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Authors	Cletus C. Coughlin, and Dennis Novy
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Federal Reserve Bank of St. Louis, Research Division, P.O. Box 442, St. Louis, MO 63166

Estimating Border Effects:
The Impact of Spatial Aggregation

Cletus C. Coughlin and Dennis Novy*

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Abstract

Trade data are typically reported at the level of regions or countries and are therefore aggregates across space. In this paper, we investigate the sensitivity of standard gravity estimation to spatial aggregation. We build a model in which symmetric 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 or countries are systematically associated with smaller border effects. The reason is that due to spatial frictions, aggregation across space increases the cost of trading within borders. The cost of trading across borders therefore appears relatively smaller. We call this mechanism the spatial attenuation effect. Even if no border frictions exist at the micro level, gravity estimation can still produce large border effects. We test our theory with trade flows at the level of U.S. states. Our results confirm the model's predictions, with quantitatively strong heterogeneity patterns.

JEL classification: F10, F15, R12
Keywords: Gravity, Geography, Border, Trade Costs, Heterogeneity, Home Bias, Spatial Attenuation, Modifiable Areal Unit Problem (MAUP)

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*Coughlin: Office of the President, Federal Reserve Bank of St. Louis, P.O. Box 442, St. Louis, MO 63166-0442, USA, coughlin@stls.frb.org. Novy: Department of Economics, University of Warwick, Coventry CV4 7AL, UK, Centre for Economic Policy Research (CEPR), Centre for Economic Performance (CEP) and CESifo, d.novy@warwick.ac.uk. A previous version of this paper was entitled "Domestic and International Border Effects: State Size Matters." We thank the editor and three referees for constructive comments. We are grateful for comments on the previous version by James Anderson, Esther Bøler, Oana Furtuna, Jason Garred, Keith Head, John Helliwell, David Jacks, Chris Meissner, Peter Neary, Krishna Pendakur, Frédéric Robert-Nicoud, Trevor Tombe, Nikolaus Wolf, as well as seminar participants at Simon Fraser University, Kiel International Economics Meeting, University of Sussex, ETSG, 2012 Midwest Trade Conference at Penn State, Federal Reserve Bank of St. Louis, CESifo Measuring Economic Integration Conference, Loughborough University Workshop on Distance and Border Effects, ESRC Scottish Centre on Constitutional Change, SIRE Workshop on Country Size and Border Effects in a Globalised World, Edinburgh, LACEA/LAMES Meetings, North American Meetings of the Regional Science Association, Higher School of Economics in Saint Petersburg, NUI Maynooth, Dundee, Strathclyde, Lancaster, London School of Economics, Oldenburg, UC Louvain, Tilburg, Hong Kong University of Science and Technology, National University of Singapore, University of Amsterdam, Essex, OECD, UC Davis, RMET, Oxford, St. Gallen, Hitotsubashi. We are also grateful to Lesli Ott for outstanding research assistance. Novy gratefully acknowledges support as a visiting scholar at the Federal Reserve Bank of St. Louis and research support from the Centre for Competitive Advantage in the Global Economy (CAGE) at the University of Warwick. The views expressed are those of the individual authors and do not necessarily reflect official positions of the Federal Reserve Bank of St. Louis, the Federal Reserve System, or the Board of Governors.

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 attempt to 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 costs of trading within the newly aggregated macro regions. As a result, aggregation increases the relative costs of trading within as opposed to across borders. Our theory shows how this shift in relative costs 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.*

This heterogeneity has important implications for the estimation of border effects as typically found in the literature. First, since standard border effects are averages of the underlying individual border effects, we get sample composition effects. That is, samples that happen to include many large regions (or countries) tend to have moderate border effects, and vice versa. Second, given that samples inevitably vary across different studies, their border effects are not directly comparable since each sample implies a different choice about the relevant spatial unit.

