregate trade costs, mismeasurement is typically not random. Instead, e_{ij} is likely correlated with the border dummy, leading to systematically mismeasured border effects. In section (4) we test and confirm this result empirically.

3.2 Spatial aggregation and the international border effect

We now develop a theory of spatial aggregation in the context of the international border effect. Our aim is to set up a model that is sufficiently simple to yield analytical results for the effect of spatial aggregation on estimated border effects.

We proceed in two steps. First, as in section 3.1 we model trade flows at the level of small geographical units, which we call ‘micro’ regions, based on a standard gravity setting. Second, we aggregate these micro regions into larger ‘macro’ regions. Gravity also holds at the macro level, and we map the trade flows and trade costs of the micro regions onto the larger spatial units of macro regions.

3.2.1 Micro and macro regions on a circle

The model consists of two symmetric countries, Home and Foreign. Each country consists of symmetric micro regions denoted by superscript S for 'small.' Micro regions get aggregated into macro regions denoted by the superscript L for 'large.' As in section 3.1, whenever necessary we use the subscripts k and l for micro regions and the subscripts i and j for macro regions. Each micro region is endowed with a differentiated good as in the Armington framework of Anderson and van Wincoop (2003) and has common income and multilateral resistance terms y_k^S and P_k^S. Gravity equation (14) holds at the micro level:

$$x_{kl}^S = \frac{y^S y^S}{y^W} \left(\frac{t_{kl}^S}{P^S P^S} \right)^{1-\sigma}, \tag{14}$$

where we drop the subscripts for all region-specific variables. As outlined by Anderson and van Wincoop (2003, footnote 12), by setting outward and inward multilateral resistance price indices equal to each other we adopt a particular normalization.[12]

We introduce a spatial topography such that frictions increase between more distant micro regions. For the purpose of obtaining analytical solutions we adopt a symmetric setting. As the simplest case of such a topography, we model each country as a circle. Micro regions are symmetric arcs of the circle, each surrounded by two neighbors. Bilateral trade costs t_h^S are equal to δ^h where $\delta \geq 1$ represents a spatial distance friction with $h \geq 1$ denoting the number of 'steps' between micro regions. Adjacent regions are one step apart with $h = 1$, and so on. Thus, bilateral trade costs between micro regions increase in distance as long as $\delta > 1$. Internal trade costs within a micro region are lower than or equal to bilateral costs between micro regions, i.e., $t_{kk}^S \leq t_h^S$ for any h.[13]

We aggregate $n \geq 1$ micro regions into a macro region denoted by superscript L with income $y^L = ny^S$. Due to symmetry at the micro level, gravity also holds at the macro level. The aggregated micro regions are adjacent on the circle such that the macro region has no 'holes.' Figure 1 illustrates an example of macro regions on the circle.

Aggregate bilateral trade costs

Here we focus on bilateral trade between macro regions both within and across borders. Those are the relevant flows for the international border effect. But for completeness, in appendix A.1 we also derive the internal trade flows of an aggregated macro region and

[12] In appendix A.2 we show that our theory holds up under the more general treatment that retains separate outward and inward multilateral resistance variables. But to keep the exposition as simple as possible, we use the more parsimonious version here that adopts the normalization of equal outward and inward multilateral resistances.

[13] The theory for the domestic border effect in appendix B can be seen as a one-country special case. The simple binary difference between bilateral and internal trade costs at the micro level can be achieved by setting $\delta = 1$ such that all bilateral trade costs become unity ($t_h^S = t^S = 1$) and by normalizing internal trade costs to a smaller value $t_{kk}^S < 1$.

the associated internal trade costs.

Bilateral trade costs at the macro level are sensitive to aggregation. Suppose we observe two macro regions of different sizes, one comprising n_1 micro regions and the other n_2. Gravity commands the bilateral trade relationship:

$$x_{1,2}^L = \frac{y_1^L y_2^L}{y^W} \left(\frac{t_{1,2}^L}{P^L P^L} \right)^{1-\sigma}, \tag{15}$$

where $x_{1,2}^L$ denotes the trade flow from the first to the second macro region with bilateral costs $t_{1,2}^L$, and y_1^L and y_2^L are their respective incomes. More specifically, the bilateral macro flow from the first to the second macro region is the aggregate of $n_1 n_2$ bilateral micro flows:

$$x_{1,2,h}^L = \sum_{v=1}^{n_1} \sum_{w=1}^{n_2} x_{h+v+w-2}^S, \tag{16}$$

where the subscript h in $x_{1,2,h}^L$ indicates the number of steps that the two macro regions are apart (h is the smallest distance between a micro region from i and a micro region from j). For instance, $x_{1,2,1}^L$ for $h = 1$ means that the two macro regions are adjacent (i.e., one step apart), and $x_{1,2,2}^L$ for $h = 2$ means the two macro regions are two steps apart etc. We have to add the micro flows $x_{h+v+w-2}^S$ with step length $h + v + w - 2$, summed over v and w, to yield the bilateral macro flow.

Combining expressions (14) through (16) we can therefore write

$$x_{1,2,h}^L = \frac{n_1 y^S n_2 y^S}{y^W} \left(\frac{t_{1,2,h}^L}{P^L P^L} \right)^{1-\sigma} = \frac{y^S y^S}{y^W} \frac{\sum_{v=1}^{n_1} \sum_{w=1}^{n_2} \left(t_{h+v+w-2}^S \right)^{1-\sigma}}{\left(P^S P^S \right)^{1-\sigma}},$$

where $t_{1,2,h}^L$ denotes aggregate bilateral trade costs for the two macro regions h steps apart. It turns out that aggregation does not change the multilateral resistance price indices, i.e., $P^S = P^L$. In appendix A.2 we show this result formally. The intuition is that aggregation does not affect the underlying trade cost structure and equilibrium of trade flows. Thus, the expression for bilateral trade costs at the macro level follows from the previous equation as

$$\left(t_{1,2,h}^L \right)^{1-\sigma} = \frac{1}{n_1 n_2} \sum_{v=1}^{n_1} \sum_{w=1}^{n_2} \left(t_{h+v+w-2}^S \right)^{1-\sigma}. \tag{17}$$

A key result is that these bilateral macro trade costs rise in the number of aggregated micro regions, i.e., $\partial t_{1,2,h}^L / \partial n_1 > 0$ and $\partial t_{1,2,h}^L / \partial n_2 > 0$. That is, all else equal, larger macro regions tend to have larger trade costs with other regions in that country. The only exception would be the special case of no spatial gradient when bilateral trade costs between micro regions are the same regardless of distance, i.e., when $\delta = 1$ such that $t_h^S = t^S$ for all h. In that case, bilateral trade costs would be the same at the micro and macro levels.

To see more clearly how bilateral trade costs depend on region size n_1 and n_2, we substitute the spatial friction $t_{h+v+w-2}^S = \delta^{h+v+w-2}$.[14] We can then decompose bilateral trade costs at the macro level into three elements as

$$t_{1,2,h}^L = \underbrace{\delta^h}_{\text{bilateral distance}} \underbrace{\left(\frac{1}{n_1}\sum_{v=1}^{n_1}\left(\delta^{v-1}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}}_{\alpha_1} \underbrace{\left(\frac{1}{n_2}\sum_{w=1}^{n_2}\left(\delta^{w-1}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}}_{\alpha_2}. \tag{18}$$

The first element δ^h denotes the bilateral distance between the two macro regions. The remaining elements α_1 and α_2 are region-specific, and more importantly they rise in the sizes n_1 and n_2 of the macro regions.[15] These terms can be interpreted as the costs of reaching the domestic borders of macro regions. For instance, suppose the first macro region consists of only one micro region ($n_1 = 1$). It follows $\alpha_1 = 1$, meaning that no distance has to be incurred to reach the domestic border. But for a macro region consisting of several micro regions ($n_1 > 1$), we get $\alpha_1 > 1$ as long as $\delta > 1$ because of the rising average internal distances of individual micro regions to the domestic border.

In summary, bilateral trade costs at the macro level increase in the size of the underlying regions because more spatial frictions within the macro regions have to be overcome. Only in the limiting case where the macro regions are micro regions ($n_1 = n_2 = 1$) does the bilateral distance δ^h fully represent the bilateral trade costs.

International trade costs

Both countries have the same internal structure of micro regions, and we therefore have two circles. We assume that bilateral international trade costs between micro regions t_{int}^S consist of a common international distance δ_{int}. The common distance can be motivated by a central port for international trade in each country. Then for each micro region the distance to the port is the same.[16] In addition, we assume a cost for crossing the international border so that we can write

$$t_{int}^S = \delta_{int} \exp\left(\frac{\beta}{1-\sigma}\right), \tag{19}$$

[14] We assume that the two macro regions are in the same semi-circle so that the shortest direction of trade is always either clockwise or counterclockwise. If the two regions straddled different semi-circles, the resulting expression for $t_{1,2,h}^L$ would be more complicated.

[15] Formally, $\partial\alpha_1/\partial n_1 > 0$ and $\partial\alpha_2/\partial n_2 > 0$.

[16] As a generalization, we could allow for bilateral distance gradients between micro regions at the international level. The relevant case would be a friction parameter that differs from the corresponding parameter δ for domestic flows.

where $\beta \leq 0$ captures the international border barrier. This structure translates into the same level of international trade costs at the aggregate level between two macro regions of size n_1 and n_2, i.e., $t^S_{int} = t^L_{1,2,int}$. The intuition is that identical trade costs are aggregated such that the appropriate theoretical average is the same. This stands in contrast to aggregate bilateral trade costs within countries as in equation (18) that do vary by macro region size.

We should briefly comment on a possible generalization. As an alternative modeling strategy, instead of just two circles representing two countries we could assume multiple circles representing multiple countries. To preserve symmetry we could have a 'pearl necklace' of countries where each pearl represents a circular economy. That is, we could arrange countries in a circular fashion similar to the way micro regions are arranged within countries. International distances would then vary by country pair in contrast to our simple common distance δ_{int}. However, this expanded model would not yield any qualitatively new insights. We therefore work with the simpler two-country setting.

The trade cost function

Comparing expressions (18) and (19) for bilateral trade costs at the domestic and international levels, we can see that region-specific terms only appear for domestic trade costs. In logarithmic form and scaled by the elasticity of substitution, we can therefore write the overall trade cost function that arises from our model as

$$\ln\left(t_{ij}^{1-\sigma}\right) = \ln\left(\delta_{ij}^{1-\sigma}\right) + \beta INT_{ij} + \phi(1 - INT_{ij})\left\{\ln(\alpha_i^{1-\sigma}) + \ln(\alpha_j^{1-\sigma})\right\} \tag{20}$$

with $\phi = 1$ where region i denotes an exporter and region j is an importer. If ij is a domestic pair, then δ_{ij} equals δ^h, and δ_{int} otherwise. 'Regions' here refer to macro regions (those will be U.S. states and foreign countries in our empirical analysis), and for simplicity we drop the L superscript. The trade cost function (20) is a special case of the general trade cost function (13) developed in section 3.1.[17]

3.2.2 Heterogeneous international border effects

The key feature of trade cost function (20) is the interaction term between the international border dummy and the region-specific terms $\ln(\alpha_i^{1-\sigma})$ and $\ln(\alpha_j^{1-\sigma})$. This interaction is absent in standard trade cost functions such as (2). It implies that in gravity estimation, the impact of the border on bilateral trade becomes heterogeneous. More

[17] The $\zeta BORDER_{ij}$ term in equation (13) corresponds to βINT_{ij} in equation (20), and $dist_{ij}^{\rho}$ corresponds to $\delta_{ij}^{1-\sigma}$. The trade cost mismeasurement term is equal to $e_{ij} = 1$ for $INT_{ij} = 1$ and equal to $e_{ij} = \alpha_i^{1-\sigma}\alpha_j^{1-\sigma}$ for $INT_{ij} = 0$ with $\phi = 1$, meaning trade costs are correctly measured for $INT_{ij} = 1$ but mismeasured for $INT_{ij} = 0$. This yields trade cost function (20).

specifically, the direct effect of INT_{ij} on bilateral trade follows as

$$\frac{\Delta \ln (x_{ij})}{\Delta INT_{ij}} = \beta + \phi \left\{ \ln(\alpha_i^{\sigma-1}) + \ln(\alpha_j^{\sigma-1}) \right\}, \tag{21}$$

where ΔINT_{ij} indicates a comparison of $INT_{ij} = 0$ with $INT_{ij} = 1$ and where for the moment we ignore general equilibrium effects including multilateral resistance effects operating through the price indices.

If an international border barrier exists, we have $\beta < 0$. In the limiting case when regions i and j are micro regions with no aggregated spatial frictions, we have $\alpha_i = \alpha_j = 1$ and the second term disappears. This would also happen if the domestic economies were frictionless in the sense of $\delta = 1$. In appendix A.3 we show formally that only if the α_i and α_j terms are unity can we obtain an unbiased estimate of β in a gravity regression with a standard international border effect. But in the more realistic case when i and j are macro regions and spatial frictions are present, the second term becomes positive and counteracts the negative effect stemming from β. Thus, larger macro regions have weaker (i.e., less negative) border effects. We call this the spatial attenuation effect. The effect of an international border dummy is therefore driven by the 'internal resistance' of the regions in question, inducing systematic heterogeneity. In the empirical part of the paper, we illustrate the heterogeneity by reporting the full range of border effects. We find that the heterogeneity is quantitatively substantial.

We note that this form of heterogeneity operates independently of heterogeneity induced by multilateral resistance effects in general equilibrium. We discuss general equilibrium effects in more detail in section 4.7.

Estimating heterogeneous international border effects

Estimation of trade cost function (20) is straightforward. The α_i and α_j terms are region-specific. We can therefore capture them with a set of region fixed effects α_r that equal unity whenever i or j appear regardless of the direction of trade.[18] As the empirical specification we obtain

$$\ln\left(t_{ij}^{1-\sigma}\right) = \underbrace{INT_{ij}\left(\beta + \phi\left\{\ln(\alpha_i^{\sigma-1}) + \ln(\alpha_j^{\sigma-1})\right\}\right)}_{\beta_r INT_{ij}\alpha_r \;=\; \beta_r INT_{ij}^r} + \ln\left(\delta_{ij}^{1-\sigma}\right) - \underbrace{\phi\left\{\ln(\alpha_i^{\sigma-1}) + \ln(\alpha_j^{\sigma-1})\right\}}_{\alpha_r}, \tag{22}$$

where β_r indicates region-specific international border coefficients and where $INT_{ij}^r \equiv INT_{ij}\alpha_r$. A simple test of border effect heterogeneity comes down to the hypothesis that the β_r coefficients differ from each other. We note that the β parameter cannot be identified due to collinearity with the fixed effects.

[18] We do not use internal trade flows in the estimation where $i = j$.

3.2.3 Testable implications

The previous analysis leads to three testable implications that we will explore in the empirical section:

1. **Heterogeneous border effects:** According to our theoretical model, we should expect heterogeneous border effects as opposed to a common border effect. Specifically, all else being equal, through equations (18) and (21) we should expect weaker border effects for larger regions. We can employ trade cost function (22) with region-specific border effects to test this prediction empirically.

2. **Systematic sample composition effects:** Related to the first implication, border effect coefficients are sensitive to sample composition in a systematic way. Specifically, adding relatively large regions to the sample pushes the border coefficient towards zero. Conversely, adding relatively small regions renders the border coefficient more negative. Such composition effects imply that standard border effect coefficients estimated in the conventional way without allowing for heterogeneity are not directly comparable across different samples. For example, suppose we obtain a coefficient of $\beta_1 = -1.5$ in one sample and a coefficient of $\beta_2 = -1$ in another, and the two coefficients are significantly different. This difference does not necessarily imply that the international border is more detrimental to trade flows in the first sample than in the second. Instead, the difference could be driven by sample composition effects.

3. **Aggregation effects:** Aggregating adjacent regions generates larger regions associated with weaker border effects. As a consequence of the second implication, we should therefore expect weaker conventional border effect coefficients in a sample with aggregated regions compared to the same sample prior to aggregation.

Before turning to the empirical analysis, we briefly review corresponding theoretical results for the domestic border effect.

3.3 Spatial aggregation and the domestic border effect

In appendix B we develop a model of spatial aggregation that is targeted towards the domestic border effect. As in the model for the international border effect in section 3.2, we work with micro regions that get aggregated into macro regions. But as a simplification, we do not model regions as being located on a circle. Similar to equation (21), we show that the direct effect of the domestic border dummy DOM_{ij} on trade is heterogeneous:

$$\frac{\Delta \ln (x_{ij})}{\Delta DOM_{ij}} = \gamma + \ln \left(t_{ii}^{\sigma-1} t_{jj}^{\sigma-1} \right)^{\frac{1}{2}}, \tag{23}$$

where ΔDOM_{ij} indicates a comparison of $DOM_{ij} = 0$ with $DOM_{ij} = 1$.[19]

The key insight is that all else equal, larger internal trade costs lead to a smaller border effect. That is, the term $\ln \left(t_{ii}^{\sigma-1} t_{jj}^{\sigma-1} \right)^{1/2}$ increases in t_{ii} and t_{jj} and thus counteracts the negative effect stemming from $\gamma < 0$. Ceteris paribus domestic border effects are therefore mechanically driven by internal trade costs and inherently heterogeneous. This is spatial attenuation in the context of the domestic border effect. The intuition is that due to aggregation, larger macro regions have larger internal trade frictions. This increases 'internal resistance', leading to relatively less internal trade and relatively more bilateral trade. As a result, the domestic border effect appears smaller.

Similar to equation (22), we show that the model implies a trade cost function with region-specific domestic border effect coefficients γ_r.[20] A simple test of border effect heterogeneity comes down to the hypothesis that the γ_r coefficients differ from each other. Similar testable implications follow as in section 3.2.3.[21] We will explore these in the subsequent section.

4 Empirical results

4.1 Data

Our two main data sources are the Commodity Flow Survey and the Origin of Movement series provided by the U.S. Census Bureau. To obtain results that are comparable to the literature, we use the same data sets as Wolf (2000) and Anderson and van Wincoop (2003) for domestic trade flows within the United States, based on the Commodity Flow Survey. The novelty of our approach is to combine these domestic trade flows with international trade flows from individual U.S. states to the 50 largest U.S. export destinations, based on the Origin of Movement series. Thus for instance, our data set comprises trade flows within Minnesota, exports from Minnesota to Texas as well as exports from Minnesota to France. We also employ trade data between foreign countries in our sample. We take data quality seriously, and in appendix C we describe our data sources and adjustments in detail, including our distance measures.

We form a balanced sample over the years 1993, 1997, 2002 and 2007. We drop Alaska,

[19] See equation (44) in appendix B.1.
[20] See equation (45) in appendix B.1.
[21] See appendix B.1 for details.

Hawaii and Washington, D.C. due to data quality concerns raised in the Commodity Flow Survey so that we are left with the 48 contiguous states. This yields 1,726 trade observations per cross-section within the U.S., including 48 intra-state observations and 1,678 state-to-state observations per cross-section.[22] The observations that involve the 50 foreign countries are made up of 2,338 export flows from U.S. states to foreign countries as well as 2,233 exports flows amongst foreign countries per cross-section.[23]

4.2 Overview

We first show in section 4.3 that our data exhibit a significant international border effect, as established by McCallum (1995). We also show that the data exhibit a substantial domestic border effect, as established by Wolf (2000).

We then explore the three testable implications from section 3.2.3. In section 4.4 we explore the first implication (heterogeneous border effects) by allowing border effects to vary across states, uncovering a great degree of heterogeneity. Section 4.5 examines the second implication (sample composition effects) where we systematically drop large and small U.S. states from our sample. Section 4.6 covers the third implication (aggregation effects) where we aggregate U.S. states into larger spatial units.

In section 4.7 we show that border effect heterogeneity is substantially more important than heterogeneity related to general equilibrium price index effects. Section 4.8 explores potential determinants of border effects, namely transport infrastructure. Finally, in section 4.9 we present additional evidence of border effect heterogeneity based on industry-level trade data. In appendix C.7 we provide numerical simulations of our model.

4.3 Estimating common border effects

In Table 1 we replicate well-known results on international and domestic border effects. As our estimating equation we use the log-linear version of gravity equation (1) in combination with trade cost function (2).

In columns 1 and 2 of Table 1 we replicate standard results for the international border effect. As is customary, we do not include trade flows within U.S. states, and the domestic

[22] The maximum possible number of U.S. observations would be $48*48 = 2,304$ per cross-section. The missing observations are due to the fact that a number of Commodity Flow Survey estimates did not meet publication standards because of high sampling variability or poor response quality. To generate a balanced sample, we drop pairs if at least one year is missing.

[23] The maximum possible number of international exports from U.S. states would be $48*50 = 2,400$ per year. We have 62 missing observations mainly because exports to Malaysia were generally not reported in 1993. Only 18 of these observations not included in our sample are most likely zeros (as opposed to missing). The maximum possible number of exports between foreign countries would be $49*50 = 2,450$ per cross-section. To generate a balanced sample, we drop pairs if least one year is missing.

border dummy is dropped as a regressor. To be able to identify the international border dummy coefficient we follow Anderson and van Wincoop (2003) and others by using state and foreign country fixed effects instead of exporter and importer fixed effects.[24] As the output regressors are collinear with these fixed effects, they are dropped from the estimation. In column 1 we estimate an international border coefficient of $\widehat{\beta} = -1.25$ for the year 1993, implying that after we control for distance and economic size, exports from U.S. states to foreign countries are about 71 percent lower than trade between U.S. states ($\exp(-1.25) = 0.29$). Assuming a value for the elasticity of substitution of $\sigma = 5$, we can translate this into a tariff equivalent of the domestic border of 37 percent.[25] In column 2 when we pool the data over the years 1993, 1997, 2002 and 2007, we obtain a similar coefficient of -1.21. These estimates are somewhat smaller in absolute magnitude but nevertheless roughly fall in the same ballpark as the estimates of around -1.6 reported by Anderson and van Wincoop (2003, Table 2) in their sample involving trade flows of U.S. states and Canadian provinces.

In columns 3 and 4 of Table 1 we estimate the domestic border dummy coefficient. We only use trade flows within the U.S. International trade flows are not included, and the international border dummy is dropped as a regressor. As typical in the literature (for instance Hillberry and Hummels 2003), we use exporter and importer fixed effects to control for multilateral resistance and all other country-specific variables such as income. As in Wolf (2000), in column 3 we only use data for 1993. In column 4 we add the data for 1997, 2002 and 2007. Our estimate of $\widehat{\gamma} = -1.48$ in column 4 is the same as Wolf's baseline coefficient.[26]

The interpretation of our coefficient is that given distance and economic size, trade between U.S. states is 77 percent lower compared to trade within U.S. states ($\exp(-1.48) = 0.23$). The corresponding tariff equivalent is 45 percent. But as we show in appendix B.1, this interpretation would only be valid under the assumption that internal trade costs within U.S. states were zero on average. For positive internal trade costs (which is the realistic scenario), the underlying tariff equivalent would be even higher.[27] Put differently, the $\widehat{\gamma}$ estimate only captures the domestic border barrier net of internal trade

[24] That is, we use fixed effects that are state-specific (in the case of U.S. states) and country-specific (in the case of foreign countries) but that do not distinguish between being an exporter or an importer.

[25] For $\ln\left(t_{ij}^{1-\sigma}\right) = -1.25$, it follows $t_{ij} = 1.37$. This is a partial equilibrium calculation in the sense that we ignore price index effects for simplicity. For general equilibrium effects, see section 4.7.

[26] Wolf's coefficient has a positive sign because his domestic border dummy is coded in the opposite way. Hillberry and Hummels (2003) reduce the magnitude of the national border coefficient by about a third when excluding wholesale shipments from the Commodity Flow Survey data. The reason is that wholesale shipments are predominantly local so that their removal disproportionately reduces the extent of intra-state trade. However, Nitsch (2000) reports higher coefficients in the range of -1.8 to -2.9 by comparing trade within European Union countries to trade between EU countries.

[27] See expression (42) in appendix B.1.

costs.

Overall, we have replicated international and domestic border coefficient estimates as typically found in the literature. In fact, our domestic point estimate exceeds the international point estimate in absolute magnitude, a finding which is consistent with Fally, Paillacar and Terra (2010) in their study of Brazilian trade data as well as Coughlin and Novy (2013).[28]

4.4 Estimating individual border effects

The general trade cost function (13) highlights how aggregation can affect the relevant distance measure. In principle, aggregation can lead to mismeasurement of trade costs within borders and across borders (where cross-border trade costs refer to international trade costs in the context of the international border effect, and to bilateral domestic trade costs in the context of the domestic border effect). If aggregation increases within-border trade costs relatively more, then the cost of trading across borders appears relatively smaller and we would infer weaker border effects for larger states. This is the scenario predicted by our theoretical models for the international border effect in section 3.2 and the domestic border effect in appendix B. The alternative hypotheses that would in principle be consistent with the general specification (13) are either no aggregation effects, or stronger border effects for larger states. We now examine the data to find out which pattern holds empirically.

We run the same regression specifications with panel data as in columns 2 and 4 of Table 1, but now allowing the international and domestic border coefficients to vary across states. That is, we estimate individual, state-specific border effects to explore the first testable implication in section 3.2.3. This approach is consistent with our theoretical results in expressions (21) and (23) where we predict that for larger states, the international and domestic border dummy coefficients should be closer to zero due to spatial attenuation.

4.4.1 Individual international border effects

We first estimate individual international border dummy coefficients for the 48 U.S. states in our sample. We obtain them by using trade cost function (22) in otherwise standard

[28] Hillberry and Hummels (2008) use ZIP code-level shipments within the U.S. and show that over very short distances, distance operates in a highly non-linear fashion due to extensive margin effects. The smallest unit in our sample (a U.S. state) has an average internal distance of 179 km as opposed to around 6 km for a ZIP code. We do not use any internal trade observations for our results on the international border effect.

gravity estimation, substituting bilateral distance for δ_{ij}.[29] More precisely, we estimate the following specification:

$$\ln(x_{ij}) = \sum_{r=1}^{48} \beta_r INT_{ij}^r + \rho \ln(dist_{ij}) + \alpha_s + \varepsilon_{ij},$$

where INT_{ij}^r is an international border dummy specific to state r, β_r is the corresponding coefficient, α_s denotes state and foreign country fixed effects and ε_{ij} is an error term.[30] As equation (21) shows, all else equal theory predicts a smaller trade effect of the international border dummy in absolute value (i.e., less negative) for regions with larger (logarithmic) internal trade costs, which are in turn associated with larger economic size.

How can we obtain a measure of internal trade costs that is consistent with the theory? Equation (26) in appendix A.1 describes how t_{ii}^L depends on the number of aggregated micro regions n and the micro frictions t_{kk}^S and t^S. But since these micro frictions are unobservable, instead we resort to gravity equation (24) to obtain a theory-consistent measure of internal trade costs.[31] Given that multilateral resistance terms are the same across macro regions, it follows that $\left(t_{ii}^L\right)^{\sigma-1}$ is proportional to the ratio $y^L y^L / x_{ii}^L$. We therefore proxy $\ln(t_{ii})$ with $\ln\left(y^L y^L / x_{ii}^L\right)$.

Figure 2 illustrates the individual coefficients plotted against our proxy of internal trade costs. As a more direct measure of economic size, Figure 3 plots the coefficients against logarithmic state GDP. Overall, the figures demonstrate a clear positive relationship. The individual estimates display a large degree of heterogeneity, falling into a range of -2.7 to 0.9. The mean estimate is -0.64.[32] The coefficients are tightly estimated with an average standard error of 0.13 (not plotted in the figure). The larger the state, the closer the individual international border coefficient tends to be to zero. For example, Wyoming as the smallest state is associated with an international border coefficient of -1.53, whereas the value for California as the largest state is -0.34. Under the assumption of $\sigma = 5$, the corresponding tariff equivalents would be 47 percent and 9 percent.

We stress that in our model, the international border friction at the micro level, β, is common across all regions (see equation 19). Through that lens the substantial difference

[29] Behrens, Ertur and Koch (2012) also estimate heterogeneous international border dummy coefficients based on a framework that allows for spatial correlation of trade flows.

[30] As in the regressions underlying columns 1 and 2 of Table 1, we follow Anderson and van Wincoop (2003) and others by using state and foreign country fixed effects to identify the international border dummy coefficients. That is, the α_s fixed effects are state-specific (in the case of U.S. states) and country-specific (in the case of foreign countries).

[31] We refer to appendix C.7 where we discuss internal trade costs in more detail.

[32] The corresponding common international border coefficient that captures international trade flows of U.S. states only is -0.60 and thus very close to the mean estimate underlying Figures 2 and 3. See section 4.7 for details.

between the above tariff equivalents can therefore be attributed to spatial aggregation as the primary driving force behind border effect estimates (see section 5 for a discussion).

4.4.2 Individual domestic border effects

We also estimate individual domestic border dummy coefficients. We obtain them by using the theoretically consistent trade cost function (45) from appendix B.1 in an otherwise standard gravity regression. That is, we estimate the following specification:

$$\ln(x_{ij}) = \sum_{r=1}^{48} \frac{\gamma_r}{2} DOM_{ij}^r + \rho \ln(dist_{ij}) + \alpha_i + \alpha_j + \varepsilon_{ij},$$

where DOM_{ij}^r is a domestic border dummy specific to state r, γ_r is the corresponding coefficient, α_i and α_j denote exporter and importer fixed effects and ε_{ij} is an error term.[33] As equation (44) shows, theory predicts that for a given U.S. state, all else being equal we should expect a smaller trade effect of the domestic border dummy in absolute magnitude (i.e., less negative) if the state has larger (logarithmic) internal trade costs.

As an illustration, in Figure 4 we plot the domestic border coefficients γ_r against our proxy of internal trade costs. Two main observations can be made. First, as with the international border coefficients there is a large degree of heterogeneity. While the mean of coefficients is -1.32 and thus close to the point estimates reported in columns 3 and 4 of Table 1, the individual border coefficients span a range of more than six log points. They are tightly estimated, with standard errors of 0.13 on average.[34]

Second, as predicted by our theory, the individual coefficients are positively related to internal trade costs. Given a correlation of 0.92 between internal trade costs and state GDP, this means the coefficients are also positively related to the economic size of states.[35] That is, the smaller the state, the more detrimental the effect of crossing a domestic border appears to be. For example, the five states with the smallest state GDPs

[33] See appendix B.1 for details. Since every domestic trade flow is captured by two region-specific border dummies (once on the exporter side and once on the importer side), the estimated coefficients $\gamma_r/2$ must be multiplied by 2 to obtain estimates of γ_r that are comparable to the common border dummy coefficient γ.

[34] Given that our sample has a number of missing observations as explained in section 4.1, we carry out a robustness check where we drop the states with the most missing observations (those with fewer than 60 bilateral observations out of a maximum of 94=2*47 per cross-section). Those states are Delaware, Idaho, Montana, North Dakota, New Hampshire, New Mexico, Nevada, Rhode Island, South Dakota, Vermont, and Wyoming. We re-estimate individual domestic border dummy coefficients based on this reduced sample. Since average state size is larger, the mean of coefficients shrinks in absolute magnitude (it is -1.21 instead of -1.32). The individual coefficients in the reduced sample are very similar to those in Figure 4. They span a range of five log points and are tightly estimated with an average standard error of 0.10. Their positive correlation with logarithmic internal trade costs is retained (the correlation is 45 percent). We conclude that the heterogeneity pattern in Figure 4 is not driven by missing observations.

[35] We also refer to appendix C.7 where we provide numerical simulations confirming the positive relationship between individual coefficients and internal costs.

(Wyoming, Vermont, North Dakota, Montana, South Dakota) have border coefficients in the vicinity of -4. The back-of-the-envelope interpretation would be that for those states, crossing a border with another state reduces trade by 98 percent.[36] At the other extreme, a few economically large states such as New Jersey and California are associated with positive border coefficients.[37] These results underline the importance of spatial attenuation effects.[38]

4.5 Sample composition effects

As shown above, border dummy coefficients can vary substantially across regions. They tend to be large in absolute magnitude for small states, and vice versa. It follows that when we estimate common border effects, our estimates should be sensitive to the distribution of state economic size in the sample (see the second testable implication in section 3.2.3). We perform a simple check of this sample composition effect.

In order to systematically change the composition of economic size in our sample, we run rolling regressions where we keep dropping states and their associated trade flows from the sample. More specifically, we start out with the international border effect regression as in column 1 of Table 1 for the year 1993 where we obtained a coefficient on the domestic border dummy of -1.25. We then drop the largest state from the sample in terms of GDP (California) and re-estimate the border coefficient. We then drop the second largest state from the sample (New York) and re-estimate, and so on, such that the smallest states are remaining. To obtain comparable estimates we keep the distance coefficient at its initial value but we allow the exporter and importer fixed effects to adjust freely.

The black dots in Figure 5 illustrate the international border coefficients. As predicted by our theory, we yield the following clear pattern: the more big states we drop from the sample, the larger the coefficients tend to become in absolute value. That is, the

[36] As $\exp(-4) = 0.02$, all else equal in partial equilibrium the border reduces trade by 98 percent relative to within-state trade. For general equilibrium effects see section 4.7.

[37] The coefficients for California, Illinois, Minnesota, Nevada, New Jersey and Virginia are positive and significant at the five percent level. In the theory in appendix B.1, the upper bound for state-specific domestic border coefficients is actually zero. In equation (37) t^L_{ii} approaches t^S for $n \rightarrow \infty$, which is the same as $t^L_{1,2}$ through equation (39). Therefore, in equation (45) it follows $\gamma_r = 0$ since $\psi = 1$. In the data, however, it is conceivable that trade costs within some macro regions are sufficiently large relative to bilateral trade costs such that positive domestic border coefficients are estimated (see equation 44).

[38] As described in appendix C.4, our measure of intra-state distance is the distance between the two largest cities in a state. We also employed two alternative intra-state distance measures. The first is the distance measure proposed by Wolf (2000) that weights the distance between a state's two largest cities by their population. The second is the measure suggested by Nitsch (2000) that is based on land area (i.e., 0.56 times the square root of a state's land area). While alternative distance measures can alter the common border effect coefficient estimate, we still obtain similar patterns of coefficient heterogeneity as in Figure 4.

smaller the average economic size of states in the sample, the further the estimated border effect tends to get pushed away from zero. The grey diamonds in Figure 5 illustrate the coefficients obtained when we drop the smallest state first (Wyoming), then the second smallest state (Vermont), and so on. As expected, we yield the opposite pattern: the international border coefficients move upwards towards zero. Overall in Figure 5, we obtain coefficients ranging from around -3.5 to 0.[39]

In Figure 6, we repeat the rolling regressions for the domestic border effect, starting out with the same regression as in column 3 of Table 1 where the obtained a coefficient of -1.47. We find a similar pattern as in Figure 5. That is, the smaller the average economic size of states in the sample, the further the estimated border effect tends to get pushed away from zero (the downward trend is reasonably clear although not strictly monotonic). The coefficients roughly fall in the range from -2 to -0.5.

Therefore, in summary we find strong sample composition effects in Figures 5 and 6. We interpret these as further evidence corroborating the impact of state size on border effects. The figures demonstrate that this impact is quantitatively strong.

4.6 Aggregating U.S. states

The individual border effects illustrated in Figures 2-4 demonstrate that larger states tend to exhibit smaller border effects in absolute magnitude. We now trace this relationship between economic size and the magnitude of border effects in a different way. We aggregate U.S. states and thus enlarge the size of the underlying spatial units (see the third testable implication in section 3.2.3).

To be specific, we aggregate the 48 contiguous U.S. states into the nine Census divisions as defined by the U.S. Census Bureau. We choose Census divisions because their borders conveniently coincide with state borders (this would not be the case with Federal Reserve Districts, for instance). But any alternative clustering of adjacent states would in principle be equally suitable for this aggregation exercise. Figure 7 provides a map of the Census divisions.

Trade flows within a division are taken to equal the sum of the internal trade flows of its states plus the flows between these states. Trade flows between divisions are given by the sum of trade flows between their respective states. Similarly, trade flows from a division to a foreign country are given as the sum of exports from the states in the division to the foreign country.

[39] Balistreri and Hillberry (2007) show that the reduction of the border effect by Anderson and van Wincoop (2003) relies on the addition of trade flows between U.S. states to the sample. Since U.S. states are on average considerably larger than Canadian provinces, we expect the addition of such flows to push the common border dummy estimate towards zero according to our result in Figure 5.

Table 2 reports regression results that correspond to Table 1. We use the simple average of distances associated with the underlying individual trade flows. The division-based international border dummy coefficients are -0.36 and -0.39 and thus considerably smaller in magnitude and significantly different from the corresponding state-based estimates of -1.25 and -1.21 in Table 1. The division-based domestic border dummy coefficients are -1.17 and -1.25 and thus smaller in magnitude than the corresponding state-based estimates of -1.47 and -1.48 in Table 1, albeit not statistically different. The distance coefficients are very similar between Tables 1 and 2. A common pattern arises: the border coefficients are further away from zero when states are the underlying spatial units, and the border coefficients are closer to zero when we use divisions as the larger underlying spatial units. This pattern mirrors the cross-sectional heterogeneity apparent in the individual border coefficients depicted in Figures 2-4.[40]

We briefly comment on the estimation method. Although the point estimates naturally change when we follow Santos Silva and Tenreyro (2006) and use Poisson pseudo maximum likelihood (PPML) estimation as opposed to OLS, the coefficient patterns are qualitatively the same. In particular, we find the same type of coefficient heterogeneity as in Figures 2-4, consistent with our theory. For the international border coefficients in Figures 2-3 we find a correlation of 75 percent between coefficients obtained with PPML and those obtained with OLS. The corresponding correlation for the domestic border coefficients in Figure 4 is 97 percent. Furthermore, the relationship between coefficients in Tables 1 and 2 is the same with PPML.

Finally, we add another aggregation exercise. Instead of using Census divisions we merge the 48 contiguous states into hypothetical U.S. regions by sequentially merging them in a quasi-randomized way.[41] Aggregating trade flows and distances in the same way as above, we form four samples: 24 regions consisting of two states each, 12 regions consisting of four states each, eight regions consisting of six states each, and six regions consisting of eight states each.[42]

In Table 3 we present regression results for data pooled over the years 1993, 1997, 2002 and 2007. Columns 1-4 report coefficients for the international border dummy across the four samples. While in column 1 based on 24 regions we obtain a coefficient of -0.64,

[40] As an alternative distance measure, we weight distances by individual trade flows. That is, distances associated with stronger trading activity are given proportionally larger weights. The international border dummy coefficients corresponding to columns 1 and 2 of Table 2 are -0.31 and -0.34 and thus roughly the same. The domestic border dummy coefficients corresponding to columns 3 and 4 are -0.92 and -0.98 and thus smaller in absolute magnitude. The reason is that weighted distances tend to be shorter than average distances such that the extent of internal trade seems less extreme.

[41] This procedure is quasi-random in the sense that we impose the restriction that no state must be left in isolation. For example, Maine is adjacent to only one state (New Hampshire) such that those two states never end up in separate regions.

[42] These regions are described in detail in appendix C.5.

its magnitude shrinks to -0.21 in column 4 based on six regions. Consistent with our theoretical prediction we find that the larger the regions, the smaller the border dummy coefficient becomes in absolute value. Columns 5-8 report results for the domestic border effect. Here we do not see a systematic change in border dummy coefficients. However, we find a clear pattern in the distance coefficients. The further we aggregate, the weaker the distance elasticity in absolute magnitude. That is, aggregation reduces the estimated trade-impeding effect of space not through the domestic border dummy coefficient but the distance elasticity.[43]

4.7 Multilateral resistance effects in general equilibrium

In their seminal paper, Anderson and van Wincoop (2003) highlight the role of general equilibrium. They show that small and large countries react differently to changes in international border barriers. Intuitively, removing the border leads to a reallocation of trade away from domestic towards international partners. But since a small country is more exposed to international trade and thus more exposed to the border barrier, this reallocation is relatively stronger for the small country.[44] This differential response between small and large countries is entirely driven by price index or 'multilateral resistance' effects.

In our theoretical framework, however, multilateral resistance is symmetric across countries (see appendix A.2). The differential trade response is instead driven by heterogeneity in the border effect itself due to spatial aggregation, as shown in equation (21).

While multilateral resistance is the same across countries in our theory, we cannot assume this to be the case with actual trade flows. In Table 4 we explore the general equilibrium counterfactuals implied by removed international border barriers, accounting for both heterogeneous border effects as well as heterogeneous multilateral resistance effects. We use the same balanced sample as for column 2 of Table 1 based on 24,996 observations for the years 1993, 1997, 2002 and 2007 (6,249 observations per year).

In panel 1 we report counterfactuals based on removing a common international border barrier as in the standard Anderson and van Wincoop (2003) model. As in column 2 of Table 1, we estimate this border barrier based on the logarithmic version of the

[43] While the average distance for cross-region trade remains roughly stable, the average distance for within-region trade increases dramatically (from 5.5 to 6.3 in logarithmic distance between columns 5 and 8 of Table 3).

[44] To be precise, the ratio of bilateral international trade to bilateral domestic trade increases more strongly for a country consisting of smaller regions such as Canada. Anderson and van Wincoop (2003, section IV.C) discuss "the relatively small size of the Canadian economy" in the context of their data set of trade flows between Canadian provinces and U.S. states.

standard gravity equation (1) with logarithmic bilateral distance and country fixed effects as additional controls. The border dummy captures the U.S. international border only.[45] We then remove the U.S. international border and recompute the associated general equilibrium.[46]

Panel 1 presents the logarithmic differences between the counterfactual and initial equilibria. Removing the U.S. border leads to an increase in bilateral trade flows by 23 percent on average (see the top row of panel 1). Trade would have increased by 31 percent just through the direct (partial equilibrium) effect of reducing bilateral trade costs.[47] This direct effect is the same for all U.S. states by construction because we impose a common border barrier. The offsetting general equilibrium effect through falling multilateral resistance is 10 percent on average but varies somewhat across states, while the increase in incomes pushes up trade by 2 percent. In sum, there is a modest degree of variation across states due to the heterogeneous general equilibrium effects. For instance, the bilateral trade of California goes up by 24 percent on average, whereas the trade of Wyoming goes up by 21 percent.

In panel 2 we report counterfactuals based on our framework with heterogeneous border barriers. We estimate state-specific border coefficients as described in section 4.4.1. Those are plotted in Figures 2 and 3. We also account for multilateral resistance effects when computing the counterfactual equilibrium. Removing the heterogeneous border barriers leads to average effects that are almost identical (see the top row of panel 2). However, the underlying effects for individual states exhibit much more variation. The key insight is that this variation is primarily driven by the heterogeneous direct effects (see column 2b), not multilateral resistance effects. The overall differences across states can be quite substantial. For instance, here the bilateral trade of California goes up by 13 percent on average, whereas the trade of Wyoming goes up over four times as much (61 percent). Consistent with our theory, small states are more affected by the removal of the border.[48]

[45] The distance and border dummy coefficients are -1.21 and -0.60, respectively, both highly significant at the 1 percent level. As the border dummy only captures the U.S. border, its coefficient is directly comparable to the individual border coefficients for U.S. states plotted in Figures 2 and 3. Their average is -0.64 and thus about the same.

[46] For the initial equilibrium we take the income data for the 48 U.S. states and 50 large foreign countries in our sample for the year 1993, thus capturing the vast majority of global economic activity. Using our estimated distance and border dummy coefficients, we use numerical methods to compute the multilateral resistance variables and construct the associated bilateral trade flows based on gravity equation (1). For the counterfactual we set the border dummy coefficient to zero and recompute the full equilibrium, assuming that the endowment quantities are fixed.

[47] Assuming $\sigma = 5$ this corresponds to a cut in trade costs by 7.75 percent since $0.31/(1-\sigma) = -0.0775$.

[48] For some states the overall trade effect shows up as slightly negative (e.g., -7 percent for Connecticut). This happens because some individual border coefficients were estimated to have a positive sign (see Figures 2 and 3). Most of these positive coefficients are not significant, but we report the associated results in Table 4 nevertheless.

Overall, we conclude that heterogeneous border barriers translate into heterogeneous trade effects. Quantitatively, this form of heterogeneity is considerably more important than heterogeneity associated with multilateral resistance effects.

4.8 Exploring potential determinants of border effects

It is conceivable that the heterogeneity of border effects documented in section 4.4 is related to features at the state level, for example differences in transport infrastructure. It is not clear a priori whether better infrastructure would be associated with weaker or stronger border effects, depending on whether infrastructure primarily facilitates within-border trade or cross-border trade (see section 3.1). Intuitively, if infrastructure facilitates all trade flows by the same degree, then it should not be systematically related to estimated border dummy coefficients.

To explore the role of transport infrastructure at the state level, we collect data on two time-varying measures: the length of public roads per capita and the number of airports per capita. As an additional potential determinant of border effects we also collect data on personal income per capita as a measure of productivity. We describe these measures in more detail in appendix C.4. We consider our panel data from Table 1, and we interact the border dummy variables with the above measures. We present regression results in Table 5. Columns 1-3 are for the international border effect, and columns 4-6 are for the domestic border effect.[49]

Column 1 shows that our measures of transport infrastructure have a negative interaction effect with the international border dummy. This means that the more roads and airports per capita there are in a state, the more negative (i.e., the larger in absolute magnitude) is the impeding effect associated with an international border. The interpretation would be that in relative terms, this transport infrastructure appears to predominantly facilitate domestic trade between U.S. states rather than international trade between U.S. states and foreign countries. Income per capita exhibits the same qualitative effect. As a comparison, in column 2 we interact the international border dummy with state GDP. The positive interaction coefficient confirms our theoretical prediction and the pattern in Figure 3: the larger a U.S. state, the smaller is the associated border effect in absolute magnitude. In column 3 we combine all regressors. The GDP interaction coefficient remains positive and significant but is reduced in magnitude.

Columns 4-6 show the corresponding interaction effects for the domestic border dummy.

[49] As we have data of the measures for U.S. states only and not for foreign countries, we interact with the logarithmic value of the exporter whenever it is a U.S. state in columns 1-3 of Table 5, and we set values to zero whenever U.S. states are not involved. As we have trade flows within the U.S. only in columns 4-6, we interact with the logarithm of the product of the exporter and importer values.

In column 4 only the interaction term of road length per capita is significant. The interpretation here would be that the road network facilitates trade within U.S. states relatively more than trade between U.S. states. The GDP interaction effect in column 5 again confirms our theoretical prediction: larger U.S. states are associated with weaker border effects in absolute magnitude. But this coefficient becomes insignificant in column 6 when we include all regressors.

We perform an additional check in Table 6. We take the individual border effect coefficients from sections 4.4.1 and 4.4.2 (also see Figures 2-4) and regress them on the infrastructure and productivity measures at the U.S. state level. In column 1 only the airport variable is significantly related to the 48 international border coefficients. Consistent with column 1 of Table 5 we find that states with more extensive airport infrastructure are associated with stronger (i.e., more negative) dummy coefficients. In column 2 we regress on GDP and again find that larger states tend to have weaker border coefficients, although the GDP coefficient becomes insignificant in column 3 when we include all regressors. The latter finding is mirrored in columns 5 and 6 for the domestic border effect. The infrastructure measures in columns 4 and 6 do not appear systematically related to the size of domestic border coefficients, with the (marginal) exception of road length per capita.

In summary, we continue to find evidence that border effects are systematically related to state size. While Table 5 shows evidence of a systematic relationship between transport infrastructure and the size of border effects, Table 6 is less clear about this link. Further evidence from different data sets would be helpful to clarify the role of transport infrastructure in determining border effect estimates.

4.9 Evidence from industry-level trade

One potential explanation for our finding of heterogeneous border effects could be differences in the industry mix across states. To account for such composition effects we estimate heterogeneous border effects based on trade flows at the industry level. If the spatial attenuation effect we document in previous sections is not related to industry composition effects, then we would expect border effect patterns at the industry level to qualitatively resemble those at the aggregate level.

For this purpose we examine trade flows at the industry level from Crafts and Klein (2015) for the year 2007, sourced from the Commodity Flow Survey. By "industry" we mean "commodity" in Commodity Flow Survey terminology. We have data on domestic flows within the U.S. but not with foreign countries. As in previous sections, we focus on the 48 contiguous states. For aggregate data ("All Commodities") we have 2,125 observations (compared to a maximum possible of $48^*48 = 2,304$ in a fully balanced data set). We naturally have fewer observations at the industry level due to missing trade flows or observations withheld due to data concerns. We describe the data in more detail in appendix C.6. For the estimation we drop industries with a very small number of observations. Specifically, our criterion is to drop industries with fewer than a quarter of the observations available for aggregate data (i.e., fewer than 532), although our results are not sensitive to this particular criterion. This leaves us with 22 industries, listed in appendix C.6.