In the empirical part of the paper, we test the predictions of our theory with a data set of domestic and international trade flows at the level of U.S. states. Our results confirm the model's predictions, in particular the systematic heterogeneity of border effects across states. For instance, 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 carry out a hypothetical scenario of aggregating U.S. states into larger spatial units, namely the nine Census divisions as 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.

While our framework is an extension of the existing literature on gravity models, it is important to note that our mechanism of spatial aggregation is separate from multilateral resistance effects in general equilibrium as highlighted by Anderson and van Wincoop (2003). 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 without multilateral resistance effects at work. In the data, when we have to keep track of varying multilateral resistances across space, we find that the heterogeneity of border effects stemming from spatial aggregation dominates by a large margin the heterogeneity coming from multilateral resistance effects.

The fundamental problem with gravity estimation of border effects is that researchers attempt to identify a border friction that occurs at the micro level faced by individual economic agents. However, spatial aggregation systematically alters the border dummy coefficients (i.e., border effects) that are obtained with gravity. Our theory sheds light on the precise nature of this mismatch between micro frictions and macro data. We show that in fact, even if no specific friction exists at the border, standard gravity estimation can still give rise to significant border dummy coefficients, and these can be very large. In that case, estimated border effects would be pure statistical artefacts. But even if a friction does exist at the micro level, gravity estimation based on aggregate data generally cannot identify the friction unless further structural assumptions are made. In that light, we see our paper as a conceptual contribution that tries to question and rethink the meaning of border effects as traditionally put forward in the literature. We discuss these conceptual issues in section 5.

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. 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.

Our approach is inspired by Hillberry and Hummels (2008) who find empirically that counterfactual ZIP code border effects 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. The link with international border effects is less obvious since their estimation does not require internal trade flows within subnational units (e.g., trade flows within Canadian provinces are not required to estimate the U.S.-Canadian border effect).

Our results on heterogeneous border effects and the spatial attenuation effect illustrate an 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 (2016) 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

[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. In this paper, we are concerned with spatial aggregation in the absence of industry variation. But we share the belief that industry aggregation is an important topic that has not received enough attention.

[2] See Fotheringham and Wong (1991).

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 2014), 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 do we, they 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 outline the typical estimation of border effects in the literature. In section 3 we present our formal model of spatial aggregation for domestic and international border effects. In section 4 we take the theory to the data and apply it to domestic and international trade flows at the level of U.S. states. We also discuss multilateral resistance effects in general equilibrium and provide simulations of our model. In section 5 we discuss the implications of our analysis for the interpretation of border effects. Section 6 concludes.

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. We then proceed to the novel part, which is to explain how spatial aggregation systematically changes border effects.

[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).

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:

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

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

[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.

log-linearize gravity equation (1) and insert the trade cost function (2) to obtain

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

where β and γ are the coefficients of interest used to compute border effects.[7] Both coefficients are typically found to be negative, and we will reproduce such standard estimates in the empirical section 4.

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 explain formally how border dummy coefficients are affected when regions are spatially aggregated. We first turn to the domestic border effect and then to the international border effect.

3.1 The domestic border effect

Our aim is to formalize the effects 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 instance, 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 Micro and macro regions

As the basic framework, we model the world as consisting of an arbitrarily large number of small 'micro' regions denoted by the superscript S for 'small.' Each 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

[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 to a reduction of international trade by 39 percent.

same internal trade costs t_{ii}^S for all i and the same bilateral trade costs t_{ij}^S between each other such that $t_{ij}^S = t^S$ for all $i \neq j$. The bilateral costs are at least as high as the internal costs ($t^S \geq t_{ii}^S \geq 1$), and they are the only bilateral friction in the model.[8] The micro regions have uniform income and multilateral resistance terms y_i^S and P_i^S.[9]

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

$$x_{ij}^S = \frac{y^S y^S}{y^W} \left(\frac{t_{ij}^S}{P^S P^S} \right)^{1-\sigma}, \tag{4}$$

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 A.1 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 denoted by the superscript L for 'large.' 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 level. For the internal trade of the macro region, we have the relationship

$$x_{ii}^L = \frac{y^L y^L}{y^W} \left(\frac{t_{ii}^L}{P^L P^L} \right)^{1-\sigma}, \tag{5}$$

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:

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

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

[9] 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 section 4.8 for examples.