We first estimate the standard common domestic border effect in exactly the same way as in column 3 of Table 1. For aggregate data the coefficient stands at -1.51 with a standard error of 0.20. It is thus virtually the same as in Table 1. We then run the same specification for each industry. In all 22 industries we estimate a negative border coefficient, and in 21 industries it is statistically significant at the 1 percent level (the average coefficient value is -1.42 with an average standard error of 0.21). This evidence is consistent with Crafts and Klein (2015) who also find statistically significant domestic border dummy coefficients.

Second and most importantly, we estimate individual domestic border effects by allowing them to vary by U.S. state, following our approach in section 4.4.2. We start by estimating these coefficients for aggregate data. The average of the 48 individual coefficients is -1.37 with an average standard error of 0.14. This is very close to the results in section 4.4.2 where we report an average coefficient of -1.32 with an average standard error of 0.13. A plot of the individual coefficients produces a heterogeneity pattern that looks very similar to Figure 4, with values spanning a range of more than six log points (the smallest being -4.40 and the largest 2.46).

We then estimate analogous individual coefficients based on industry-level data, obtained from separate regressions for each industry. To convey a visual impression, in Figure 8 we illustrate the coefficients for the five industries with the largest number of observations. We plot them against the same measure of logarithmic internal trade costs as in Figure 4. The correlation stands at 56 percent, and the corresponding correlation with logarithmic state GDP is 49 percent. This relationship becomes noisier for the full set of 22 industries, but we still find a clear positive relationship (the correlation is 35 percent with internal trade costs and 28 percent with GDP).

Overall, we find strong additional evidence based on industry-level trade flows that is consistent with the theoretical prediction of spatial attenuation. That is, individual border dummy coefficients at the industry level display the same pattern of heterogeneity as in aggregate data: larger states are systematically associated with weaker border effects.

5 Discussion: Are border effects statistical artefacts?

The aim of much of the empirical literature on border effects is to identify the parameters β (for the international border effect) and γ (for the domestic border effect). However, as we have shown in the context of equations (22) and (45), these parameters cannot be identified empirically in standard gravity regressions.[50] The reason is that their estimates are subject to spatial attenuation effects.

We add a note on the interpretation of domestic border effects. While there is a friction t^S between states in our model of the domestic border effect, this friction is not specific to state borders in our model. Rather, it is a general spatial friction that appears between micro regions regardless of whether they happen to be in different states or not. This general spatial friction nevertheless leads to significant domestic border dummy coefficients. That is, even if no specific frictions exist at the border, traditional gravity estimation can still indicate significant border effects, and these can be very large. It would therefore be wrong to interpret such border coefficients as solely reflecting frictions associated with state borders. Through the lens of our model the domestic border effect can therefore be seen as a statistical artefact (in the sense that it identifies frictions that are not specific to domestic borders).

In actual data, however, those coefficients might reflect a combination of general spatial frictions and – to the extent that they exist – frictions that specifically accrue at state borders. For economically less relevant entities (such as ZIP codes or U.S. Census divisions) it is hard to see domestic border effects as anything else than statistical artefacts. But for economically more meaningful entities such as important administrative units, domestic border effects are plausible. For instance, Nitsch and Wolf (2013) argue that domestic border effects might stem from informational frictions in the form of separate social and business networks. Similarly, Wrona (2018) provides a network-based explanation for domestic border effects, induced by long-lasting shocks throughout Japanese history. Using Commodity Flow Survey data Felbermayr and Gröschl (2014) identify a friction between U.S. states that is associated with the divisive history of the Union-Confederacy border.

For the international border effect, there is a friction specific to crossing an international border in our model as long as we have $\beta < 0$.[51] This friction generally cannot

[50] This insight is similar in spirit to the result by Gorodnichenko and Tesar (2009) who show that based on price data, border effects cannot be identified by comparing price dispersion across countries.

[51] If $\beta = 0$, the international border friction does not exist. But as equation (21) demonstrates,

be identified from traditional gravity estimation. But overall, we have little doubt that international border effects exist given the real counterparts in terms of tariffs, customs checks, regulatory differences in product standards etc. Nevertheless, spatial attenuation effects also occur in the international context. As soon as we aggregate across space, international border dummy coefficients are pushed upwards towards zero.

6 Conclusion

We build a model of spatial aggregation that yields precise analytical results for border effects. Symmetric micro regions are aggregated into larger macro regions. Our theory shows how spatial aggregation affects the internal and bilateral trade costs of aggregated regions, and in turn estimated border effects. The main theoretical result is that aggregation leads to border effect heterogeneity: larger regions or countries are associated with border effects closer to zero, and vice versa. We call this the spatial attenuation effect. The intuition is that due to spatial frictions, aggregation across space increases the cost of trading within borders relative to trading across borders.

As an empirical test of the implications of our model, we collect a data set of U.S. exports that combines three types of trade flows: trade within an individual state (Minnesota-Minnesota), trade between U.S. states (Minnesota-Texas) as well as trade flows from an individual U.S. state to a foreign country (Minnesota-France). This data set allows us to estimate the trade effects of crossing the domestic state border and the U.S. international border. It also allows us to estimate these effects individually by state.

As predicted by our theoretical framework, we find that the larger the state, the weaker its domestic border effect and the weaker its international border effect. In addition, both border effects decline in magnitude when we aggregate states into larger units. We also find substantial sample composition effects when small and large states are systematically dropped from the sample. Overall, we conclude that border effects are inherently heterogeneous. This underlying heterogeneity drives the magnitude of standard common border dummy coefficients.

How should researchers proceed in practice? Of course, many researchers might still want to estimate standard border effects, not least because of the established convention in the literature. But in our view it would be useful to follow four steps. First, researchers can estimate heterogeneous border effects and report their range. Second, they can verify that their results are not driven by sample composition effects that depend on the size of spatial units. Third, researchers can replicate their results at different levels of

estimation based on aggregate data would still yield heterogeneous coefficients. In our model those would be *positive*.

aggregation. And fourth, researchers can exercise more caution when it comes to the interpretation of their results. They need to take into account that the magnitude of border effects might in part be a statistical artefact of aggregation stemming from spatial attenuation.

APPENDIX

“Estimating Border Effects: The Impact of Spatial Aggregation”

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Table of Contents

Appendix A: The international border effect

This appendix contains a number of derivations referred to in the main text.

A.1 Aggregate internal trade costs

Gravity holds at the macro level so that the following relationship describes the internal trade of a macro region:

$$x_{ii}^L = \frac{y^L y^L}{y^W}\left(\frac{t_{ii}^L}{P^L P^L}\right)^{1-\sigma}, \tag{24}$$

where t_{ii}^L denotes the internal trade costs within the macro region. This internal macro flow is the aggregate of the n internal flows of the original micro regions and their $n(n-1)$ bilateral flows:

$$\begin{aligned} x_{ii}^L &= \sum_{k\epsilon i} x_{kk}^S + \sum_{k\epsilon i}\sum_{l\epsilon i, l\neq k} x_{kl}^S \\ &= \sum_{k\epsilon i} x_{kk}^S + 2\sum_{h=1}^{n-1}(n-h)x_h^S, \end{aligned}$$

where the second term on the right-hand side captures all bilateral micro flows and x_h^S denotes trade between micro regions that are h steps apart.

Combining the corresponding gravity relationships at the macro and micro levels, we obtain the following expression:

$$\underbrace{\frac{ny^S ny^S}{y^W}\left(\frac{t_{ii}^L}{P^L P^L}\right)^{1-\sigma}}_{x_{ii}^L} = \sum_{k\epsilon i} \underbrace{\frac{y^S y^S}{y^W}\left(\frac{t_{kk}^S}{P^S P^S}\right)^{1-\sigma}}_{x_{kk}^S} + 2\sum_{h=1}^{n-1}(n-h)\underbrace{\frac{y^S y^S}{y^W}\left(\frac{t_h^S}{P^S P^S}\right)^{1-\sigma}}_{x_h^S}. \tag{25}$$

Given that multilateral resistance is unaffected by aggregation, the internal trade costs of the macro region therefore follow from equation (25) as

$$\left(t_{ii}^L\right)^{1-\sigma} = \frac{1}{n}\left(t_{kk}^S\right)^{1-\sigma} + 2\sum_{h=1}^{n-1}\frac{n-h}{n^2}\left(t_h^S\right)^{1-\sigma}. \tag{26}$$

If bilateral costs are higher than internal costs at the micro level ($t_h^S > t_{kk}^S$), then internal trade costs at the macro level grow in the number of aggregated micro regions ($\partial t_{ii}^L/\partial n > 0$). The only exception is the limiting case of no spatial frictions in the sense of $t_h^S = t_{kk}^S$. In that case, internal trade costs at the macro level are the same as micro-level costs ($t_{ii}^L = t_h^S = t_{kk}^S$).

A.2 Aggregation and multilateral resistance

It is also the case for the model of the international border effect that aggregation leaves the multilateral resistance price indices unaffected. The proof is as follows.

As in Anderson and van Wincoop (2003), the general equilibrium price index for each micro region is given by

$$\left(P_k^S\right)^{1-\sigma} = \sum_{l=1}^{2R} \frac{y_l^S}{y^W} \left(\frac{t_{lk}^S}{P_l^S}\right)^{1-\sigma},$$

where R is the number of Home micro regions and $R^* = R$ is the number of Foreign micro regions. Thus, the price index aggregates trade costs over $R + R^* = 2R$ micro regions. The bilateral trade cost term t_{lk}^S refers to t_h^S for trade with other micro regions in the same country that are h steps away, and to t_{int}^S for trade with micro regions in the other country. Due to symmetry we have $y_l^S/y^W = 1/(2R)$ and $P_l^S = P^S$. Therefore we can write the price index for a Home region as

$$\left(P^S\right)^{1-\sigma} = \frac{1}{2R}\left(\frac{t_{kk}^S}{P^S}\right)^{1-\sigma} + \frac{1}{2R}\sum_{l\epsilon R, l\neq k}\left(\frac{t_{lk}^S}{P^S}\right)^{1-\sigma} + \frac{1}{2}\left(\frac{t_{int}^S}{P^S}\right)^{1-\sigma}, \tag{27}$$

where the first term reflects the trade of the micro region with itself, the second term captures the relationships with all other Home micro regions, and the third term captures the relationships with all Foreign micro regions. We can solve for P^S as

$$\left(P^S\right)^{1-\sigma} = \left(\frac{1}{2R}\left(t_{kk}^S\right)^{1-\sigma} + \frac{1}{2R}\sum_{l\epsilon R, l\neq k}\left(t_{lk}^S\right)^{1-\sigma} + \frac{1}{2}\left(t_{int}^S\right)^{1-\sigma}\right)^{\frac{1}{2}} \tag{28}$$

so that the price index is pinned down by the number of micro regions and their trade costs. The analogous steps apply for the price index of a Foreign micro region.

Now suppose n micro regions in the Home country are aggregated into a macro region denoted by the subscript i. Analogous to (27), we can then write the micro price index from the perspective of a remaining Home micro region as

$$\left(P^S\right)^{1-\sigma} = \frac{1}{2R}\left(\frac{t_{kk}^S}{P^S}\right)^{1-\sigma} + \frac{1}{2R}\sum_{l\epsilon R, l\neq k,i}\left(\frac{t_{lk}^S}{P^S}\right)^{1-\sigma} + \frac{n}{2R}\left(\frac{t_{ik}^L}{P^L}\right)^{1-\sigma} + \frac{1}{2}\left(\frac{t_{int}^S}{P^S}\right)^{1-\sigma}, \tag{29}$$

where the first term reflects the internal part. The second term captures the remaining Home micro regions. The third term captures the relationship with the macro region, weighted by its share $n/(2R)$ of the global economy. The macro price index P^L appears here together with the bilateral trade costs t_{ik}^L between the macro region and the micro region. The fourth term captures the international relationships.

From gravity equation (24) at the macro level, we can solve for the macro price index as

$$\left(P^L\right)^{1-\sigma} = \left(\frac{y_i^L y_i^L}{x_{ii}^L y^W}\left(t_{ii}^L\right)^{1-\sigma}\right)^{\frac{1}{2}}.$$

We use (25) to replace x_{ii}^L as well as $y_i^L = ny^S$ to obtain

$$\left(P^L\right)^{1-\sigma} = \left(P^S\right)^{1-\sigma}\left(\frac{\left(t_{ii}^L\right)^{1-\sigma}}{\frac{1}{n}\left(t_{kk}^S\right)^{1-\sigma} + \frac{2}{n^2}\sum_{h=1}^{n-1}(n-h)\left(t_h^S\right)^{1-\sigma}}\right)^{\frac{1}{2}}.$$

For brevity, we set

$$\lambda^{1-\sigma} \equiv \left(\frac{\left(t_{ii}^{L}\right)^{1-\sigma}}{\frac{1}{n}\left(t_{kk}^{S}\right)^{1-\sigma} + \frac{2}{n^2}\sum_{h=1}^{n-1}(n-h)\left(t_{h}^{S}\right)^{1-\sigma}} \right)^{\frac{1}{2}} \tag{30}$$

so that we have

$$\left(P^{L}\right)^{1-\sigma} = \left(\lambda P^{S}\right)^{1-\sigma}. \tag{31}$$

We insert this result back into expression (29) and solve for the micro price index as

$$\left(P^{S}\right)^{1-\sigma} = \left(\frac{1}{2R}\left(t_{kk}^{S}\right)^{1-\sigma} + \frac{1}{2R}\sum_{l\epsilon R, l\neq k,i}\left(t_{lk}^{S}\right)^{1-\sigma} + \frac{n}{2R}\left(\frac{t_{ik}^{L}}{\lambda}\right)^{1-\sigma} + \frac{1}{2}\left(t_{int}^{S}\right)^{1-\sigma} \right)^{\frac{1}{2}}. \tag{32}$$

Setting this result equal to expression (28), we obtain

$$n\left(\frac{t_{ik}^{L}}{\lambda}\right)^{1-\sigma} + \sum_{l\epsilon R, l\neq k,i}\left(t_{lk}^{S}\right)^{1-\sigma} = \sum_{l\epsilon R, l\neq k}\left(t_{lk}^{S}\right)^{1-\sigma}.$$

The t_{lk}^{S} terms between k and those micro regions l that were not aggregated are the same on both sides of the equation. We therefore have

$$n\left(\frac{t_{ik}^{L}}{\lambda}\right)^{1-\sigma} = \sum_{l\epsilon i}\left(t_{lk}^{S}\right)^{1-\sigma}, \tag{33}$$

where the right-hand side only sums over those micro regions l that were aggregated.

In equation (29) we write down the post-aggregation price index of a micro region. Analogously, the post-aggregation price index for the macro region in the Home country is given by

$$\left(P^{L}\right)^{1-\sigma} = \frac{n}{2R}\left(\frac{t_{ii}^{L}}{P^{L}}\right)^{1-\sigma} + \frac{1}{2R}\sum_{l\epsilon R, l\neq i}\left(\frac{t_{li}^{L}}{P^{S}}\right)^{1-\sigma} + \frac{1}{2}\left(\frac{t_{int}^{S}}{P^{S}}\right)^{1-\sigma},$$

where the first term reflects trade within the macro region. The second term captures the relationships with the remaining micro regions. The third term captures the international relationships, where we use the result surrounding equation (19) that international trade costs are unaffected by aggregation and thus equal to t_{int}^{S}.

We then substitute the relationship (31) and solve for the micro price index as

$$\left(P^{S}\right)^{1-\sigma} = \left(\frac{1}{\lambda^{1-\sigma}}\right)^{\frac{1}{2}} \left(\frac{n}{2R}\left(\frac{t_{ii}^{L}}{\lambda}\right)^{1-\sigma} + \frac{1}{2R}\sum_{l\epsilon R, l\neq i}\left(t_{li}^{L}\right)^{1-\sigma} + \frac{1}{2}\left(t_{int}^{S}\right)^{1-\sigma} \right)^{\frac{1}{2}}.$$

We set this result equal to equation (32). To replace the $\left(t_{ii}^{L}\right)^{1-\sigma}$ term, we use the definition of λ in equation (30). To replace the $\left(t_{ik}^{L}/\lambda\right)^{1-\sigma}$ term in equation (32), we use the result in (33). We also note that due to symmetry, we have $\left(t_{li}^{L}\right)^{1-\sigma} = \left(t_{il}^{L}\right)^{1-\sigma}$.

Through equation (33) this is the same as

$$\left(t_{li}^{L}\right)^{1-\sigma}=\left(t_{il}^{L}\right)^{1-\sigma}=\frac{\lambda^{1-\sigma}}{n}\sum_{k\epsilon i}\left(t_{kl}^{S}\right)^{1-\sigma}.$$

Collecting terms and simplifying, we obtain

$$\begin{aligned}&\left(t_{kk}^{S}\right)^{1-\sigma}+\frac{2}{n}\sum_{h=1}^{n-1}(n-h)\left(t_{h}^{S}\right)^{1-\sigma}+\frac{1}{n}\sum_{l\epsilon R,l\neq i}\sum_{k\epsilon i}\left(t_{kl}^{S}\right)^{1-\sigma}+\frac{1}{\lambda^{1-\sigma}}R\left(t_{int}^{S}\right)^{1-\sigma}\\=\;&\left(t_{kk}^{S}\right)^{1-\sigma}+\sum_{l\epsilon R,l\neq k}\left(t_{lk}^{S}\right)^{1-\sigma}+R\left(t_{int}^{S}\right)^{1-\sigma}.\end{aligned}$$

We note that the second term on the left-hand side of the last equation captures all bilateral trade costs amongst the micro regions that were aggregated. We can write this as

$$\frac{2}{n}\sum_{h=1}^{n-1}(n-h)\left(t_{h}^{S}\right)^{1-\sigma}=\frac{1}{n}\sum_{l\epsilon i}\sum_{k\epsilon i,k\neq l}\left(t_{kl}^{S}\right)^{1-\sigma}.$$

We also note that

$$\begin{aligned}&\frac{1}{n}\sum_{l\epsilon R,l\neq i}\sum_{k\epsilon i}\left(t_{kl}^{S}\right)^{1-\sigma}+\frac{1}{n}\sum_{l\epsilon i}\sum_{k\epsilon i,k\neq l}\left(t_{kl}^{S}\right)^{1-\sigma}\\=\;&\sum_{l\epsilon R,l\neq k}\left(t_{kl}^{S}\right)^{1-\sigma}=\sum_{l\epsilon R,l\neq k}\left(t_{lk}^{S}\right)^{1-\sigma}\end{aligned}$$

so that ultimately, after dropping equal terms on both sides of the equation, we obtain

$$\frac{1}{\lambda^{1-\sigma}}R\left(t_{int}^{S}\right)^{1-\sigma}=R\left(t_{int}^{S}\right)^{1-\sigma}.$$

This implies $\lambda^{1-\sigma}=1$. Through equation (31) we therefore arrive at the result that the price index is unaffected by aggregation, i.e., $P^{L}=P^{S}$.

A.3 The bias of omitting the interaction term

The trade cost function (20) includes an interaction term that combines the international border dummy with region-specific α_i and α_j variables. We can rewrite this trade cost function with $\phi=1$ as

$$\ln\left(t_{ij}^{1-\sigma}\right)=\beta INT_{ij}+\ln\left(\delta_{ij}^{1-\sigma}\right)+\ln(\alpha_i\alpha_j)^{1-\sigma}-INT_{ij}\ln(\alpha_i\alpha_j)^{1-\sigma}.$$

Imagine a researcher imposes the traditional trade cost function without the interaction term. The β international border coefficient in the traditional function is then unbiased only in the special case of a zero covariance between the border dummy and the interaction term. Formally, we can state this condition as

$$\operatorname{Cov}\left(INT_{ij},INT_{ij}\ln\left(\alpha_i\alpha_j\right)^{1-\sigma}\right)=0. \tag{34}$$

To simplify notation let

$$\begin{aligned} A_{ij} &= INT_{ij}, \\ B_{ij} &= INT_{ij} \ln \left(\alpha_i \alpha_j\right)^{1-\sigma}. \end{aligned}$$

so that condition (34) becomes

$$\begin{aligned} \operatorname{Cov}\left(A_{ij}, B_{ij}\right) = 0 \\ \Leftrightarrow \sum_{ij} \left(A_{ij} - \overline{A}\right)\left(B_{ij} - \overline{B}\right) = 0, \end{aligned}$$

where $\overline{A}$ and $\overline{B}$ denote the arithmetic averages of A_{ij} and B_{ij}.

Assume a sample with K domestic trade observations for which $INT_{ij} = 0$ and M international observations for which $INT_{ij} = 1$ such that we have $K + M$ total observations. We can rewrite the previous equation as

$$\begin{aligned} K\left(-\overline{A}\right)\left(-\overline{B}\right) + \sum_{ij, INT_{ij}=1} \left(1 - \overline{A}\right)\left(B_{ij} - \overline{B}\right) &= 0 \\ \Leftrightarrow K\overline{AB} + \left(1 - \overline{A}\right) \sum_{ij, INT_{ij}=1} \left(B_{ij} - \overline{B}\right) &= 0 \end{aligned}$$

where the first term reflects the K domestic observations. We can rearrange the last equation as

$$\begin{aligned} K\overline{AB} - \left(1 - \overline{A}\right) M\overline{B} + \left(1 - \overline{A}\right) \sum_{ij, INT_{ij}=1} B_{ij} &= 0 \\ \Leftrightarrow (K + M)\,\overline{AB} - M\overline{B} + \left(1 - \overline{A}\right) \sum_{ij, INT_{ij}=1} B_{ij} &= 0. \end{aligned}$$

Note that $\overline{A} = M/(K + M)$. The last equation thus simplifies to

$$\begin{aligned} \left(1 - \overline{A}\right) \sum_{ij, INT_{ij}=1} B_{ij} &= 0 \\ \Leftrightarrow \sum_{ij, INT_{ij}=1} \ln \left(\alpha_i \alpha_j\right)^{1-\sigma} &= 0 \\ \Leftrightarrow \sum_{ij, INT_{ij}=1} \left[\ln\left(\alpha_i\right) + \ln\left(\alpha_j\right)\right] &= 0. \end{aligned}$$

There are two partner regions (one exporter i and one exporter j) for each of the M international observations. Let m_i denote the relative frequency with which region i appears as a partner in those observations (either as an exporter or as an importer). Then we can rewrite the last expression as

$$\begin{aligned} \sum_{i=1}^{N} m_i \ln\left(\alpha_i\right) &= 0 \\ \Leftrightarrow \prod_{i=1}^{N} \alpha_i^{m_i} &= 1, \end{aligned}$$

where N is the number of regions in the sample. That is, the geometric average of the region-specific α_i terms, weighted by the frequency in bilateral observations, is equal to 1. Given that $\alpha_i \geq 1$, it must be that $\alpha_i = 1$ holds for all i. This condition can only hold if region i is a micro region ($n_i = 1$) or if there are no spatial frictions ($\delta = 1$).

Appendix B: The domestic border effect

This appendix develops a theory of spatial aggregation in the context of the domestic border effect. We set up a simple model that yields analytical results for the effect of spatial aggregation on estimated border effects.

B.1 Spatial aggregation and the domestic border effect

Micro and macro regions

As in section 3.2, we model the economy as consisting of an arbitrary number of small 'micro' regions denoted by the superscript S for 'small.' Micro regions get aggregated into 'macro' regions denoted by the superscript L for 'large.' As in section 3.1, whenever necessary we use the subscripts k and l for micro regions and the subscripts i and j for macro regions.