Combining the three previous equations we obtain

$$\underbrace{\frac{ny^S ny^S}{y^W}\left(\frac{t^L_{ii}}{P^L P^L}\right)^{1-\sigma}}_{x^L_{ii}} = n\underbrace{\frac{y^S y^S}{y^W}\left(\frac{t^S_{ii}}{P^S P^S}\right)^{1-\sigma}}_{x^S_{ii}} + n(n-1)\underbrace{\frac{y^S y^S}{y^W}\left(\frac{t^S}{P^S P^S}\right)^{1-\sigma}}_{x^S_{ij}}. \tag{6}$$

Multilateral resistance is unaffected by aggregation

In appendix A.1 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 (6) simplifies to

$$\left(t^L_{ii}\right)^{1-\sigma} = \frac{1}{n}\left(t^S_{ii}\right)^{1-\sigma} + \frac{n-1}{n}\left(t^S\right)^{1-\sigma}. \tag{7}$$

If the economy faces higher bilateral than internal costs at the micro level ($t^S > t^S_{ii}$), then internal trade costs at the macro level grow in the number of aggregated micro regions ($\partial t^L_{ii}/\partial n > 0$).[10] The only exception is the limiting case of no spatial frictions in the sense of $t^S = t^S_{ii}$. In that case, internal trade costs at the macro level are the same as at the micro level ($t^L_{ii} = t^S_{ii}$). Thus, the frictionless world is the only case where aggregation is irrelevant since border effects are then by construction zero.[11]

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

$$x^L_{1,2} = \frac{y^L_1 y^L_2}{y^W}\left(\frac{t^L_{1,2}}{P^L P^L}\right)^{1-\sigma}, \tag{8}$$

where $x^L_{1,2}$ denotes the trade flow from the first to the second macro region with bilateral costs $t^L_{1,2}$, and y^L_1 and y^L_2 are their respective incomes. This flow is the aggregate of $n_1 n_2$ bilateral micro flows:

$$x^L_{1,2} = n_1 n_2 x^S_{ij}.$$

[10] 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 $t^S_{ii} = 1$ as a normalization.

[11] The frictionless world would correspond to $t^S_{ij} = t^S = 1$ for all i, j. But we could normalize trade costs to any other positive uniform level.

We can therefore write

$$\underbrace{\frac{n_1 y^S n_2 y^S}{y^W}\left(\frac{t_{1,2}^L}{P^L P^L}\right)^{1-\sigma}}_{x_{1,2}^L} = n_1 n_2 \underbrace{\frac{y^S y^S}{y^W}\left(\frac{t^S}{P^S P^S}\right)^{1-\sigma}}_{x_{ij}^S}. \tag{9}$$

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

$$t_{1,2}^L = t^S \tag{10}$$

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.

3.1.2 Estimating the traditional border effect

Having characterized the full set of aggregate internal and bilateral trade costs for macro regions in equations (7) and (10) 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}:

$$\ln\left(t_{ij}^{1-\sigma}\right) = \gamma DOM_{ij}, \tag{11}$$

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 will be U.S. states in our empirical analysis), and for simplicity we drop the L superscript. From equation (10) we note that $t_{ij} = t^S$ for all $i \neq j$. We deliberately ignore other trade cost components but those could be added.[12] From equations (10) and (11) we have $\gamma = \ln\left(t^S\right)^{1-\sigma} \leq 0$ for $DOM_{ij} = 1$. Thus, trade cost function (11) is consistent with bilateral trade costs as they appear in our model.