Each micro region is endowed with a differentiated good as in the Armington framework of Anderson and van Wincoop (2003). To be able to obtain analytical solutions, we impose symmetry across these basic spatial units. That is, we assume they have the same frictions at the micro level: the same internal trade costs t_{kk}^S for all k and the same bilateral trade costs t_{kl}^S between each other such that $t_{kl}^S = t^S$ for all $k \neq l$. The bilateral costs are at least as high as the internal costs ($t^S \geq t_{kk}^S \geq 1$), and they are the only bilateral friction in the model.[52] The micro regions have uniform income and multilateral resistance terms y_k^S and P_k^S.[53]

As a consequence, all micro regions have the same internal trade flows x_{kk}^S and the same bilateral trade flows x_{kl}^S. The same gravity equation as (1) applies at the micro level, i.e.,

$$x_{kl}^S = \frac{y^S y^S}{y^W} \left(\frac{t_{kl}^S}{P^S P^S} \right)^{1-\sigma},$$

where we drop the subscripts for all region-specific variables. As outlined by Anderson and van Wincoop (2003, footnote 12), by setting outward and inward multilateral resistance price indices equal to each other we adopt a particular normalization. In appendix B.2 we show that our theory holds up under the more general treatment that retains separate outward and inward multilateral resistance variables. But to keep the exposition as simple as possible, we use the more parsimonious version here that adopts the normalization of equal outward and inward multilateral resistances.

Aggregation

As the next step, we aggregate $n \geq 2$ micro regions into a macro region. The income of this aggregated region follows as $y^L = ny^S$. We do not impose any additional frictions. In particular, we do not impose any additional friction between different macro regions.

Given our symmetry assumption, we can show that gravity applies again at the macro

[52] We assume symmetric preference weights across micro regions. See Anderson and van Wincoop (2003, equation 4) for the underlying utility specification with preference weights.

[53] Implicitly, if R is the number of micro regions, then we have a space of dimension $R - 1$. The bilateral friction at the level of micro regions can also be interpreted as one unit of distance. For more complicated settings with asymmetric micro regions (characterized by different sizes or different trade costs), we generally have to resort to numerical methods. See appendix C.7 for examples.

level. For the internal trade of the macro region, we have the relationship

$$x_{ii}^L = \frac{y^L y^L}{y^W}\left(\frac{t_{ii}^L}{P^L P^L}\right)^{1-\sigma}, \tag{35}$$

where t_{ii}^L denotes the internal trade costs within the macro region. This internal macro flow is the aggregate of the n internal flows of the original micro regions as well as their $n(n-1)$ bilateral flows:

$$x_{ii}^L = n x_{kk}^S + n(n-1)x_{kl}^S.$$

Combining the three previous equations we obtain

$$\underbrace{\frac{ny^S ny^S}{y^W}\left(\frac{t_{ii}^L}{P^L P^L}\right)^{1-\sigma}}_{x_{ii}^L} = \underbrace{n\frac{y^S y^S}{y^W}\left(\frac{t_{kk}^S}{P^S P^S}\right)^{1-\sigma}}_{x_{kk}^S} + \underbrace{n(n-1)\frac{y^S y^S}{y^W}\left(\frac{t^S}{P^S P^S}\right)^{1-\sigma}}_{x_{kl}^S}. \tag{36}$$

Multilateral resistance is unaffected by aggregation

In appendix B.2 we show that aggregation does not affect the multilateral resistance price index, i.e., $P^S = P^L$. The intuition is that due to the initial symmetry, aggregation does not change the underlying trade flow equilibrium and trade cost structure. The price index therefore preserves the incidence interpretation of carrying goods to and from the same hypothetical world market as in Anderson and Yotov (2010).

Aggregate internal and bilateral trade costs

Given that the price indices are the same across micro and macro regions, equation (36) simplifies to

$$\left(t_{ii}^L\right)^{1-\sigma} = \frac{1}{n}\left(t_{kk}^S\right)^{1-\sigma} + \frac{n-1}{n}\left(t^S\right)^{1-\sigma}. \tag{37}$$

If the economy faces higher bilateral than internal costs at the micro level ($t^S > t_{kk}^S$), then internal trade costs at the macro level grow in the number of aggregated micro regions ($\partial t_{ii}^L/\partial n > 0$).[54] The only exception is the limiting case of no spatial frictions in the sense of $t^S = t_{kk}^S$. In that case, internal trade costs at the macro level are the same as at the micro level ($t_{ii}^L = t_{kk}^S$). Thus, the frictionless world is the only case where aggregation is irrelevant since border effects are then by construction zero.[55]

In contrast to internal trade costs, *bilateral* trade costs are not affected by aggregation and remain the same for micro and macro regions. Suppose we observe two macro regions of different size, one comprising n_1 micro regions and the other n_2. Gravity commands the bilateral trade relationship (15)

$$x_{1,2}^L = \frac{y_1^L y_2^L}{y^W}\left(\frac{t_{1,2}^L}{P^L P^L}\right)^{1-\sigma},$$

where $x_{1,2}^L$ denotes the trade flow from the first to the second macro region with bilateral costs $t_{1,2}^L$, and y_1^L and y_2^L are their respective incomes. This flow is the aggregate of $n_1 n_2$

[54] See Ramondo, Rodríguez-Clare and Saborío-Rodríguez (2016, equation 11) for a similar derivation based on the Eaton and Kortum (2002) model for the special case of $t_{kk}^S = 1$ as a normalization.

[55] The frictionless world would correspond to $t_{kl}^S = t^S = 1$ for all k, l, and it would be an example of the special case described in section 3.1.2. We could normalize trade costs to any other positive uniform level.

bilateral micro flows:

$$x_{1,2}^L = n_1 n_2 x_{kl}^S.$$

We can therefore write

$$\underbrace{\frac{n_1 y^S n_2 y^S}{y^W}\left(\frac{t_{1,2}^L}{P^L P^L}\right)^{1-\sigma}}_{x_{1,2}^L} = n_1 n_2 \underbrace{\frac{y^S y^S}{y^W}\left(\frac{t^S}{P^S P^S}\right)^{1-\sigma}}_{x_{kl}^S}. \tag{38}$$

Given $P^S = P^L$, it follows

$$t_{ij}^L = t^S \tag{39}$$

such that bilateral trade costs between any two regions are the same regardless of the degree of aggregation. Thus, while the bilateral friction t^S is specified at the lowest level of spatial aggregation (i.e., at the level of micro regions), no additional friction appears by crossing the border from one macro region and another.

Estimating the traditional border effect

Having characterized the full set of aggregate internal and bilateral trade costs for macro regions in equations (37) and (39) in our model, we now formally derive the border effect coefficient as traditionally estimated in the literature. That is, if the above model is true but we use standard gravity estimation in combination with the (erroneous) traditional trade cost function, what result do we get?

To keep the exposition as clear as possible, we use a simplified version of the traditional trade cost function (2) that only consists of the dummy variable for bilateral domestic trade flows DOM_{ij}:

$$\ln\left(t_{ij}^{1-\sigma}\right) = \gamma DOM_{ij}, \tag{40}$$

where we revert to the standard notation with i denoting an exporting region and j denoting an importing region. 'Regions' here in the context of estimation refer to macro regions (those are U.S. states in our empirical analysis in section 4), and for simplicity we drop the L superscript. From equation (39) we note that $t_{ij} = t^S$ for all $i \neq j$. We deliberately ignore other trade cost components but those could be added.[56] From equations (39) and (40) we have $\gamma = \ln\left(t^S\right)^{1-\sigma} \leq 0$ for $DOM_{ij} = 1$. Thus, trade cost function (40) is consistent with bilateral trade costs as they appear in our model.

In contrast, trade cost function (40) is not consistent with internal trade costs as they appear in our model. The simplified trade cost function (40) implies that internal trade costs within macro regions are zero with $DOM_{ii} = 0$ and hence (erroneously) imposes $t_{ii} = 1$. Most important for our purposes, this condition would hold for *all* macro regions i. The trade cost function (40) therefore imposes a one-size-fits-all restriction on internal trade costs. This goes beyond a normalization whereby internal trade costs are set to a particular value for *one* region. As equation (37) shows, internal trade costs t_{ii} in fact vary by macro region size.

The parameter of interest is γ, representing the border friction at the micro level.[57]

[56] In appendix B.6 we show that our results go through for a more conventional specification that includes bilateral distance as an additional trade cost component.

[57] From equations (39) and (40) we have $\gamma = \ln\left(t^S\right)^{1-\sigma} \leq 0$ for $DOM_{ij} = 1$.

We use the log-linearized form of gravity equation (1)

$$\ln\left(\frac{x_{ij}}{y_i y_j}\right) = c + (1-\sigma)\ln(t_{ij}) = c + \gamma DOM_{ij},$$

where we take the income terms onto the left-hand side. Since the multilateral resistance terms do not vary across macro regions in our model, they are absorbed by the constant $c = -\ln\left(y^W\right) + \ln\left(P_i^{\sigma-1}\right) + \ln\left(P_j^{\sigma-1}\right)$. This simple regression model with a constant and a single explanatory variable leads to the OLS estimate

$$\widehat{\gamma} = \frac{\mathrm{Cov}\left(\ln\left(\frac{x_{ij}}{y_i y_j}\right), DOM_{ij}\right)}{\mathrm{Var}\left(DOM_{ij}\right)}. \tag{41}$$

As shown in appendix B.3, we can derive the coefficient estimate as

$$\widehat{\gamma} = \gamma + \underbrace{\ln\left(\prod_{i=1}^{N}\left(t_{ii}^{\sigma-1}\right)^{\frac{1}{N}}\right)}_{\text{bias}}, \tag{42}$$

where N is the number of regions in the estimation sample. We therefore obtain a biased estimate. The bias is the logarithm of the geometric average of internal trade cost factors scaled by the elasticity of substitution. To be more specific, given that γ is typically negative and given that internal trade costs are typically positive in the data (i.e., $t_{ii} > 1$) as well as in our model through equation (37), we have an upward bias: the larger internal trade costs are in the sample, the closer the estimate $\widehat{\gamma}$ will be pushed towards zero.

To be clear, this is not an econometric bias in the sense that the estimation method is inappropriate.[58] Rather, it is an aggregation bias in the sense that estimation with aggregate data does not identify the underlying micro friction.

Once we acknowledge positive internal trade frictions, we need to adjust our interpretation of border coefficients estimated with the traditional dummy variable. We highlight three important implications that follow from the result in (42) and that we will explore in the empirical section:[59]

1. **Interpretation relative to a zero-internal-frictions benchmark:** As the one exception, the bias would disappear only if internal trade costs were on average zero.[60] For the interpretation of trade cost function (40) we therefore have to adopt the implicit normalization of zero average internal trade costs.[61] The correct interpretation based on the traditional trade cost function would be: "All else being equal, trade flows across domestic borders are estimated to be only the fraction

[58] Apart from OLS, PPML estimation following Santos Silva and Tenreyro (2006) generates qualitatively the same estimates. See section 4 for details.

[59] These implications are similar to those in section 3.2.3 for the international border effect.

[60] Formally, only if $\prod_{i=1}^{N}\left(t_{ii}^{\sigma-1}\right)^{1/N} = 1$.

[61] If other controls such as distance are added to the trade cost function, the bias generally does not disappear (see appendix B.6).

$\exp(\gamma)$ of internal trade flows *under the assumption* that internal trade costs are zero on average."

2. **No direct comparability across samples:** Border effect coefficients are generally not directly comparable across different samples because of the heterogeneity of internal trade costs. For example, suppose we obtain a coefficient of $\gamma_1 = -1$ in one sample and a coefficient of $\gamma_2 = -0.5$ in another, and the two coefficients are significantly different. This difference does not necessarily imply that the domestic border is more detrimental to trade flows in the first sample than in the second.

3. **Systematic sample composition effects:** Related to the second implication, border effect coefficients are sensitive to sample composition in a systematic way. More specifically, adding macro regions to the sample with relatively large internal trade costs pushes the border coefficient towards zero. Vice versa, adding macro regions with relatively small internal trade costs renders the border coefficient more negative. In the empirical section we show that these sample composition effects are substantial from a quantitative point of view.

A heterogeneous trade cost function

Once we aggregate across space as implied by equation (37), internal trade costs become heterogeneous across macro regions with $t_{ii} \neq t_{jj}$ for all $i \neq j$ in general. The one-size-fits-all restriction implicit in the simple DOM_{ij} dummy then renders trade cost function (40) misspecified. As shown by equation (42) and in appendix B.5, this tension generates an omitted variable bias in standard gravity estimation of border effects. Trade cost function (40) with a simple dummy is therefore unsuitable for spatial aggregation as it does not accommodate the heterogeneous nature of internal trade costs.

This problem can be addressed by augmenting the function to a heterogeneous trade cost function consistent with the theory:

$$\ln\left(t_{ij}^{1-\sigma}\right) = \gamma DOM_{ij} + \psi\left(1 - DOM_{ij}\right)\ln\left(t_{ii}^{1-\sigma}t_{jj}^{1-\sigma}\right)^{\frac{1}{2}} \tag{43}$$

with $\psi = 1$. It reduces to equation (40) for $i \neq j$. The key feature of the heterogeneous trade cost function (43) is the interaction term between the dummy and internal trade costs. Unlike (40), it thus allows for heterogeneous internal trade costs in the case of $i = j$.[62] It is a special case of the general trade cost function (13) developed in section 3.1.[63]

If the heterogeneous trade cost function (43) is used in a gravity equation such as (1), then the direct effect of DOM_{ij} on trade (ignoring the general equilibrium and multilateral resistance effects) is given by

$$\frac{\Delta\ln\left(x_{ij}\right)}{\Delta DOM_{ij}} = \gamma + \psi\ln\left(t_{ii}^{\sigma-1}t_{jj}^{\sigma-1}\right)^{\frac{1}{2}}, \tag{44}$$

[62] Given $\psi = 1$, for $i = j$ equation (43) becomes an identity. Unlike in equation (40) internal trade costs are thus not set to zero. In the special case of $\psi = 0$ equation (43) nests the simple trade cost function (40). This parameter restriction on ψ comes down to a straightforward testable hypothesis of border effect heterogeneity that we consider in the empirical section.

[63] The $\zeta BORDER_{ij}$ term in equation (13) corresponds to γDOM_{ij} in equation (43), abstracting from the distance component. The trade cost mismeasurement term is equal to $e_{ij} = 1$ for $DOM_{ij} = 1$ and equal to $e_{ij} = \left(t_{ii}^{1-\sigma}t_{jj}^{1-\sigma}\right)^{1/2}$ for $DOM_{ij} = 0$ with $\psi = 1$, meaning trade costs are correctly measured for $DOM_{ij} = 1$ but mismeasured for $DOM_{ij} = 0$. This yields trade cost function (43).

where ΔDOM_{ij} indicates a comparison of $DOM_{ij} = 0$ with $DOM_{ij} = 1$. As we show in appendix B.4, this effect is invariant to the specific normalization chosen for trade costs.[64] That is, suppose we renormalize trade costs by setting $t_{i'j'} = 1$ for trade costs between macro regions i' and j'. The magnitude of the effect in (44) remains unchanged.

The key insight is that all else equal, larger internal trade costs lead to a smaller border effect. That is, the second term $\psi \ln \left(t_{ii}^{\sigma-1} t_{jj}^{\sigma-1}\right)^{1/2}$ increases in t_{ii} and t_{jj} and thus counteracts the negative effect stemming from $\gamma < 0$.[65] Ceteris paribus border effects are therefore mechanically driven by internal trade costs and inherently heterogeneous, in contrast to the traditional trade cost function (40). We call this the spatial attenuation effect. In the empirical part of the paper, we illustrate the heterogeneity by reporting the full range of border effects across macro regions in our sample.

The intuition is that due to aggregation, larger macro regions have larger internal trade frictions. This increases 'internal resistance', leading to relatively less internal trade and relatively more bilateral trade. As a result, the domestic border effect appears smaller. In section 4.7 we show that this mechanism is entirely separate from general equilibrium multilateral resistance effects as highlighted by Anderson and van Wincoop (2003).

Estimating heterogeneous domestic border effects

The right-hand side variables of the heterogeneous trade cost function (43) do not only include the domestic border dummy DOM_{ij} but also the internal trade costs of the two macro regions in each pair, t_{ii} and t_{jj}, and most crucially their interaction. Internal trade costs are typically not directly observable, but this does not pose a problem since we can use appropriate fixed effects to control for them.[66]

More specifically, we can break down trade cost function (43) into region-specific terms as

$$\ln\left(t_{ij}^{1-\sigma}\right) = \underbrace{\gamma DOM_{ij} - \left\{\psi DOM_{ij} \ln\left(t_{ii}^{1-\sigma}\right)^{\frac{1}{2}} + \psi DOM_{ij} \ln\left(t_{jj}^{1-\sigma}\right)^{\frac{1}{2}}\right\}}_{\frac{\gamma_r}{2} DOM_{ij}\alpha_r \;=\; \frac{\gamma_r}{2} DOM_{ij}^r} + \underbrace{\psi \ln\left(t_{ii}^{1-\sigma}\right)^{\frac{1}{2}}}_{\alpha_i} + \underbrace{\psi \ln\left(t_{jj}^{1-\sigma}\right)^{\frac{1}{2}}}_{\alpha_j}. \tag{45}$$

In a standard log-linearized gravity regression based on equation (1), we can absorb the last two terms by *exporter* and *importer* fixed effects α_i and α_j that also capture income and multilateral resistance terms. At first glance it may seem that the terms in curly brackets could be estimated by interacting the domestic border dummy DOM_{ij} with the α_i and α_j fixed effects. However, this would lead to perfect collinearity with the last two terms, α_i and α_j (see below for an example). Instead, the first three terms can be estimated through an interaction of the DOM_{ij} dummy with *region* fixed effects α_r that equal unity whenever r is an exporter $(r = i)$ or an importer $(r = j)$ with $r = 1, ..., N$. This is equivalent to region-specific DOM_{ij}^r dummies with coefficients $\gamma_r/2$ and where

[64] In the Anderson and van Wincoop (2003) model, trade shares are homogeneous of degree zero in trade costs t_{ij} for all i, j (including internal trade costs). Therefore, trade costs can be arbitrarily normalized.

[65] Note that in the theory, $\gamma < 0$ if $t^S > t_{kk}^S$ and $\sigma - 1 > 0$. In the data, for sufficiently large t_{ii} and t_{jj} the border effect can even become positive in total. See section 4.4 for examples.

[66] An alternative would be to use internal distance as a proxy for internal trade costs. We prefer the fixed effects approach due to its simplicity. Head and Mayer (2009) construct a theory-based alternative distance measure and find that it reduces estimated border effects but does not eliminate them. Hinz (2016) constructs novel distance measures based on satellite imagery. He constructs internal distance from point data in the appropriate way for estimating border effects consistently. We also refer to appendix B.6 where we derive a theory-consistent measure of internal distance.

$DOM_{ij}^r \equiv DOM_{ij}\alpha_r$. Since every domestic trade flow is captured by two region-specific border dummies (once on the exporter side and once on the importer side), the estimated coefficients $\gamma_r/2$ must be multiplied by 2 to obtain estimates of γ_r that are comparable to the common border dummy coefficient γ. A simple test of border effect heterogeneity comes down to the hypothesis that the γ_r coefficients differ from each other. We note that the common γ coefficient in (45) cannot be identified since it would be collinear with the γ_r's.

To illustrate the collinearity problem, consider an example of three regions that trade internally and with each other. We have nine trade observations in total, which we stack in the vector x_{ij}. We define η_i to be the vector of $\psi \ln \left(t_{ii}^{1-\sigma}\right)^{1/2}$ values that appear in equation (45). Recall that as defined in section 2.2, DOM_{ij} takes on the value 1 for bilateral flows, implying that a domestic border has been crossed. We then have

$$x_{ij} = \begin{bmatrix} x11 \\ x22 \\ x33 \\ x12 \\ x13 \\ x21 \\ x23 \\ x31 \\ x32 \end{bmatrix}, DOM_{ij} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}, \eta_i = \begin{bmatrix} \psi \ln \left(t_{11}^{1-\sigma}\right)^{1/2} \\ \psi \ln \left(t_{22}^{1-\sigma}\right)^{1/2} \\ \psi \ln \left(t_{33}^{1-\sigma}\right)^{1/2} \\ \psi \ln \left(t_{11}^{1-\sigma}\right)^{1/2} \\ \psi \ln \left(t_{11}^{1-\sigma}\right)^{1/2} \\ \psi \ln \left(t_{22}^{1-\sigma}\right)^{1/2} \\ \psi \ln \left(t_{22}^{1-\sigma}\right)^{1/2} \\ \psi \ln \left(t_{33}^{1-\sigma}\right)^{1/2} \\ \psi \ln \left(t_{33}^{1-\sigma}\right)^{1/2} \end{bmatrix}, \eta_j = \begin{bmatrix} \psi \ln \left(t_{11}^{1-\sigma}\right)^{1/2} \\ \psi \ln \left(t_{22}^{1-\sigma}\right)^{1/2} \\ \psi \ln \left(t_{33}^{1-\sigma}\right)^{1/2} \\ \psi \ln \left(t_{22}^{1-\sigma}\right)^{1/2} \\ \psi \ln \left(t_{33}^{1-\sigma}\right)^{1/2} \\ \psi \ln \left(t_{11}^{1-\sigma}\right)^{1/2} \\ \psi \ln \left(t_{33}^{1-\sigma}\right)^{1/2} \\ \psi \ln \left(t_{11}^{1-\sigma}\right)^{1/2} \\ \psi \ln \left(t_{22}^{1-\sigma}\right)^{1/2} \end{bmatrix},$$

where we list internal flows at the top followed by bilateral flows. It follows

$$DOM_{ij}\eta_i = \begin{bmatrix} 0 \\ 0 \\ 0 \\ \psi \ln \left(t_{11}^{1-\sigma}\right)^{1/2} \\ \psi \ln \left(t_{11}^{1-\sigma}\right)^{1/2} \\ \psi \ln \left(t_{22}^{1-\sigma}\right)^{1/2} \\ \psi \ln \left(t_{22}^{1-\sigma}\right)^{1/2} \\ \psi \ln \left(t_{33}^{1-\sigma}\right)^{1/2} \\ \psi \ln \left(t_{33}^{1-\sigma}\right)^{1/2} \end{bmatrix}, DOM_{ij}\eta_j = \begin{bmatrix} 0 \\ 0 \\ 0 \\ \psi \ln \left(t_{22}^{1-\sigma}\right)^{1/2} \\ \psi \ln \left(t_{33}^{1-\sigma}\right)^{1/2} \\ \psi \ln \left(t_{11}^{1-\sigma}\right)^{1/2} \\ \psi \ln \left(t_{33}^{1-\sigma}\right)^{1/2} \\ \psi \ln \left(t_{11}^{1-\sigma}\right)^{1/2} \\ \psi \ln \left(t_{22}^{1-\sigma}\right)^{1/2} \end{bmatrix}.$$

Collinearity arises because

$$\eta_i + DOM_{ij}\eta_j = \eta_j + DOM_{ij}\eta_i = \begin{bmatrix} \psi \ln\left(t_{11}^{1-\sigma}\right)^{1/2} \\ \psi \ln\left(t_{22}^{1-\sigma}\right)^{1/2} \\ \psi \ln\left(t_{33}^{1-\sigma}\right)^{1/2} \\ \psi \ln\left(t_{11}^{1-\sigma}\right)^{1/2} + \psi \ln\left(t_{22}^{1-\sigma}\right)^{1/2} \\ \psi \ln\left(t_{11}^{1-\sigma}\right)^{1/2} + \psi \ln\left(t_{33}^{1-\sigma}\right)^{1/2} \\ \psi \ln\left(t_{22}^{1-\sigma}\right)^{1/2} + \psi \ln\left(t_{11}^{1-\sigma}\right)^{1/2} \\ \psi \ln\left(t_{22}^{1-\sigma}\right)^{1/2} + \psi \ln\left(t_{33}^{1-\sigma}\right)^{1/2} \\ \psi \ln\left(t_{33}^{1-\sigma}\right)^{1/2} + \psi \ln\left(t_{11}^{1-\sigma}\right)^{1/2} \\ \psi \ln\left(t_{33}^{1-\sigma}\right)^{1/2} + \psi \ln\left(t_{22}^{1-\sigma}\right)^{1/2} \end{bmatrix}.$$

In addition, we note that the η_i and η_j terms are collinear with exporter and importer fixed effects α_i and α_j. Therefore, if we run a standard log-linearized gravity regression with exporter and importer fixed effects, the collinearity problem persists and we would not be able to identify the coefficients of the domestic border dummy interacted with exporter and importer-specific variables.

As a solution, we interact the domestic border dummy with region fixed effects α_r. We then have

$$\alpha_{r=1} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 1 \\ 1 \\ 1 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \alpha_{r=2} = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 1 \\ 0 \\ 1 \\ 1 \\ 0 \\ 1 \end{bmatrix}, \alpha_{r=3} = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 1 \\ 0 \\ 1 \\ 1 \\ 1 \end{bmatrix}$$

and

$$DOM_{ij}^1 = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 1 \\ 1 \\ 0 \\ 1 \\ 0 \end{bmatrix}, DOM_{ij}^2 = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ 1 \\ 1 \\ 0 \\ 1 \end{bmatrix}, DOM_{ij}^3 = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ 1 \\ 1 \\ 1 \end{bmatrix}.$$

The coefficients of the region-specific domestic border dummies DOM_{ij}^1, DOM_{ij}^2 and DOM_{ij}^3 can be identified in an otherwise standard gravity regression with exporter and importer fixed effects.

B.2 Aggregation and multilateral resistance

We characterize the multilateral resistance price indices in the context of aggregation. As a more general treatment, we initially retain the gravity equation that allows for separate outward and inward multilateral resistance price indices. That is, in contrast to equation (14), we start with the more general version

$$x_{kl}^S = \frac{y^S y^S}{y^W} \left(\frac{t_{kl}^S}{\Pi^S P^S} \right)^{1-\sigma},$$

where Π^S denotes outward multilateral resistance. We then show why the specification in equation (14) without separate outward multilateral resistance is sufficient for our purposes.

Consistent with Anderson and van Wincoop (2003, equation 11), the inward price index for each micro region is given by

$$\left(P_k^S\right)^{1-\sigma} = \sum_{l=1}^{R} \frac{y_l^S}{y^W} \left(\frac{t_{lk}^S}{\Pi_l^S} \right)^{1-\sigma},$$

where R is the number of micro regions. Due to symmetry we have $t_{lk}^S = t_{kl}^S = t^S$ for all $l \neq k$ as well as $y_l^S / y^W = 1/R$, $P_l^S = P^S$ and $\Pi_l^S = \Pi^S$, and therefore

$$\left(P^S\right)^{1-\sigma} = \frac{1}{R} \left(\frac{t_{kk}^S}{\Pi^S} \right)^{1-\sigma} + \frac{R-1}{R} \left(\frac{t^S}{\Pi^S} \right)^{1-\sigma}, \tag{46}$$

where the first term reflects the internal part, and the second term captures the relationships with all other micro regions. We can solve for $\Pi^S P^S$ as

$$\left(\Pi^S P^S\right)^{1-\sigma} = \frac{1}{R} \left(t_{kk}^S\right)^{1-\sigma} + \frac{R-1}{R} \left(t^S\right)^{1-\sigma} \tag{47}$$

so that the product of the price indices is pinned down by the number of micro regions and their trade costs.

Now suppose n micro regions are aggregated into a macro region. Analogous to (46), we can then write the micro price index from the perspective of a remaining micro region as

$$\left(P^S\right)^{1-\sigma} = \frac{1}{R} \left(\frac{t_{kk}^S}{\Pi^S} \right)^{1-\sigma} + \frac{R-1-n}{R} \left(\frac{t^S}{\Pi^S} \right)^{1-\sigma} + \frac{n}{R} \left(\frac{t^S}{\Pi^L} \right)^{1-\sigma}, \tag{48}$$

where the first term reflects the internal part. The second term captures the remaining $R-1-n$ micro regions. The third term captures the relationship with the macro region, weighted by its share n/R of the global economy. The macro outward price index Π^L appears in that last term. We can rearrange this expression as

$$\left(\Pi^S P^S\right)^{1-\sigma} = \frac{1}{R} \left(t_{kk}^S\right)^{1-\sigma} + \frac{R-1-n}{R} \left(t^S\right)^{1-\sigma} + \frac{n}{R} \left(\frac{t^S \Pi^S}{\Pi^L} \right)^{1-\sigma}. \tag{49}$$

We set equations (47) and (49) equal to obtain

$$\Pi^S = \Pi^L. \tag{50}$$

From a gravity equation at the macro level similar to (35) that allows for separate outward and inward multilateral resistance price indices, we can solve for the product of the macro price indices as

$$\left(\Pi^L P^L\right)^{1-\sigma} = \frac{y^L y^L}{x_{ii}^L y^W} \left(t_{ii}^L\right)^{1-\sigma}.$$

We use a version of (36) that again allows for separate outward and inward price indices to replace x_{ii}^L as well as $y^L = ny^S$ to obtain

$$\left(\Pi^L P^L\right)^{1-\sigma} = \frac{\left(t_{ii}^L\right)^{1-\sigma}}{\frac{1}{n}\left(t_{kk}^S\right)^{1-\sigma} + \frac{n-1}{n}\left(t^S\right)^{1-\sigma}} \left(\Pi^S P^S\right)^{1-\sigma}.$$

For brevity, we define

$$\lambda^{1-\sigma} \equiv \frac{\left(t_{ii}^L\right)^{1-\sigma}}{\frac{1}{n}\left(t_{kk}^S\right)^{1-\sigma} + \frac{n-1}{n}\left(t^S\right)^{1-\sigma}} \tag{51}$$

and use the result in equation (50) to obtain

$$\left(P^L\right)^{1-\sigma} = \left(\lambda P^S\right)^{1-\sigma}. \tag{52}$$

Analogous to (48), we can write the macro price index as

$$\left(P^L\right)^{1-\sigma} = \frac{n}{R}\left(\frac{t_{ii}^L}{\Pi^L}\right)^{1-\sigma} + \frac{R-n}{R}\left(\frac{t^S}{\Pi^S}\right)^{1-\sigma},$$

where the first term reflects the internal part, and the second term captures the relationships with the remaining micro regions. Using (50) we can rearrange this as

$$\left(\Pi^L P^L\right)^{1-\sigma} = \frac{n}{R}\left(t_{ii}^L\right)^{1-\sigma} + \frac{R-n}{R}\left(t^S\right)^{1-\sigma}.$$

Using (50) and (52) we can rewrite this as

$$\left(\Pi^S P^S\right)^{1-\sigma} = \frac{n}{R}\left(\frac{t_{ii}^L}{\lambda}\right)^{1-\sigma} + \frac{R-n}{R}\left(\frac{t^S}{\lambda}\right)^{1-\sigma}.$$

We set (47) equal to the last expression and eliminate t_{ii}^L by using (51). We yield

$$\frac{1}{R}\left(t_{kk}^S\right)^{1-\sigma} + \frac{R-1}{R}\left(t^S\right)^{1-\sigma} = \frac{1}{R}\left(t_{kk}^S\right)^{1-\sigma} + \frac{n-1}{R}\left(t^S\right)^{1-\sigma} + \frac{R-n}{R}\left(\frac{t^S}{\lambda}\right)^{1-\sigma},$$

which implies $\lambda^{1-\sigma} = 1$. Note that $\lambda^{1-\sigma} = 1$ also implies the expression in equation (37) for internal trade costs in the macro region.

Inserting this result into (52), we find that the inward multilateral resistance price index is unaffected by the aggregation of symmetric regions, i.e., $P^L = P^S$. From (50) we also have that the outward multilateral resistance price index is unaffected, i.e., $\Pi^L = \Pi^S$. If we choose the normalization $\Pi^S = P^S$, it follows $\Pi^L = P^L$. We therefore use the more parsimonious specifications in equations (14) and (35) without separate outward multilateral resistance variables.

B.3 Estimating the border effect

As expressed in equation (41), the coefficient estimate for γ is given by

$$\widehat{\gamma} = \frac{\operatorname{Cov}\left(\ln\left(\frac{x_{ij}}{y_i y_j}\right), DOM_{ij}\right)}{\operatorname{Var}\left(DOM_{ij}\right)}.$$

Our aim is to derive an analytical solution for this expression. Since $x_{ij}/\left(y_i y_j\right)$ and $t_{ij}^{1-\sigma}$ are proportional, it can be rewritten as

$$\widehat{\gamma} = \frac{\operatorname{Cov}\left(\ln\left(t_{ij}^{1-\sigma}\right), DOM_{ij}\right)}{\operatorname{Var}\left(DOM_{ij}\right)}. \tag{53}$$

We assume a sample with K internal trade observations with $DOM_{ij} = 0$ and M other observations with $DOM_{ij} = 1$ such that we have $K + M$ total observations. To simplify notation let $A_{ij} = DOM_{ij}$. Then the denominator is

$$\begin{aligned} \operatorname{Var}\left(DOM_{ij}\right) &= \frac{1}{K+M}\sum_{ij}\left(A_{ij}-\overline{A}\right)\left(A_{ij}-\overline{A}\right) \\ &= \frac{1}{K+M}\left[\sum_{ij,DOM_{ij}=0}\left(-\overline{A}\right)^2 + \sum_{ij,DOM_{ij}=1}\left(1-\overline{A}\right)^2\right], \end{aligned}$$

where the first term in the brackets reflects the K internal observations. Using $\overline{A} = M/\left(K+M\right)$ for the average of the A_{ij}'s we then obtain the solution

$$\operatorname{Var}\left(DOM_{ij}\right) = \frac{KM}{\left(K+M\right)^2}.$$

Setting $B_{ij} = \ln\left(t_{ij}^{1-\sigma}\right)$, we can write the numerator of (53) as

$$\begin{aligned} &\operatorname{Cov}\left(\ln\left(t_{ij}^{1-\sigma}\right), DOM_{ij}\right) \\ =\ &\frac{1}{K+M}\sum_{ij}\left(B_{ij}-\overline{B}\right)\left(A_{ij}-\overline{A}\right) \\ =\ &\frac{1}{K+M}\left[\sum_{i=1,DOM_{ij}=0}^{K}\left(\ln\left(t_{ii}^{1-\sigma}\right)-\overline{B}\right)\left(-\overline{A}\right) + \sum_{ij,DOM_{ij}=1}\left(\gamma-\overline{B}\right)\left(1-\overline{A}\right)\right], \end{aligned}$$

where the first term in the brackets reflects the K internal observations. Using

$$\overline{B} = \gamma\overline{A} + \frac{1}{K+M}\sum_{k=1}^{K}\ln\left(t_{kk}^{1-\sigma}\right)$$

we can rewrite the expression as

$$
\begin{aligned}
& \operatorname{Cov}\left(\ln\left(t_{ij}^{1-\sigma}\right), DOM_{ij}\right) \\
= {} & \gamma \operatorname{Var}\left(DOM_{ij}\right) + \frac{1}{K+M}\left[\begin{array}{c} \sum_{i=1, DOM_{ij}=0}^{K}\left(\ln\left(t_{ii}^{1-\sigma}\right) - \frac{1}{K+M}\sum_{k=1}^{K}\ln\left(t_{kk}^{1-\sigma}\right)\right)\left(-\overline{A}\right) \\ + \sum_{ij, DOM_{ij}=1}\left(-\frac{1}{K+M}\sum_{k=1}^{K}\ln\left(t_{kk}^{1-\sigma}\right)\right)\left(1-\overline{A}\right) \end{array}\right] \\
= {} & \gamma \operatorname{Var}\left(DOM_{ij}\right) + \frac{1}{K+M}\left[-\left(\frac{M}{K+M}\right)^2 \sum_{k=1}^{K}\ln\left(t_{kk}^{1-\sigma}\right) - \frac{KM}{(K+M)^2}\sum_{k=1}^{K}\ln\left(t_{kk}^{1-\sigma}\right)\right] \\
= {} & \gamma \operatorname{Var}\left(DOM_{ij}\right) + \frac{KM}{(K+M)^2}\ln\left(\prod_{k=1}^{K}\left(t_{kk}^{\sigma-1}\right)^{\frac{1}{K}}\right),
\end{aligned}
$$

where the last term in parentheses is the geometric average of internal trade costs in the sample. Inserting this result into (53) we obtain

$$
\widehat{\gamma} = \gamma + \ln\left(\prod_{k=1}^{K}\left(t_{kk}^{\sigma-1}\right)^{\frac{1}{K}}\right).
$$

Let us consider a sample that is 'balanced' in the sense that no internal or bilateral observations are missing. We have N^2 total observations with $K = N$ internal and $M = N(N-1)$ bilateral flows. We then get the result in equation (42).

B.4 Invariance of the border effect to normalization

A key feature of the generalized trade cost function (43) introduced in appendix B.1 is that its implied border effect (44) is invariant to the specific normalization chosen for trade costs. For instance, suppose we choose the new normalization $t_{i'j'} = 1$ for trade costs between regions i' and j'. This normalization implies that trade costs $t_{ij}^{1-\sigma}$ for all i, j get multiplied by a constant $q \equiv 1/t_{i'j'}^{1-\sigma} > 0$ such that

$$
\begin{aligned}
\ln\left(t_{ij}^{1-\sigma} q\right) &= \gamma DOM_{ij} + \psi\left(1 - DOM_{ij}\right)\ln\left(t_{ii}^{1-\sigma} t_{jj}^{1-\sigma}\right)^{\frac{1}{2}} + \ln(q) \\
&= \gamma DOM_{ij} + \psi\left(1 - DOM_{ij}\right)\ln\left(\left(t_{ii}^{1-\sigma} q\right)\left(t_{jj}^{1-\sigma} q\right)\right)^{\frac{1}{2}} + \left(1 - \psi\left(1 - DOM_{ij}\right)\right)\ln(q).
\end{aligned}
$$

The border effect follows as

$$
\begin{aligned}
\frac{\Delta \ln\left(x_{ij}\right)}{\Delta DOM_{ij}} &= \gamma - \psi \ln\left(\left(t_{ii}^{1-\sigma} q\right)\left(t_{jj}^{1-\sigma} q\right)\right)^{\frac{1}{2}} + \psi \ln(q) \\
&= \gamma - \psi \ln\left(t_{ii}^{1-\sigma} t_{jj}^{1-\sigma}\right)^{\frac{1}{2}},
\end{aligned}
$$

where the latter equation gives the same result as in (44). Note that the traditional trade cost function (40) is also invariant to renormalization since

$$
\ln\left(t_{ij}^{1-\sigma} q\right) = \gamma DOM_{ij} + \ln(q)
$$

such that

$$
\frac{\Delta \ln\left(x_{ij}\right)}{\Delta DOM_{ij}} = \gamma
$$

irrespective of q.

B.5 The bias of omitting internal trade costs

We show that ignoring the interaction term between the border dummy and internal trade costs leads to omitted variable bias unless internal trade costs are zero on average. The proof is as follows.

The heterogeneous trade cost function (43) can be expanded as

$$\ln\left(t_{ij}^{1-\sigma}\right) = \gamma DOM_{ij} + \psi \ln\left(t_{ii}^{1-\sigma} t_{jj}^{1-\sigma}\right)^{\frac{1}{2}} - \psi DOM_{ij} \ln\left(t_{ii}^{1-\sigma} t_{jj}^{1-\sigma}\right)^{\frac{1}{2}}.$$

The last term, $\psi DOM_{ij} \ln\left(t_{ii}^{1-\sigma} t_{jj}^{1-\sigma}\right)^{1/2}$, introduces an interaction between the domestic border dummy DOM_{ij} and internal trade costs that vary across regions.

Imagine a researcher imposes the traditional trade cost function (40), thus omitting the interaction term. The γ domestic border coefficient in the traditional function is then unbiased only in the special case of a zero covariance between the border dummy and the interaction term. Formally, we can state this condition as

$$\operatorname{Cov}\left(DOM_{ij}, DOM_{ij} \ln\left(t_{ii}^{1-\sigma} t_{jj}^{1-\sigma}\right)^{\frac{1}{2}}\right) = 0. \tag{54}$$

To simplify notation let

$$\begin{aligned} A_{ij} &= DOM_{ij}, \\ B_{ij} &= DOM_{ij} \ln\left(t_{ii}^{1-\sigma} t_{jj}^{1-\sigma}\right)^{\frac{1}{2}}. \end{aligned}$$

so that condition (54) becomes

$$\begin{aligned} &\operatorname{Cov}\left(A_{ij}, B_{ij}\right) = 0 \\ \Leftrightarrow &\sum_{ij} \left(A_{ij} - \overline{A}\right)\left(B_{ij} - \overline{B}\right) = 0, \end{aligned}$$

where $\overline{A}$ and $\overline{B}$ denote the arithmetic averages of A_{ij} and B_{ij}.

Assume a sample with K internal trade observations with $DOM_{ij} = 0$ as well as M other observations with $DOM_{ij} = 1$ such that we have $K + M$ total observations. We can rewrite the previous equation as

$$\begin{aligned} K\left(-\overline{A}\right)\left(-\overline{B}\right) + \sum_{ij, DOM_{ij}=1} \left(1 - \overline{A}\right)\left(B_{ij} - \overline{B}\right) &= 0 \\ \Leftrightarrow K\overline{A}\overline{B} + \left(1 - \overline{A}\right) \sum_{ij, DOM_{ij}=1} \left(B_{ij} - \overline{B}\right) &= 0, \end{aligned}$$

where the first term reflects the K internal observations. We can rearrange the last equation as

$$
\begin{aligned}
K\overline{AB} - \left(1-\overline{A}\right) M\overline{B} + \left(1-\overline{A}\right) \sum_{ij,DOM_{ij}=1} B_{ij} &= 0 \\
\Leftrightarrow (K+M)\,\overline{AB} - M\overline{B} + \left(1-\overline{A}\right) \sum_{ij,DOM_{ij}=1} B_{ij} &= 0.
\end{aligned}
$$

Note that $\overline{A} = M/\left(K+M\right)$. The last equation thus simplifies to

$$
\begin{aligned}
\left(1-\overline{A}\right) \sum_{ij,DOM_{ij}=1} B_{ij} &= 0 \\
\Leftrightarrow \sum_{ij,DOM_{ij}=1} \ln\left(t_{ii}^{1-\sigma} t_{jj}^{1-\sigma}\right)^{\frac{1}{2}} &= 0 \\
\Leftrightarrow \sum_{ij,DOM_{ij}=1} \left[\ln\left(t_{ii}\right) + \ln\left(t_{jj}\right)\right] &= 0.
\end{aligned}
$$

There are two partner regions (one exporter i and one exporter j) for each of the M non-internal observations. Let m_i denote the relative frequency with which region i appears as a partner in those observations (either as an exporter or as an importer). Then we can rewrite the last expression as

$$
\begin{aligned}
\sum_{i=1}^{N} m_i \ln\left(t_{ii}\right) &= 0 \\
\Leftrightarrow \prod_{i=1}^{N} t_{ii}^{m_i} &= 1,
\end{aligned}
$$

where N is the number of regions in the sample. That is, the geometric average of internal trade cost factors, weighted by the frequency of appearance in bilateral observations, is equal to 1.

In a 'balanced' sample with no missing internal or bilateral observations, we have N^2 total observations with $K = N$ internal and $M = N(N-1)$ bilateral flows. The frequency of observations per region is therefore uniform with $m_i = 1/N \ \forall i$. As a special case, we then have

$$
\prod_{i=1}^{N} t_{ii}^{\frac{1}{N}} = 1.
$$

That is, the unweighted geometric average of internal trade cost factors is equal to 1.

B.6 A trade cost function with distance

In appendix B.1 we use a model without spatial distance frictions. As a result, the trade cost function (40) only contains a dummy variable for the domestic border.

In this appendix, we generalize the trade cost function to the more conventional and realistic case that includes distance. In particular, we abandon the assumption that all bilateral trade costs at the micro level are the same. Instead, in addition to a domestic border dummy DOM_{ij}, we introduce a distance friction δ^h as in the model for the international border effect. To preserve symmetry, we model the economy as a circle as in section 3.2. But since we focus on the domestic border effect, we only need to consider one country and can ignore all international flows. We therefore have the following trade cost function at the micro level:

$$\ln\left(t_h^S\right)^{1-\sigma} = \gamma DOM_h + \ln\left(\delta^h\right)^{1-\sigma},$$

where as in section 3.2 h denotes the number of steps between micro regions, with adjacent regions one step ($h = 1$) apart and so on. We have $DOM_h = 1$ for all bilateral flows ($h \geq 1$) and $DOM_h = 0$ for internal flows ($h = 0$).

Given the above micro structure of trade costs, bilateral trade costs between two aggregated regions at the macro level follow from equations (17) and (18) as

$$\left(t_{1,2,h}^L\right)^{1-\sigma} = \exp\left(\gamma DOM_h\right)\left(\delta^h\right)^{1-\sigma}\left(\alpha_1\right)^{1-\sigma}\left(\alpha_2\right)^{1-\sigma}.$$

For internal trade costs of a macro region m of aggregated size n we have from equation (26)

$$\begin{aligned}\left(t_{mm}^L\right)^{1-\sigma} &= \frac{1}{n}\left(t_{kk}^S\right)^{1-\sigma} + 2\sum_{h=1}^{n-1}\frac{n-h}{n^2}\left(t_h^S\right)^{1-\sigma} \\ &= \frac{1}{n}\left(t_{kk}^S\right)^{1-\sigma} + \exp\left(\gamma DOM_h\right)\underbrace{2\sum_{h=1}^{n-1}\frac{n-h}{n^2}\left(\delta^h\right)^{1-\sigma}}_{\left(\delta_{mm}\right)^{1-\sigma}}, \qquad (55)\end{aligned}$$

where we define the last term as the internal distance friction δ_{mm}, scaled by $(1-\sigma)$, since it represents the appropriately weighted underlying frictions δ^h within region m. It is multiplied by the term $\exp\left(\gamma DOM_h\right)$ with $h \geq 1$.

Assuming the distance relationship $\left(\delta^h\right)^{1-\sigma} = dist_h^\rho$, we obtain bilateral trade costs

$$\ln\left(t_{1,2,h}^L\right)^{1-\sigma} = \gamma DOM_h + \rho\ln\left(dist_h\right) + \ln\left(\alpha_1\right)^{1-\sigma} + \ln\left(\alpha_2\right)^{1-\sigma}.$$

For internal trade costs, $\ln\left(t_{mm}^L\right)^{1-\sigma}$ cannot be written as a log-linear function of DOM_h and $dist_{mm}$ because expression (55) is not multiplicative.

Overall, to combine bilateral and internal trade costs we set up a heterogeneous trade cost function similar to (43)

$$\ln\left(t_{ij}^{1-\sigma}\right) = \gamma DOM_{ij} + \rho\ln\left(dist_{ij}\right) + \ln\left(\alpha_i\right)^{1-\sigma} + \ln\left(\alpha_j\right)^{1-\sigma} + \left(1 - DOM_{ij}\right)\ln\left(\kappa_i\kappa_j\right)^{\frac{1-\sigma}{2}}. \qquad (56)$$

Trade cost function (56) captures bilateral trade costs when $DOM_{ij} = 1$ for $i \neq j$ and internal trade costs when $DOM_{ij} = 0$ for $i = j$ with

$$\ln\left(\kappa_i\right)^{1-\sigma} = -\rho\ln\left(dist_{ii}\right) - \ln\left(\alpha_i\right)^{(1-\sigma)2} + \ln\left(t_{ii}\right)^{1-\sigma}$$

and where we now use i and j to denote the exporter and importer. Crucially, this trade cost function features an interaction effect as in equation (43). It can be estimated as outlined in appendix B.1 and equation (45). That is, exporter and importer fixed effects are used in combination with region-specific domestic border dummies. The only difference is the addition of the standard bilateral distance regressor.

Appendix C: Data and numerical simulations

This appendix describes our data sources in detail (C.1-C.6) and provides numerical simulations (C.7).