In contrast, trade cost function (11) is not consistent with internal trade costs as they appear in our model. The simplified trade cost function (11) 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

[12] In appendix A.5 we show that our results go through for a more conventional specification that includes bilateral distance as an additional trade cost component.

i. The trade cost function (11) 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 (7) 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.[13] We use the log-linearized form of gravity equation (1)

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

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

$$\widehat{\gamma} = \frac{\mathrm{Cov}\left(\ln\left(\frac{x_{ij}}{y_i y_j}\right), DOM_{ij}\right)}{\mathrm{Var}\left(DOM_{ij}\right)}. \tag{12}$$

As shown in appendix A.2, we can derive the coefficient estimate as

$$\widehat{\gamma} = \gamma + \underbrace{\ln\left(\prod_{i=1}^{N}\left(t_{ii}^{\sigma-1}\right)^{\frac{1}{N}}\right)}_{\text{bias}}. \tag{13}$$

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 (7), 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.[14] 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 (13) and that we will explore

[13] From equations (10) and (11) we have $\gamma = \ln\left(t^S\right)^{1-\sigma} \leq 0$ for $DOM_{ij} = 1$.

[14] Apart from OLS, PPML estimation following Santos Silva and Tenreyro (2006) and Fally (2015) generates qualitatively the same estimates. See section 4 for details.

in the empirical section:

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.[15] For the interpretation of trade cost function (11) we therefore have to adopt the implicit normalization of zero average internal trade costs.[16] 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 $\exp(\gamma)$ 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.

3.1.3 A heterogeneous trade cost function

Once we aggregate across space as implied by equation (7), 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 (11) misspecified. As shown by equation (13) and in appendix A.4, this tension generates an omitted variable bias in standard gravity estimation of border effects. Trade cost function (11) with a simple dummy is therefore unsuitable for spatial aggregation as it does not accommodate the heterogeneous nature of internal trade costs.

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

[16] If other controls such as distance are added to the trade cost function, the bias generally does not disappear (see appendix A.5).

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

$$\ln\left(t_{ij}^{1-\sigma}\right) = \gamma DOM_{ij} + \psi\left(1 - DOM_{ij}\right)\ln\left(t_{ii}^{1-\sigma}t_{jj}^{1-\sigma}\right)^{\frac{1}{2}} \tag{14}$$

with $\psi = 1$. It reduces to equation (11) for $i \neq j$. But the key feature of the heterogeneous trade cost function (14) is the interaction term between the dummy and internal trade costs. Unlike (11), it thus allows for heterogeneous internal trade costs in the case of $i = j$.[17]

If the heterogeneous trade cost function (14) is used in a gravity equation such as (1), then the direct effect of DOM_{ij} on trade (ignoring the general equilibrium multilateral resistance effects) is given by

$$\frac{\mathrm{d}\ln\left(x_{ij}\right)}{\mathrm{d}\,DOM_{ij}} = \gamma + \psi\ln\left(t_{ii}^{\sigma-1}t_{jj}^{\sigma-1}\right)^{\frac{1}{2}}. \tag{15}$$

As we show in appendix A.3, this effect is invariant to the specific normalization chosen for trade costs.[18] That is, suppose we renormalize trade costs by setting $t_{kl} = 1$ for trade costs between macro regions k and l. The magnitude of the effect in (15) 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 $\gamma < 0$.[19] Ceteris paribus border effects are therefore mechanically driven by internal trade costs and inherently heterogeneous, in contrast to the traditional trade cost function (11). 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).

[17] Given $\psi = 1$, for $i = j$ equation (14) becomes an identity. Unlike in equation (11) internal trade costs are thus not set to zero. In the special case of $\psi = 0$ equation (14) nests the simple trade cost function (11). This parameter restriction on ψ comes down to a straightforward testable hypothesis of border effect heterogeneity that we consider in the empirical section.

[18] 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.