C.1 Domestic exports: Commodity Flow Survey

For our measures of the shipments of goods within and across U.S. states, we use aggregate trade data from the Commodity Flow Survey, which is a joint effort of the Bureau of Transportation Statistics and the Census Bureau. We use survey results from 1993, 1997, 2002, and 2007. The survey covers the origin and destination of shipments of manufacturing, mining, wholesale trade, and selected retail establishments. The survey excludes shipments in the following sectors: services, crude petroleum and natural gas extraction, farm, forestry, fishery, construction, government, and most retail. Shipments from foreign establishments are also excluded; import shipments are excluded until they reach a domestic shipper. U.S. export (i.e., trans-border) shipments are also excluded.[67]

C.2 International exports from U.S. states: Origin of Movement

Our data on exports by U.S. states to foreign destinations are from the Origin of Movement series.[68] These data are compiled by the Foreign Trade Division of the U.S. Census Bureau. The data in this series identify the state from which an export begins its journey to a foreign country. However, we would like to know the state in which the export was produced. Below we provide details on the Origin of Movement series and its suitability as a measure of the origin of production.[69]

Beginning in 1987, the Origin of Movement series provides the current-year export sales, or free-alongside-ship (f.a.s.) costs if not sold, for 54 'states' to 242 foreign destinations. These export sales are for merchandise sales only and do not include services exports. The 54 'states' include the 50 U.S. states plus the District of Columbia, Puerto Rico, U.S. Virgin Islands, and unknown. Following Wolf (2000), we use the 48 contiguous U.S. states. Rather than all 242 destinations, we use the 50 leading export destinations for U.S. exports for 2005.[70] We use the annual data from 1993, 1997, 2002, and 2007 for total merchandise exports.[71]

[67] Erlbaum and Holguin-Veras (2006) note that sample size has been a major issue. The 1993 survey collected data from 200,000 establishments and the size was subsequently reduced to 100,000 in 1997 and 50,000 in 2002. In response to complaints from the freight data users community, the sample size was increased to 100,000 in 2007.

[68] Other studies that have used the Origin of Movement series include Smith (1999), Coughlin and Wall (2003) and Coughlin (2004).

[69] The highlighted details as well as much additional information can be found in Cassey (2009).

[70] In alphabetical order, these countries are Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Colombia, Costa Rica, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Finland, France, Germany, Guatemala, Honduras, Hong Kong, India, Indonesia, Ireland, Israel, Italy, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Panama, Peru, Philippines, Russia, Saudi Arabia, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, United Arab Emirates, United Kingdom, and Venezuela.

[71] We have also tried the data for manufacturing only (as opposed to total merchandise). The two series are very highly correlated (99 percent). The regression results are almost identical and we therefore do not report them.

Concerns about using the Origin of Movement series to identify the location of production are especially pertinent for agricultural and mining exports. We, however, focus on manufactured goods. Cassey (2009) has examined the issue of the coincidence of the state origin of movement and the state of production for manufactured goods.[72] The reason for restricting the focus to manufacturing is that the best source for location-based data on export production, "Exports from Manufacturing Establishments," covers only manufacturing.[73]

Cassey's key finding relevant to our analysis is that, overall, the Origin of Movement data is of sufficient quality to be used as the origin of the production of exports. Nonetheless, the data for specific states may not be of sufficient quality as the origin of production. These states are: Alaska, Arkansas, Delaware, Florida, Hawaii, New Mexico, South Dakota, Texas, Vermont, and Wyoming. He recommends the removal of Alaska and Hawaii in particular. As we use the 48 contiguous U.S. states, our data set is consistent with this recommendation.

C.3 Adjustments to the state trade data

Our simultaneous use of the intra-state and inter-state shipments data from the Commodity Flow Survey and the merchandise international trade data from the Origin of Movement series requires an adjustment to increase the comparability of these data sets. Such an adjustment arises because of three important differences between the data sources. First, the merchandise international trade data measures a shipment from the source to the port of exit just once, whereas the commodity flow data likely measures a good in a shipment more than once. For example, a good may be shipped from a plant to a warehouse and, later, to a retailer. Second, goods destined for foreign countries, when they are shipped to a port of exit, are included in domestic shipments. Third, the coverage of sectors differs between the data sources. The Commodity Flow Survey includes shipments of manufactured goods, but it excludes agriculture and part of mining. Meanwhile, the merchandise trade data includes all goods.

Identical to Anderson and van Wincoop (2003), we scale down the data in the Commodity Flow Survey by the ratio of total domestic merchandise trade to total domestic shipments from the Commodity Flow Survey. Total domestic merchandise trade is approximated by gross output in the goods-producing sectors (i.e., agriculture, mining, and manufacturing) minus international merchandise exports.[74] This calculation yields adjustment factors of 0.495 for 1993, 0.508 for 1997, 0.430 for 2002, and 0.405 for 2007.[75] Similar to Anderson and van Wincoop (2003) and as discussed by Balistreri and Hillberry (2007), our adjustment to the commodity flow data does not solve all the measurement problems, but it is the best feasible option.

[72] For the initial work on this issue, see Coughlin and Mandelbaum (1991) and Cronovich and Gazel (1999). As Cassey's (2009) analysis refers to manufactured goods, we note that we have also tried the Origin of Movement manufacturing data (as opposed to total merchandise) with virtually identical results.

[73] The data in the "Exports from Manufacturing Establishments" is available at http://www.census.gov/mcd/exports/ but does not contain destination information, so it cannot be used for the current research project.

[74] See Helliwell (1997, 1998) and Wei (1996).

[75] The difference between our adjustment factor for 1993 and that of Anderson and van Wincoop, 0.495 vs. 0.517, is due to data revision.

C.4 Other data

The rest of the data used in our empirical work can be characterized as well-known. We take export data between the 50 foreign countries in our sample from the IMF Direction of Trade Statistics. For individual U.S. states we use state gross domestic product data from the U.S. Bureau of Economic Analysis. For foreign countries, we use data on gross domestic product taken from the IMF World Economic Outlook Database (October 2007 edition).

We use the standard great circle distance formula to measure inter-state and international distances between capital cities in kilometers. As intra-state distance, we use the distance between the two largest cities in a state.

We source data on public road length (in miles) across U.S. states from the Federal Highway Administration (Highway Statistics Series Publications, Section V, Table HM-10: Classified by Ownership/Jurisdiction, Total). Data on the number of airports across U.S. states are taken from the Bureau of Transportation Statistics (Aviation Master Coordinate Table). We compute per capita values with the help of population data across U.S. states from Haver Analytics. Data on personal income per capita across U.S. states are unadjusted for inflation, also sourced from Haver Analytics. These data are annual for 1993, 1997, 2002 and 2007.

C.5 Aggregating U.S. states

The regions of Table 3 in section 4.6 merge states as follows. The sample of 24 regions consists of aggregates of Oregon - Washington, Arizona - California, Idaho - Montana, Nevada - Utah, Colorado - Wyoming, New Mexico - Texas, North Dakota - South Dakota, Iowa - Nebraska, Kansas - Missouri, Arkansas - Oklahoma, Minnesota - Wisconsin, Louisiana - Mississippi, Illinois - Kentucky, Alabama - Tennessee, Indiana - Michigan, Ohio - West Virginia, Florida - Georgia, North Carolina - South Carolina, Maryland - Virginia, Delaware - Pennsylvania, New Jersey - New York, Maine - New Hampshire, Massachusetts - Vermont, Connecticut - Rhode Island.

The sample of 12 regions consists of aggregates of Idaho - Montana - Washington - Wyoming, Arizona - California - Nevada - Oregon, Colorado - Kansas - Nebraska - Utah, Kentucky - Missouri - New Mexico - Oklahoma, Alabama - Louisiana - Mississippi - Texas, Arkansas - Tennessee - Virginia - West Virginia, Florida - Georgia - North Carolina - South Carolina, Iowa - Minnesota - North Dakota - South Dakota, Illinois - Indiana - Michigan - Wisconsin, Delaware - Maryland - Ohio - Pennsylvania, Connecticut - New Jersey - New York - Vermont, Massachusetts - Maine - New Hampshire - Rhode Island.

The sample of 8 regions consists of aggregates of Arizona - California - Idaho - Nevada - Oregon - Washington, Iowa - Illinois - Montana - Nebraska - South Dakota - Wyoming, Arkansas - Colorado - New Mexico - Tennessee - Texas - Utah, Michigan - Minnesota - North Dakota - Ohio - Pennsylvania - Wisconsin, Indiana - Kansas - Kentucky - Missouri - Oklahoma - West Virginia, Alabama - Florida - Georgia - Louisiana - Mississippi - South Carolina, Delaware - Maryland - North Carolina - New Jersey - New York - Virginia, Connecticut - Massachusetts - Maine - New Hampshire - Rhode Island - Vermont.

The sample of 6 regions consists of aggregates of Iowa - Idaho - Minnesota - Montana - North Dakota - South Dakota - Washington - Wisconsin, Arizona - California - Colorado

- New Mexico - Nevada - Oregon - Utah - Wyoming, Arkansas - Kansas - Louisiana - Missouri - Mississippi - Nebraska - Oklahoma - Texas, Alabama - Florida - Georgia - Kentucky - North Carolina - South Carolina - Tennessee - Virginia, Delaware - Illinois - Indiana - Maryland - Michigan - Ohio - Pennsylvania - West Virginia, Connecticut - Massachusetts - Maine - New Hampshire - New Jersey - New York - Rhode Island - Vermont.

C.6 Industry-level trade data

We use Commodity Flow Survey data from Crafts and Klein (2015) for the year 2007 at the level of commodities ("industries"). We supplement these data with additional observations that were missing (in particular for New Mexico) from the Commodity Flow Survey Tables available on the U.S. Census Bureau website. We drop trade flows with the industry labelled as "Commodity Unknown". We also drop observations that are not displayed due to data concerns (code S) or rounded to zero (code Z). Our data comprise the following 22 industries (with commodity codes and the number of observations in parentheses):
Meat, fish, seafood, and their preparations (code 5 with 843 observations)
Milled grain products and preparations and bakery products (code 6 with 750 observations)
Other prepared foodstuffs and fats and oils (code 7 with 1,124 observations)
Basic chemicals (code 20 with 767 observations)
Pharmaceutical products (code 21 with 729 observations)
Chemical products and preparations (code 23 with 937 observations)
Plastics and rubber (code 24 with 1,394 observations)
Wood products (code 26 with 1,050 observations)
Pulp, newsprint, paper, and paperboard (code 27 with 861 observations)
Paper or paperboard articles (code 28 with 755 observations)
Printed products (code 29 with 995 observations)
Textiles, leather, and articles of textiles or leather (code 30 with 1,120 observations)
Nonmetallic mineral products (code 31 with 958 observations)
Base metal in primary or semifinished forms and in finished basic shapes (code 32 with 1,043 observations)
Articles of base metal (code 33 with 1,231 observations)
Machinery (code 34 with 1,227 observations)
Electronic and other electrical equipment and components and office equipment (code 35 with 1,257 observations)
Motorized and other vehicles (including parts) (code 36 with 919 observations)
Precision instruments and apparatus (code 38 with 853 observations)
Furniture, mattresses and mattress supports, lamps, lighting fittings, and illuminated signs (code 39 with 902 observations)
Miscellaneous manufactured products (code 40 with 1,457 observations)
Mixed freight (code 43 with 958 observations)

C.7 Border effect simulations

To get a better quantitative sense of the spatial attenuation effect, we illustrate the domestic border effect with a number of examples.

Aggregation of symmetric micro regions

Based on the model in appendix B we assume 100 symmetric micro regions with equal incomes.[76] We set values of $t_{kk}^{S} = 1$ for internal trade costs within micro regions and $t^{S} = 1.2$ for bilateral trade costs between micro regions. We assume $\sigma = 5$. As outlined in the context of equation (40), these assumptions imply a value of the domestic border effect coefficient of $\gamma = \ln\left(t^{S}\right)^{1-\sigma} = -0.73$. We report this coefficient in the first column of Table C.1.

We then aggregate the 100 micro regions into symmetric macro regions in various ways. We first aggregate them into 50 macro regions consisting of 2 micro regions each. We then form 25 macro regions consisting of 4 micro regions, followed by 10 macro regions consisting of 10 micro regions, and finally 20 macro regions consisting of 5 micro regions. The last four columns of Table C.1 report each case. We compute the implied internal trade costs of the macro regions with the help of equation (37). As the corresponding row in Table C.1 shows, aggregation increases internal trade costs.

Table C.1 also reports the corresponding common border coefficients estimated in OLS regressions. As our analytical solution in equation (42) shows, aggregation pushes the estimated coefficients towards zero. Quantitatively, this effect is substantial. When macro regions consist of four micro regions, compared to its true value of -0.73 the estimated coefficient is more than halved to -0.24. This spatial attenuation effect is driven by the increase in internal costs such that in relative terms, the bilateral costs appear smaller. The effect is non-linear in that the biggest absolute changes in estimated border coefficients arise at the initial stages of aggregation.

Next, suppose we aggregate the 100 micro regions such that we obtain a sample with a mix of the different macro regions listed in Table C.1 (i.e., a sample with a mix of macro regions consisting of 1, 2, 4, 10 and 20 underlying micro regions). If we then *pool* these asymmetric macro regions and estimate heterogeneous border effects, we obtain *exactly the same* coefficient values as those reported in the respective columns of Table C.1. This means that border effect heterogeneity arises once micro regions are aggregated into macro regions of different sizes, whether pooled or not. This result is consistent with the testable implications in section 3.2.3. It also implies sample composition effects. The more we increase the size of macro regions in the sample (holding the number of underlying micro regions fixed), the more the common border effect is pushed upwards towards zero. The coefficient values in Table C.1 imply that these sample composition effects can be quantitatively substantial.

The above results confirm the importance of border effect heterogeneity. Short of allowing for fully heterogeneous border effects, how could researchers get a quick indication of the potential severity of misspecification through a common border dummy? As a simple check, we could allow for a *binary* form of heterogeneity with separate border effects for small vs. large regions. That is, we allocate regions of below-median size into a small region bin and regions of above-median size into a large region bin and then estimate the two corresponding border coefficients. Adopting this approach with our pooled sample of asymmetric macro regions as described above, we obtain coefficients of -0.61 for the

[76] This is equivalent to assuming equal endowments.

small region bin and −0.20 for the large region bin.[77] These should be compared to the true value of −0.73 in Table C.1. Given that the two coefficients differ by a factor of three and are significantly different from each other, we get an indication that the underlying border effect heterogeneity is likely strong.

Macro regions resembling U.S. states

The symmetry assumptions underlying our theoretical framework are useful in that they allow us to derive an analytical solution for the border coefficient estimate.[78] But when we apply the model to data for U.S. states, the symmetry assumptions are likely unrealistic. We therefore introduce asymmetric features that aim at reflecting U.S. states more accurately. We resort to numerical simulations.

As a reference point, we initially retain the assumption of symmetric micro regions. In our first simulation, we treat U.S. states as clusters of symmetric micro regions. Recall the example of California and Vermont mentioned at the beginning of section 3.1. We model California as a macro region consisting of many micro regions, and Vermont consisting of only a few. This approach is therefore similar to the example in Table C.1 but with macro regions of different sizes.

More specifically, we retain the same values of t^S_{kk} and t^S for micro regions as above as well as the same value for σ. We use population data for U.S. states for the year 2000, sourced from the U.S. Census Bureau, as a measure of n, which represents the number of micro regions per state. We set $n = 1$ for Wyoming, which is the state with the smallest population, and we measure the number of micro regions for other states proportionately. Equation (37) then provides us with the implied internal trade costs of states. Furthermore, we use population weights as measures of states' income shares (those shares would correspond to y^L/y^W in appendix B.1). California as the state with the largest population has an income share of 12.1 percent, followed by 7.5 percent for Texas.

We then compute the implied trade flows within and between states and estimate heterogeneous domestic border effect coefficients. In Figure C.1 we plot those simulated coefficients against the ones obtained based on actual trade flows between U.S. states (the latter are the same as in Figure 4). The correlation between the two sets of coefficients in Figure C.1 stands at 48 percent. We conclude that the simple underlying model with symmetric micro regions works reasonably well qualitatively in generating realistic border effect patterns. However, the absolute magnitudes for the simulated coefficients are lower. But we could bring them in line more closely with the actual magnitudes by setting a higher value for t^S. For instance, for $t^S = 2.1$ we would get roughly the same average border coefficient estimate (−1.34 compared to −1.32 in the actual data). This value of t^S would correspond to an average value of 1.52 for states' internal trade costs. The correlation of border effect coefficients would be similar at 45 percent. What

[77] The sample has 20 macro regions and thus 20*20 = 400 trade flows including internal trade flows. There are 6 regions consisting of one micro region, 6 consisting of two, 3 consisting of four, 3 consisting of ten and 2 consisting of twenty micro regions. To get coefficients comparable to Table C.1, the two bin-specific border variables must add up to the common border dummy (i.e., they are assigned a value of 0.5 whenever two regions trade across bins so that these variables take on three values: 0, 0.5 and 1; for further context see the explanation in appendix B.1 as to why the γ_r coefficients need to be multiplied by 2 for comparability). Apart from the two border variables the regression includes exporter and importer fixed effects. Bin variables as main effects do not need to be included as they are collinear with exporter and importer fixed effects.

[78] See equation (42) in appendix B.1.

is the economic meaning of these parameter values? Trade cost factors of 2.1 and 1.52 correspond to tariff equivalents of 110 percent and 52 percent. The interpretation then is that to match border coefficients in the data, our model implies trade frictions (expressed as tariff equivalents) that are on average about twice as large between U.S. states as within U.S. states.

In our second simulation, we focus on surface area as the basic geographic unit (we source data on surface area from the U.S. Census Bureau), and we combine it with data on population. We set our measure of surface area equal to 1 unit for Rhode Island, which is the smallest state by area. All other states consist of a proportionately larger number of units, rounded to the closest integer. For example, Delaware consists of two units and Connecticut of four. Texas as the largest state by area in our sample consists of 174 surface units. We introduce asymmetry by exploiting different population densities across states, where population density is the ratio of population over surface area units, normalized to 1 for Wyoming as the state with the lowest population density. Population density then becomes our measure of n in equation (37). We retain the underlying frictions within micro regions, t_{kk}^S and t^S, using the same baseline values as above. As in equation (39), bilateral trade costs are also kept at t^S. As above, population weights determine states' income shares.

This setting means that states with higher population density face higher internal trade costs. The reason is that bilateral micro frictions t^S accrue more frequently in those states due to the higher number of individuals per area and thus the higher density of bilateral relationships (see equation 37). The asymmetry introduced through different population densities means that internal trade costs within micro regions and thus within states no longer increase monotonically in overall economic size. In Figure C.2 we plot the population shares of U.S. states (which are an indicator of economic size) against the simulated measure of internal trade costs. There is a clear positive relationship. The correlation between the two variables (in logarithms) is 63 percent. But in the case of symmetry as in our first simulation, the correlation would be 92 percent.

We then compute the trade flows within and between states and estimate heterogeneous border effect coefficients. The overall relationship between simulated and actual coefficients looks similar to the one depicted in Figure C.1. Their correlation stands at 49 percent. The absolute magnitude of the simulated coefficients is again smaller but can be increased by choosing higher values of t^S. We note that different values for σ hardly affect the relationship between simulated and actual coefficients.

In summary, once we allow for asymmetries as above, our main result on spatial aggregation goes through. That is, smaller units tend to be associated with larger border effects. Of course, the asymmetric features we employ are simplistic. Further refinements are possible. For instance, differences in human capital could be captured by asymmetric endowments. Topological features such as mountainous terrain, lakes, oceans and deserts could also be incorporated.

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Table 1: International and domestic border effects

Sample	U.S. and foreign countries		U.S. only	
Year	1993	1993, 1997, 2002, 2007	1993	1993, 1997, 2002, 2007
	(1)	(2)	(3)	(4)
$\ln(dist_{ij})$	-1.19***	-1.21***	-1.07***	-1.08***
	(0.02)	(0.02)	(0.03)	(0.03)
INT_{ij} (international border dummy)	-1.25***	-1.21***		
	(0.08)	(0.06)		
DOM_{ij} (domestic border dummy)			-1.47***	-1.48***
			(0.20)	(0.19)
Internal trade (within U.S. states)	no	no	yes	yes
Domestic trade (between U.S. states)	yes	yes	yes	yes
International trade (with foreign countries)	yes	yes	no	no
Observations	6,249	24,996	1,726	6,904
Clusters	--	6,249	--	1,726
Fixed effects	yes	yes	yes	yes
R-squared	0.81	0.82	0.90	0.90

Notes: The dependent variable is $\ln(x_{ij})$. OLS estimation. Robust standard errors are reported in parentheses, clustered around bilateral pairs ij in columns 2 and 4. State and foreign country fixed effects in columns 1 and 2; exporter and importer fixed effects in columns 3 and 4; those fixed effects are time-varying in columns 2 and 4.
*** significant at 1% level.

Table 2: International and domestic border effects based on U.S. Census divisions

Sample	U.S. and foreign countries		U.S. only	
Year	1993	1993, 1997, 2002, 2007	1993	1993, 1997, 2002, 2007
	(1)	(2)	(3)	(4)
$\ln(dist_{ij})$	-1.17***	-1.21***	-1.07***	-1.04***
	(0.03)	(0.03)	(0.10)	(0.08)
INT_{ij} (international border dummy)	-0.36***	-0.39***		
	(0.11)	(0.10)		
DOM_{ij} (domestic border dummy)			-1.17***	-1.25***
			(0.18)	(0.17)
Internal trade (within Census divisions)	no	no	yes	yes
Domestic trade (between Census divisions)	yes	yes	yes	yes
International trade (with foreign countries)	yes	yes	no	no
Observations	2,746	10,984	81	324
Clusters	--	2,746	--	81
Fixed effects	yes	yes	yes	yes
R-squared	0.78	0.79	0.95	0.96

Notes: The dependent variable is $\ln(x_{ij})$. OLS estimation. Robust standard errors are reported in parentheses, clustered around bilateral pairs ij in columns 2 and 4. Division and foreign country fixed effects in columns 1 and 2; exporter and importer fixed effects in columns 3 and 4; those fixed effects are time-varying in columns 2 and 4. *** significant at 1% level.

Table 3: International and domestic border effects based on quasi-randomly aggregated U.S. states

Sample	U.S. and foreign countries				U.S. only			
Number of hypothetical U.S. regions	24	12	8	6	24	12	8	6
Number of U.S. states per region	2	4	6	8	2	4	6	8
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(dist_{ij})$	-1.23***	-1.21***	-1.22***	-1.21***	-1.29***	-1.13***	-0.95***	-0.70***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.06)	(0.10)	(0.12)
INT_{ij} (international border dummy)	-0.64***	-0.44***	-0.39***	-0.21*				
	(0.08)	(0.09)	(0.11)	(0.12)				
DOM_{ij} (domestic border dummy)					-1.36***	-1.43***	-1.35***	-1.47***
					(0.18)	(0.20)	(0.16)	(0.22)
Internal trade (within U.S. regions)	no	no	no	no	yes	yes	yes	yes
Domestic trade (between U.S. regions)	yes	yes	yes	yes	yes	yes	yes	yes
International trade (with foreign countries)	yes	yes	yes	yes	no	no	no	no
Observations	15,772	11,812	10,724	10,228	2,232	576	256	144
Clusters	3,943	2,953	2,681	2,557	558	144	64	36
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
R-squared	0.80	0.79	0.79	0.78	0.90	0.94	0.95	0.96

Notes: The dependent variable is $\ln(x_{ij})$. Data are for the years 1993, 1997, 2002 and 2007. The 48 contiguous U.S. states are aggregated quasi-randomly into hypothetical U.S. regions with 24 regions in columns 1 and 5, 12 regions in columns 2 and 6, 8 regions in columns 3 and 7, and 6 regions in columns 4 and 8. For more information see the main text. OLS estimation. Robust standard errors are reported in parentheses, clustered around bilateral pairs ij. Time-varying U.S. region and foreign country fixed effects in columns 1-4; time-varying exporter and importer fixed effects in columns 4-8. * significant at 10% level, *** significant at 1% level.

Table 4: General equilibrium effects in response to removing the U.S. international border

U.S. state	Panel 1: Common border effect								Panel 2: Heterogeneous border effects							
	Total effect		Direct effect		Indirect GE effects				Total effect		Direct effect		Indirect GE effects			
	$\Delta \ln(x_{ij})$	=	$(1-\sigma)\ \Delta \ln(t_{ij})$	+	$(\sigma-1)\ \Delta \ln(P_iP_j)$	+	$\Delta \ln(y_iy_j/y^W)$		$\Delta \ln(x_{ij})$	=	$(1-\sigma)\ \Delta \ln(t_{ij})$	+	$(\sigma-1)\ \Delta \ln(P_iP_j)$	+	$\Delta \ln(y_iy_j/y^W)$	
	(1a)		(1b)		(1c)		(1d)		(2a)		(2b)		(2c)		(2d)	
Average	**0.23**	**=**	**0.31**	**+**	**-0.10**	**+**	**0.02**		**0.24**	**=**	**0.33**	**+**	**-0.11**	**+**	**0.02**	
AL	0.24	=	0.31	+	-0.08	+	0.01		0.11	=	0.18	+	-0.10	+	0.02	
AR	0.22	=	0.31	+	-0.10	+	0.02		0.45	=	0.60	+	-0.19	+	0.04	
AZ	0.21	=	0.31	+	-0.12	+	0.02		0.32	=	0.45	+	-0.17	+	0.03	
CA	0.24	=	0.31	+	-0.08	+	0.01		0.13	=	0.18	+	-0.06	+	0.01	
CO	0.23	=	0.31	+	-0.10	+	0.02		0.40	=	0.51	+	-0.14	+	0.03	
CT	0.25	=	0.31	+	-0.06	+	0.01		-0.07	=	-0.04	+	-0.03	+	0.00	
DE	0.25	=	0.31	+	-0.06	+	0.01		0.01	=	0.05	+	-0.05	+	0.01	
FL	0.21	=	0.31	+	-0.12	+	0.02		-0.13	=	-0.18	+	0.08	+	-0.02	
GA	0.23	=	0.31	+	-0.09	+	0.01		0.01	=	0.05	+	-0.05	+	0.01	
IA	0.22	=	0.31	+	-0.10	+	0.02		0.30	=	0.40	+	-0.13	+	0.03	
ID	0.23	=	0.31	+	-0.09	+	0.01		0.58	=	0.71	+	-0.16	+	0.03	
IL	0.25	=	0.31	+	-0.07	+	0.01		0.07	=	0.11	+	-0.04	+	0.01	
IN	0.24	=	0.31	+	-0.09	+	0.01		0.23	=	0.31	+	-0.10	+	0.02	
KS	0.22	=	0.31	+	-0.10	+	0.02		0.16	=	0.23	+	-0.09	+	0.02	
KY	0.24	=	0.31	+	-0.08	+	0.01		0.18	=	0.25	+	-0.09	+	0.02	
LA	0.22	=	0.31	+	-0.10	+	0.02		-0.27	=	-0.45	+	0.23	+	-0.05	
MA	0.23	=	0.31	+	-0.09	+	0.01		0.03	=	0.08	+	-0.06	+	0.01	
MD	0.25	=	0.31	+	-0.07	+	0.01		0.12	=	0.17	+	-0.06	+	0.01	
ME	0.20	=	0.31	+	-0.13	+	0.02		0.44	=	0.66	+	-0.28	+	0.05	
MI	0.22	=	0.31	+	-0.10	+	0.02		0.18	=	0.27	+	-0.12	+	0.02	
MN	0.25	=	0.31	+	-0.06	+	0.01		0.20	=	0.25	+	-0.06	+	0.01	
MO	0.23	=	0.31	+	-0.10	+	0.02		0.37	=	0.49	+	-0.15	+	0.03	
MS	0.22	=	0.31	+	-0.10	+	0.02		0.20	=	0.32	+	-0.15	+	0.03	

MT	0.18	=	0.31	+	-0.15	+	0.03		1.08	=	1.37	+	-0.36	+	0.07
NC	0.22	=	0.31	+	-0.10	+	0.02		0.03	=	0.08	+	-0.06	+	0.01
ND	0.19	=	0.31	+	-0.15	+	0.03		0.77	=	1.03	+	-0.32	+	0.06
NE	0.23	=	0.31	+	-0.10	+	0.02		0.48	=	0.61	+	-0.16	+	0.03
NH	0.23	=	0.31	+	-0.09	+	0.01		0.28	=	0.42	+	-0.17	+	0.03
NJ	0.26	=	0.31	+	-0.05	+	0.01		0.03	=	0.06	+	-0.04	+	0.01
NM	0.20	=	0.31	+	-0.13	+	0.02		0.51	=	0.70	+	-0.24	+	0.05
NV	0.25	=	0.31	+	-0.06	+	0.01		0.83	=	0.91	+	-0.11	+	0.02
NY	0.18	=	0.31	+	-0.15	+	0.03		-0.05	=	-0.10	+	0.06	+	-0.01
OH	0.23	=	0.31	+	-0.09	+	0.01		0.14	=	0.21	+	-0.09	+	0.02
OK	0.22	=	0.31	+	-0.10	+	0.02		0.35	=	0.48	+	-0.17	+	0.03
OR	0.23	=	0.31	+	-0.09	+	0.01		0.27	=	0.37	+	-0.12	+	0.02
PA	0.22	=	0.31	+	-0.11	+	0.02		0.14	=	0.25	+	-0.13	+	0.02
RI	0.25	=	0.31	+	-0.07	+	0.01		0.19	=	0.28	+	-0.10	+	0.02
SC	0.23	=	0.31	+	-0.10	+	0.01		0.00	=	0.04	+	-0.04	+	0.01
SD	0.20	=	0.31	+	-0.14	+	0.02		0.86	=	1.11	+	-0.30	+	0.06
TN	0.23	=	0.31	+	-0.09	+	0.01		0.18	=	0.26	+	-0.11	+	0.02
TX	0.21	=	0.31	+	-0.11	+	0.02		-0.09	=	-0.10	+	0.02	+	0.00
UT	0.22	=	0.31	+	-0.10	+	0.02		0.42	=	0.54	+	-0.15	+	0.03
VA	0.25	=	0.31	+	-0.07	+	0.01		-0.03	=	-0.01	+	-0.03	+	0.00
VT	0.19	=	0.31	+	-0.14	+	0.02		0.21	=	0.42	+	-0.26	+	0.05
WA	0.20	=	0.31	+	-0.13	+	0.02		-0.09	=	-0.12	+	0.05	+	-0.01
WI	0.23	=	0.31	+	-0.10	+	0.01		0.11	=	0.17	+	-0.07	+	0.01
WV	0.23	=	0.31	+	-0.09	+	0.01		0.20	=	0.28	+	-0.10	+	0.02
WY	0.21	=	0.31	+	-0.11	+	0.02		0.61	=	0.78	+	-0.21	+	0.04

Notes: This table reports logarithmic differences of variables between an initial equilibrium with international border barriers and a counterfactual equilibrium where these border barriers are removed. Two scenarios are considered. The first scenario in panel 1 is based on a common international border barrier for all 48 U.S. states in the sample. The second scenario in panel 2 is based on heterogeneous international border barriers across U.S. states. The sample is balanced over the years 1993, 1997, 2002 and 2007 with 24,996 observations in total (6,249 for each year). Apart from the international border dummies the underlying regressions include log distance and time-varying state and country fixed effects. Columns 1a and 2a: average change in bilateral trade (total effect); columns 1b and 2b: change in bilateral trade costs scaled by the substitution elasticity due to the removal of the international border; columns 1c and 2c: average change in multilateral resistances scaled by the substitution elasticity; columns 1d and 2d: average change in incomes. The first row reports the simple average across all states. The reported numbers are rounded off to two decimal digits. For more information see the main text.

Table 5: International and domestic border effects interacted with potential determinants

Sample	U.S. and foreign countries			U.S. only		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(dist_{ij})$	-1.22***	-1.20***	-1.21***	-1.09***	-1.08***	-1.09***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
INT_{ij}	-12.42***	-11.00***	-9.55***			
	(1.38)	(0.52)	(1.52)			
INT_{ij} * ln(road length per $capita_i$)	-0.43***		-0.40***			
	(0.05)		(0.05)			
INT_{ij} * ln(airports per $capita_i$)	-0.31***		-0.12*			
	(0.06)		(0.07)			
INT_{ij} * ln(income per $capita_i$)	-0.24***		-0.39***			
	(0.09)		(0.09)			
INT_{ij} * $\ln(GDP_i)$		0.41***	0.19***			
		(0.02)	(0.03)			
DOM_{ij}				-10.74**	-8.16***	-9.62*
				(4.77)	(1.89)	(5.34)
DOM_{ij} * ln(road length per $capita_{ij}$)				-0.41***		-0.41***
				(0.14)		(0.14)
DOM_{ij} * ln(airports per $capita_{ij}$)				-0.12		-0.07
				(0.17)		(0.19)
DOM_{ij} * ln(income per $capita_{ij}$)				0.14		0.09
				(0.13)		(0.17)
DOM_{ij} * $\ln(GDP_{ij})$					0.30***	0.05
					(0.08)	(0.11)
Internal trade (within U.S. states)	no	no	no	yes	yes	yes
Domestic trade (between U.S. states)	yes	yes	yes	yes	yes	yes
International trade (with foreign countries)	yes	yes	yes	no	no	no
Observations	24,996	24,996	24,996	6,904	6,904	6,904

Clusters	6,249	6,249	6,249	1,726	1,726	1,726
Fixed effects	yes	yes	yes	yes	yes	yes
R-squared	0.83	0.83	0.83	0.90	0.90	0.90

Notes: The dependent variable is $\ln(x_{ij})$. Data are for the years 1993, 1997, 2002 and 2007. The interacted determinants in columns 1-3 are the logarithmic values of exporting U.S. states only; their main effects are included but not reported; the interacted determinants in columns 4-6 are the logarithmic values of the products of the exporter and the importer values of U.S. states; their main effects are collinear with the fixed effects and thus drop out. OLS estimation. Robust standard errors are reported in parentheses, clustered around bilateral pairs ij. Time-varying state and foreign country fixed effects in columns 1-3; time-varying exporter and importer fixed effects in columns 4-6. * significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Table 6: Regressing individual border effects on potential determinants

	International border dummy coefficients			Domestic border dummy coefficients		
Dependent variable	$ß_r$	$ß_r$	$ß_r$	γ_r	γ_r	γ_r
	(1)	(2)	(3)	(4)	(5)	(6)
ln(road length per capita$_r$)	-0.20		-0.19	-0.73*		-0.71*
	(0.15)		(0.15)	(0.40)		(0.41)
ln(airports per capita$_r$)	-0.63***		-0.53***	-0.31		-0.17
	(0.16)		(0.19)	(0.44)		(0.51)
ln(income per capita$_r$)	-0.25		-0.24	1.88		1.88
	(0.48)		(0.48)	(1.30)		(1.31)
ln(GDP$_r$)		0.44***	0.10		0.66***	0.13
		(0.07)	(0.09)		(0.18)	(0.25)
Observations	48	48	48	48	48	48
R-squared	0.64	0.46	0.65	0.41	0.23	0.42

Notes: The dependent variables are the international border dummy coefficients $ß_r$ in columns 1-3 and the domestic border dummy coefficients γ_r in columns 4-6 (one for each of the 48 contiguous U.S. states). The regressor values are for the year 2007. OLS estimation. Robust standard errors are reported in parentheses (not bootstrapped). A constant is included but not reported. * significant at 10% level, *** significant at 1% level.

Table C.1: Aggregation and the domestic border effect (symmetric regions)

	Original sample	Aggregation into macro regions			
# Micro regions per region	1	2	4	10	20
# Regions in sample	100	50	25	10	5
Total # micro regions	100	100	100	100	100
Internal trade costs	1	1.08	1.13	1.17	1.18
Estimated domestic border coefficient	**-0.73**	**-0.43**	**-0.24**	**-0.10**	**-0.05**
True domestic border coefficient γ	-0.73	-0.73	-0.73	-0.73	-0.73

Notes: This table presents simulation results for a sample consisting of 100 symmetric micro regions. Trade costs are t_{kk}^S = 1 within micro regions and t^S = 1.2 between micro regions, with σ = 5. The micro regions are then aggregated into symmetric macro regions, holding the total number of underlying micro regions constant. Estimated common domestic border effect coefficients are reported alongside the true coefficient.

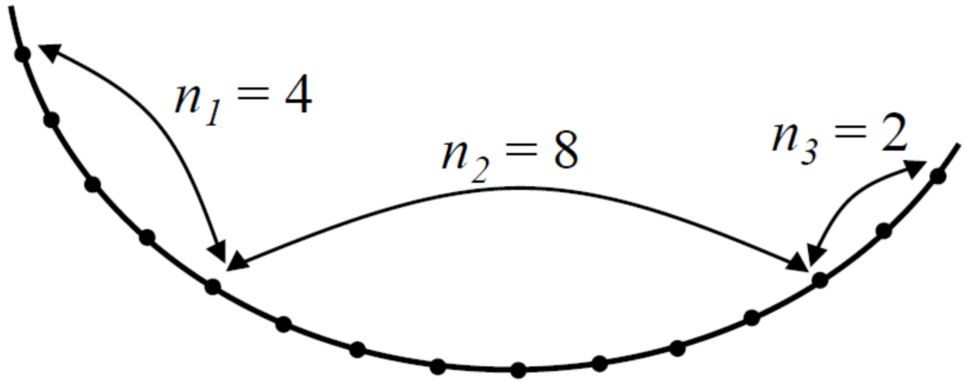

Figure 1: Illustration of a section of the circle representing an economy. Micro regions are symmetric arcs on the circle. Macro regions are aggregates of adjacent micro regions. Here, the first macro region consists of $n_1 = 4$ micro regions, the second consists of $n_2 = 8$ micro regions, and the third consists of $n_3 = 2$ micro regions.

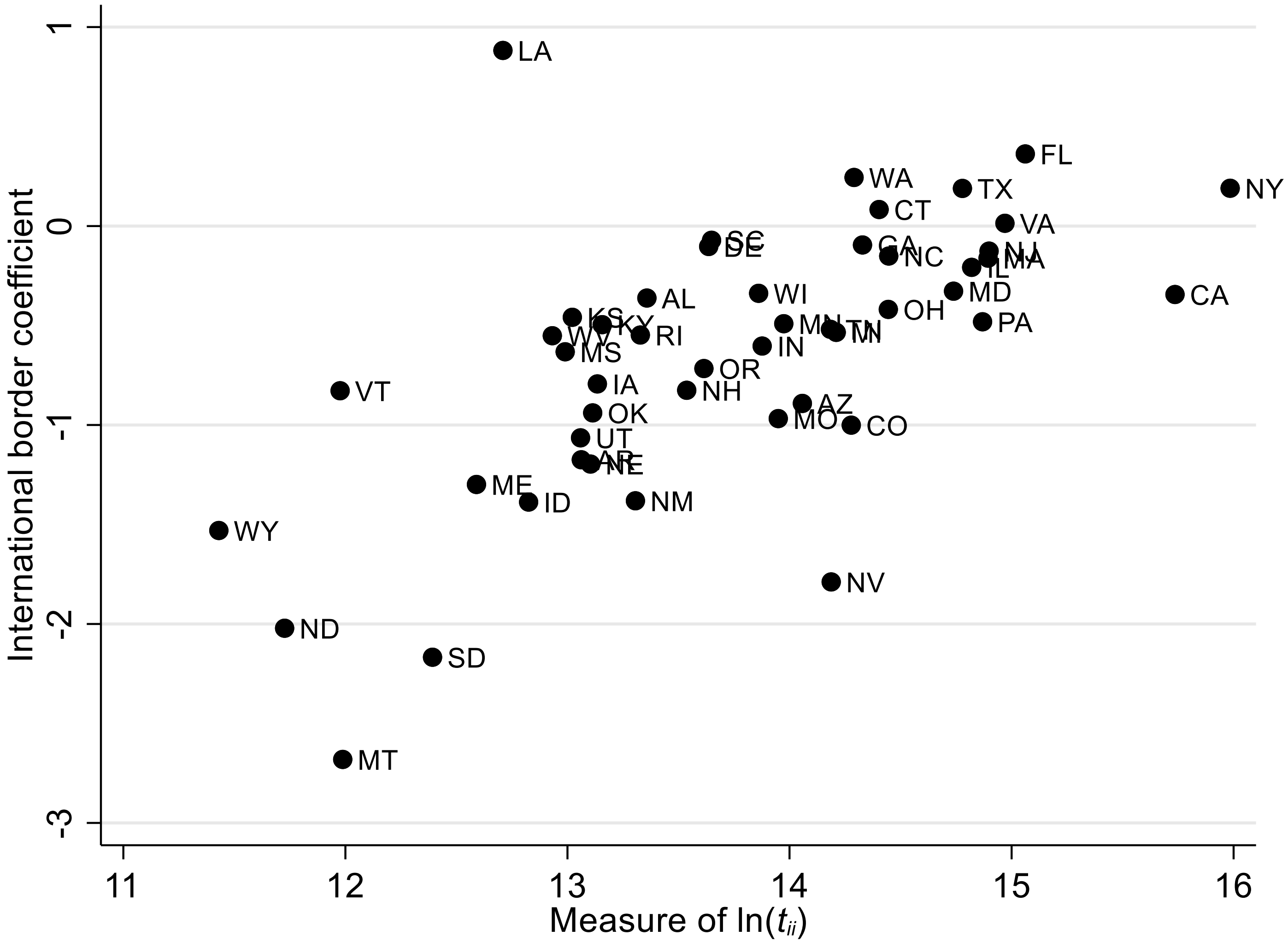

Figure 2: Plot of international border dummy coefficients for the 48 contiguous U.S. states against the logarithm of a model-consistent proxy for internal trade costs t_{ii}. The mean of the coefficients is -0.64. The average standard error is 0.13 (not plotted). More details are provided in the main text.

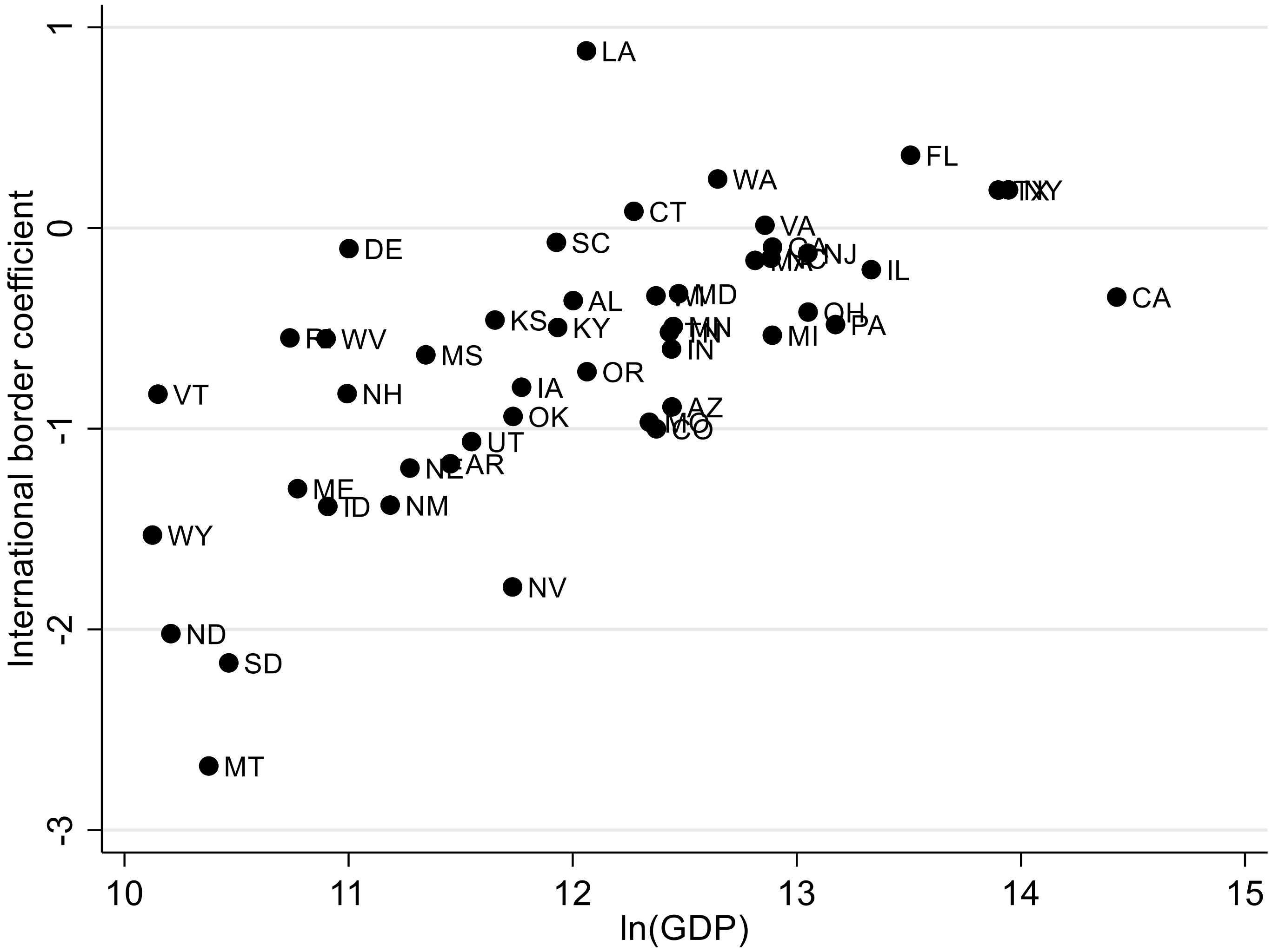

Figure 3: Plot of international border dummy coefficients for the 48 contiguous U.S. states against the logarithm of state GDP. The mean of the coefficients is -0.64. The average standard error is 0.13 (not plotted). More details are provided in the main text.

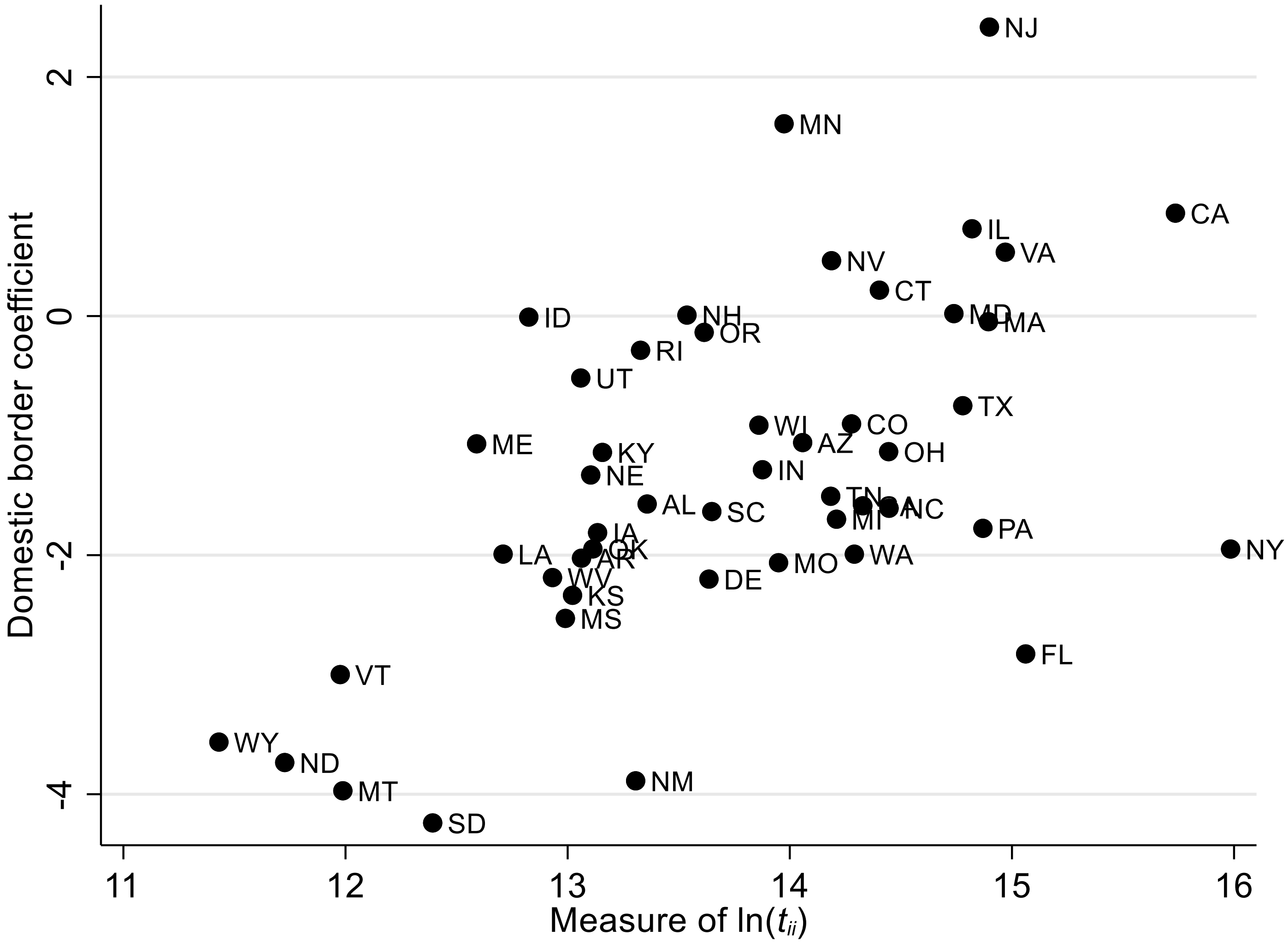

Figure 4: Plot of domestic border dummy coefficients for the 48 contiguous U.S. states against the logarithm of a model-consistent proxy for internal trade costs t_{ii}. The mean of the coefficients is -1.32. The average standard error is 0.13 (not plotted). More details are provided in the main text.