[19] Note that in the theory, $\gamma < 0$ if $t^S > t_{ii}^S$ 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.

3.1.4 Estimating heterogeneous domestic border effects

The right-hand side variables of the heterogeneous trade cost function (14) 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.[20]

More specifically, we can break down trade cost function (14) into region-specific terms as

$$\ln\left(t_{ij}^{1-\sigma}\right) = \underbrace{\gamma DOM_{ij} - \left\{\psi DOM_{ij}\ln\left(t_{ii}^{1-\sigma}\right)^{\frac{1}{2}} + \psi DOM_{ij}\ln\left(t_{jj}^{1-\sigma}\right)^{\frac{1}{2}}\right\}}_{\frac{\gamma_k}{2}DOM_{ij}\alpha_k \;=\; \frac{\gamma_k}{2}DOM_{ij}^k} + \underbrace{\psi\ln\left(t_{ii}^{1-\sigma}\right)^{\frac{1}{2}}}_{\alpha_i} + \underbrace{\psi\ln\left(t_{jj}^{1-\sigma}\right)^{\frac{1}{2}}}_{\alpha_j}. \quad (16)$$

In a standard log-linearized regression based on gravity equation (1), the last two terms would be absorbed 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 α_i and α_j. However, this would lead to perfect collinearity with the last two terms, α_i and α_j.[21] Instead, the first three terms can be estimated through an interaction of the DOM_{ij} dummy with *region* fixed effects α_k that equal unity whenever k is an exporter ($k = i$) or an importer ($k = j$) with $k = 1, ..., N$. This is equivalent to region-specific DOM_{ij}^k dummies with coefficients $\gamma_k/2$.[22] A simple test of border effect heterogeneity comes down to the hypothesis that the γ_k coefficients differ from each other. We note that the common γ coefficient in (16) cannot be identified since it would be collinear with the γ_k's.

3.2 The international border effect

We proceed in two steps. First, we model trade flows at the level of small geographical units, which we call 'micro' regions, based on a standard gravity setting. Second, as in the

[20] 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 A.5 where we derive a theory-consistent measure of internal distance.

[21] The collinearity would arise because adding up the two interaction effects with the exporter and importer fixed effects would yield twice the constant term. That is, $DOM_{ij}\alpha_i + DOM_{ij}\alpha_j + \alpha_i + \alpha_j = 2$ for each observation.

[22] Since the region-specific dummies capture every domestic trade flow twice (once on the exporter side and once on the importer side), the estimated coefficients $\gamma_k/2$ must be multiplied by 2 to obtain estimates of γ_k. The latter are comparable to the standard border coefficient.

model for the domestic border effect, 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. Our purpose is to explore the implications of this aggregation for gravity estimates of the international border effect.

The global economy consists of two symmetric countries, Home and Foreign. We first describe the trade flows within one country and then across countries.

3.2.1 Micro and macro regions on a circle

As in section 3.1 the world consists of symmetric micro regions denoted by superscript S. Each region is endowed with a differentiated good and has uniform income and multilateral resistance terms y_i^S and P_i^S. Gravity equation (4) holds at the micro level.

As will become apparent shortly, to deal with the international border effect it is no longer sufficient to just have a binary difference between internal trade costs t_{ii}^S and bilateral trade costs t^S at the micro level as in section 3.1. Instead, we need to introduce a spatial topography such that frictions increase between more distant micro regions. At the same time, we would like to preserve symmetry to be able to obtain analytical solutions.

Therefore, as the simplest case of such a topography, we model the domestic economy as a circle. Micro regions are symmetric segments 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, i.e., $t_{ii}^S \leq t_h^S$ for any h.[23]

Aggregate bilateral trade costs

We aggregate $n \geq 2$ micro regions into a macro region denoted by superscript L with income $y^L = ny^S$. Due to symmetry gravity also holds at the macro level. The aggregated micro regions are adjacent on the circle such that the macro region has no 'holes.' 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 B.1 we also derive the internal trade flows of an aggregated macro region and the associated internal trade costs.