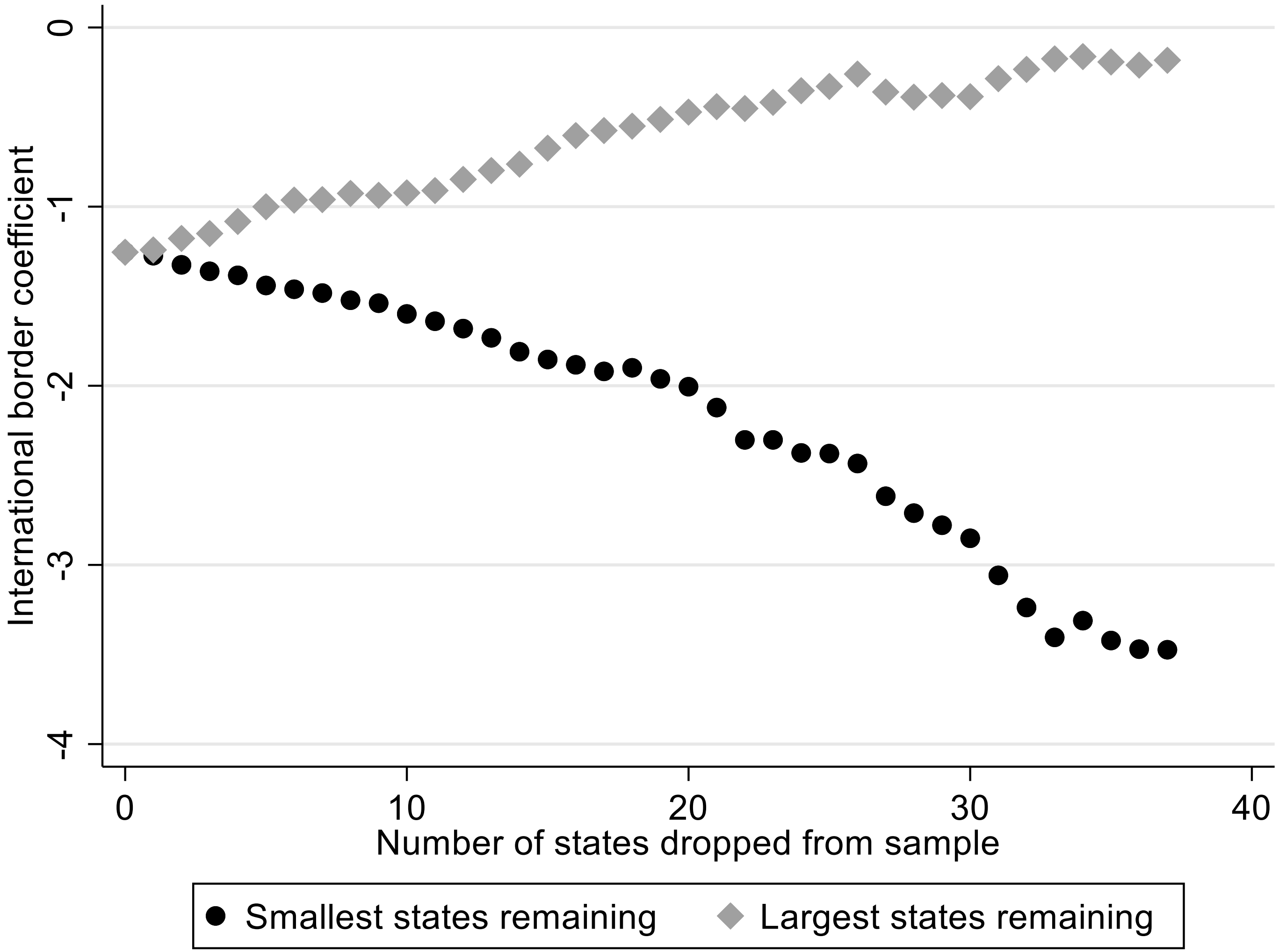

Figure 5: Plot of common international border dummy coefficients estimated for different samples of U.S. states. When zero states are dropped, the coefficient is -1.25 as in column 1 of Table 1. Black dots plot the coefficients obtained by successively dropping the largest remaining state from the sample such that the smallest states are remaining. The grey diamonds plot the coefficients obtained by successively dropping the smallest remaining state such that the largest states are remaining. More details are provided in the main text.

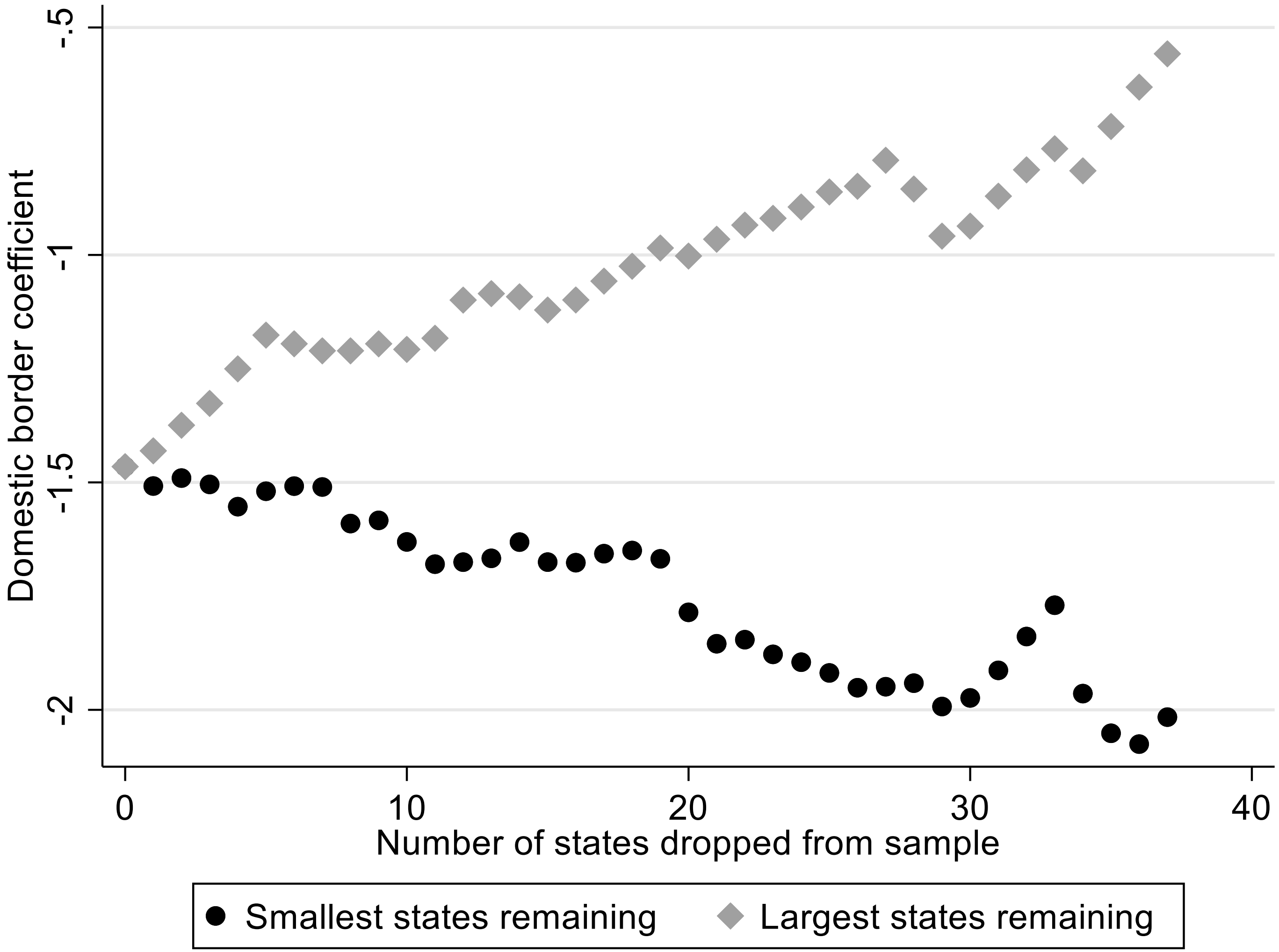

Figure 6: Plot of common domestic border dummy coefficients estimated for different samples of U.S. states. When zero states are dropped, the coefficient is -1.47 as in column 3 of Table 1. Black dots plot the coefficients obtained by successively dropping the largest remaining state from the sample such that the smallest states are remaining. The grey diamonds plot the coefficients obtained by successively dropping the smallest remaining state such that the largest states are remaining. More details are provided in the main text.

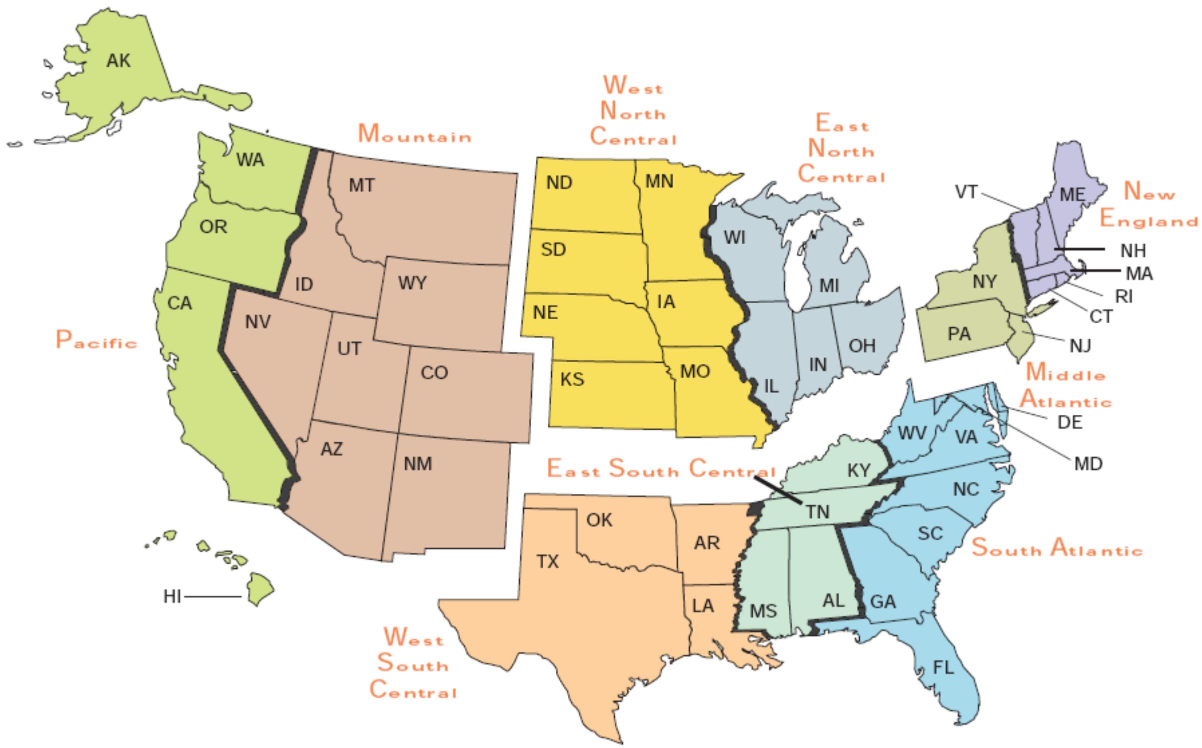

Figure 7: A map of the nine U.S. Census divisions (source: U.S. Department of Energy).

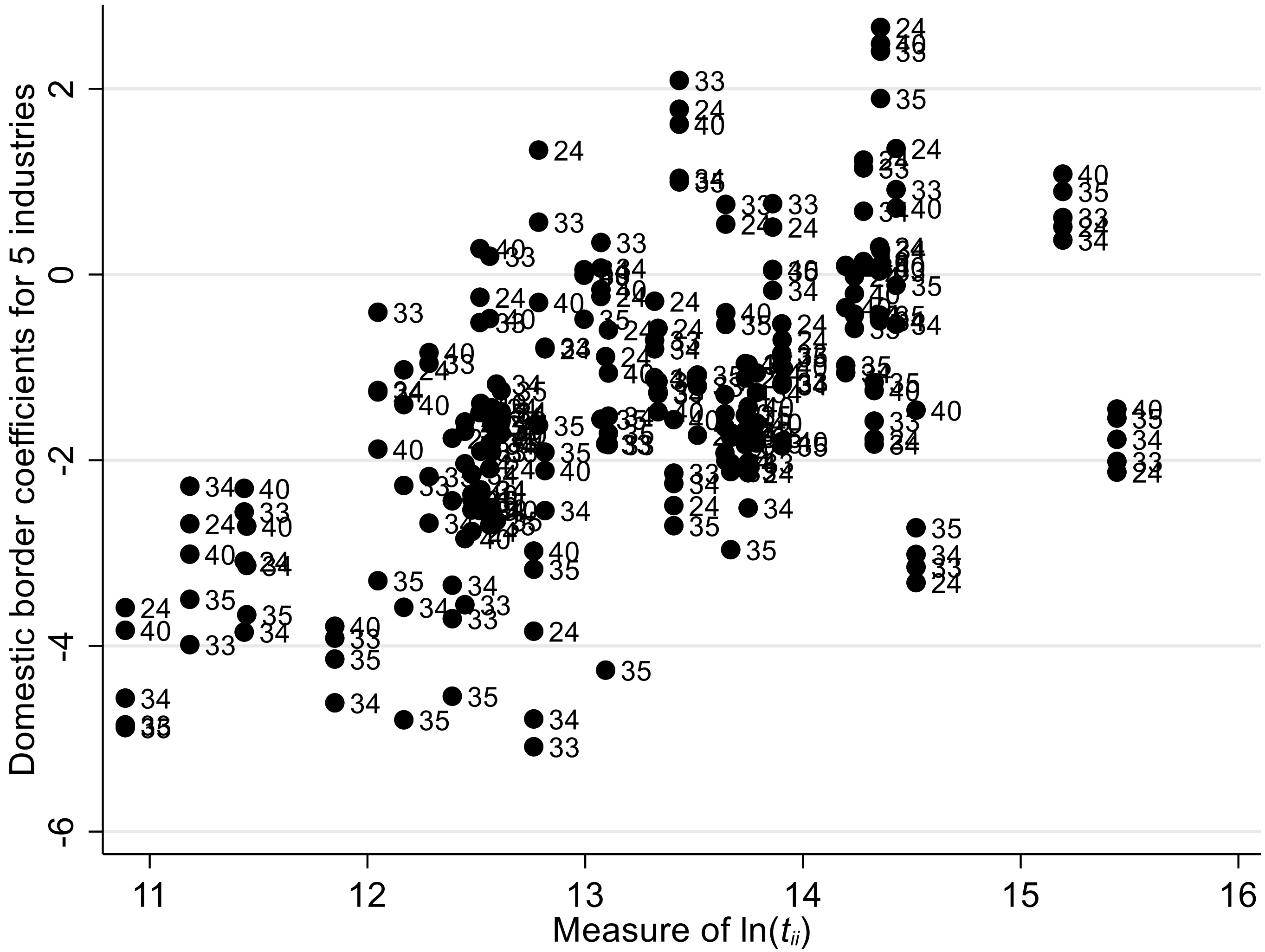

Figure 8: Plot of domestic border dummy coefficients based on industry-level trade flows for the 48 contiguous U.S. states against the logarithm of a model-consistent proxy for aggregate internal trade costs t_{ii}. The five industries are Plastics and rubber (code 24), Articles of base metal (code 33), Machinery (code 34), Electronic and other electrical equipment and components and office equipment (code 35), Miscellaneous manufactured products (code 40). The coefficients, although plotted jointly, are obtained from separate regressions for each industry. The mean of the coefficients is -1.40. The average standard error is 0.27 (not plotted). More details are provided in the main text.

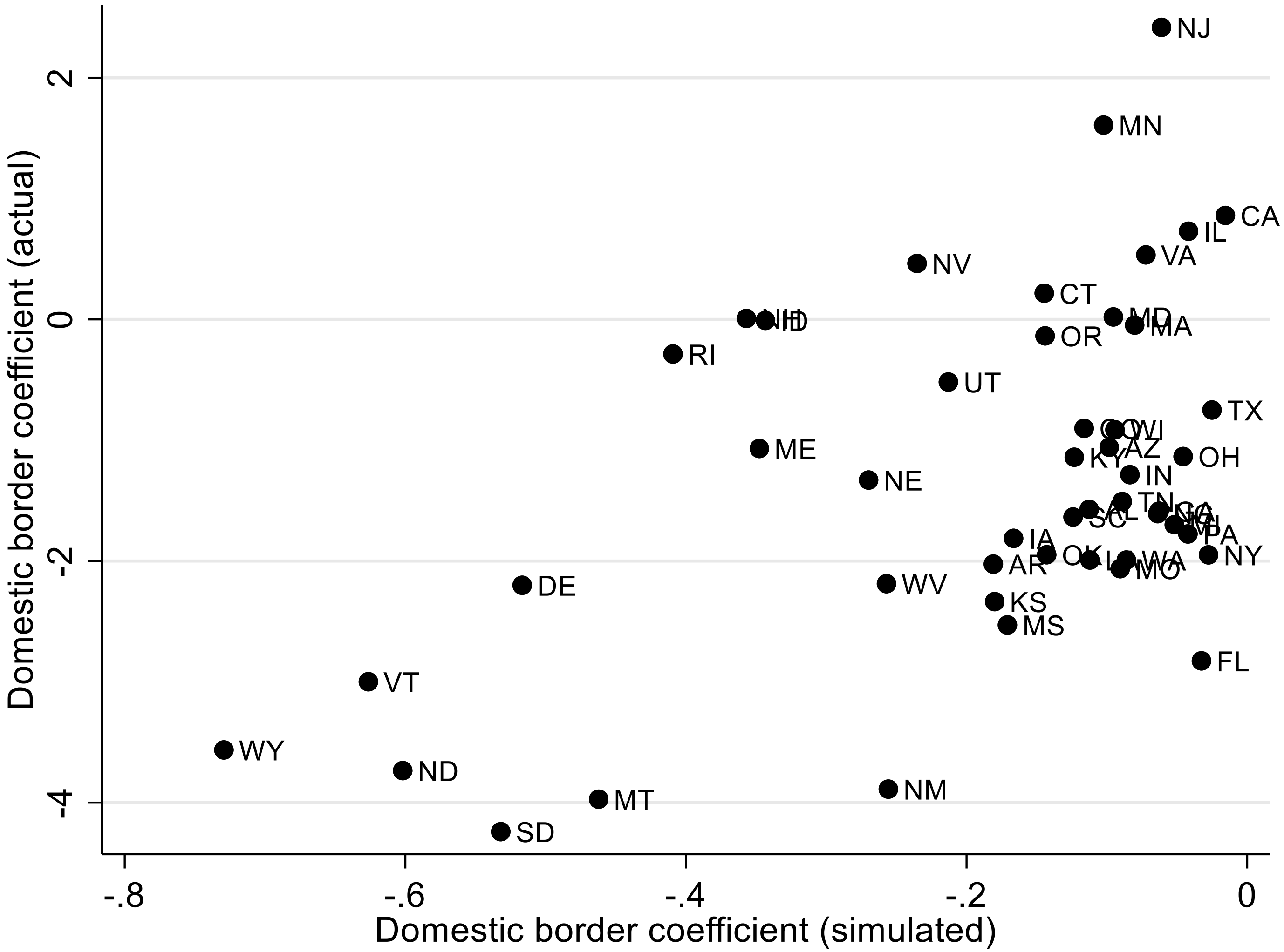

Figure C.1: Plot of domestic border dummy coefficients for the 48 contiguous U.S. states based on actual data (as in Figure 4) against domestic border dummy coefficients based on simulated data. Their correlation is 48 percent. More details are provided in appendix C.7.

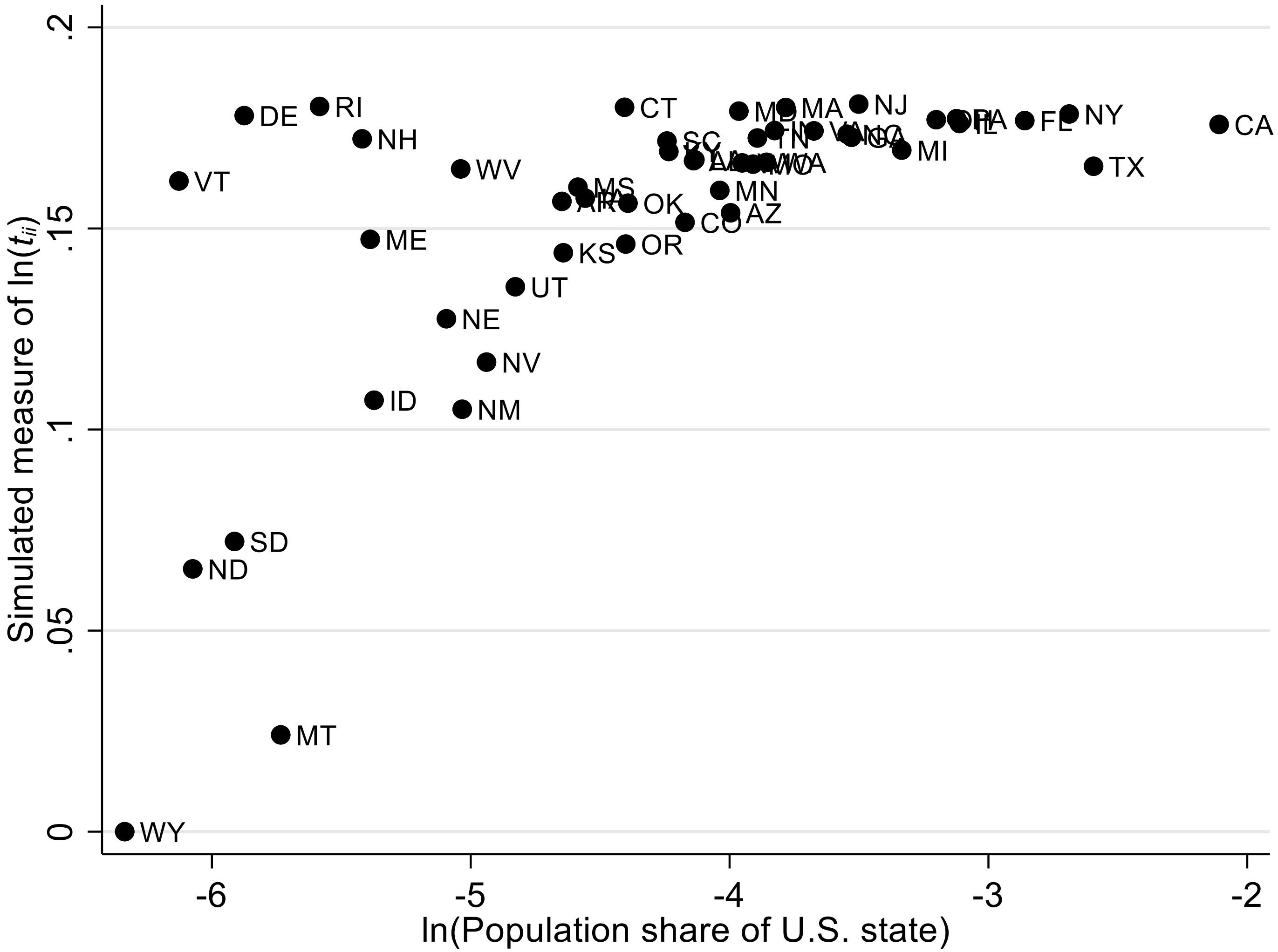

Figure C.2: Plot of a simulated measure of logarithmic trade costs t_{ii} for U.S. states against population shares of U.S. states (both in logarithms).Their correlation is 63 percent. More details are provided in appendix C.7.