[23]The theory for the domestic border effect in section 3.1 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 $t_{ii}^S < 1$.

In contrast to the domestic border setting in section 3.1, bilateral trade costs at the macro level are sensitive to aggregation. 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 (8). The bilateral macro flow from the first to the second macro region is the aggregate of $n_1 n_2$ bilateral micro flows:

$$x^L_{1,2,h} = \sum_{v=1}^{n_1} \sum_{w=1}^{n_2} x^S_{h+v+w-2},$$

where the subscript h in $x^L_{1,2,h}$ indicates the number of steps that the two macro regions are apart. For instance, $x^L_{1,2,1}$ for $h = 1$ means that the two macro regions are adjacent (i.e., one step apart), and $x^L_{1,2,2}$ for $h = 2$ means the two macro regions are two steps apart etc. This means we have to add the micro flows $x^S_{h+v+w-2}$ with step length $h+v+w-2$, summed over v and w, to yield the bilateral macro flow.

As in the model for the domestic border effect, it turns out that aggregation does not change the multilateral resistance price indices, i.e., $P^S = P^L$. In appendix B.2, we show this result formally. The intuition is that aggregation does not affect the underlying trade cost structure and equilibrium of trade flows.

Using a relationship as in equation (9) and given that multilateral resistances are the same across micro and macro regions, we can derive the expression for bilateral trade costs at the macro level as

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

A key result is that these bilateral macro trade costs rise in the number of aggregated micro regions, i.e., $\partial t^L_{1,2,h}/\partial n_1 > 0$ and $\partial t^L_{1,2,h}/\partial n_2 > 0$. 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 $t^S_h = t^S$ for all h. In that case, bilateral trade costs would be the same at the micro and macro levels as in equation (10).

To see more clearly how bilateral trade costs depend on region size n_1 and n_2, we substitute the spatial friction $t^S_{h+v+w-2} = \delta^{h+v+w-2}$.[24] We can then decompose bilateral

[24] 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 $t^L_{1,2,h}$ would be more complicated.

trade costs at the macro level into three elements as

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

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.[25] 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^S_{int} 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.[26] In addition, we assume a cost for crossing the international border so that we can write

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

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

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

[26] 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.

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.

As we discuss in more detail in section 5, the model on the international border effect is more complex than the model on the domestic border effect in section 3.1 because it features a discrete barrier β that is specific to the border (it does not arise between micro regions in general). At a fundamental level, the model on the domestic border effect can be set up involving only two tiers of trade flows: domestic bilateral flows between different micro regions of the same country, and internal flows within micro regions. The model on the international border effect requires international flows as a third tier.

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.

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

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

where for the moment we ignore the general equilibrium 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 $\delta = 1$. 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. This is the spatial attenuation effect in the context of the international border effect. In appendix B.3 we show 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.

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

Ceteris paribus 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.

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 region fixed effects α_k that equal unity whenever $i = k$ or $j = k$ regardless of the direction of trade.[27] As the empirical specification we obtain

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

where β_k indicates region-specific international border coefficients. A simple test of border effect heterogeneity comes down to the hypothesis that the β_k coefficients differ from each other. We note that the β parameter cannot be identified due to collinearity with the fixed effects.

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

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, our data set comprises, for instance, 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, 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.[28] 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.[29]

4.2 Overview

We first show in section 4.3 that our data exhibit a substantial domestic border effect, as established by Wolf (2000). We also show that the data exhibit a significant international border effect, as established by McCallum (1995). In a second step in section 4.4, we move away from border effects that are common across states, as typically imposed in the literature. Instead, consistent with our theory we estimate individual border effects that are allowed to vary across states, thus uncovering a large degree of underlying hetero-

[28] 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.

[29] Our entire sample thus comprises $6,297$ observations per cross-section, or $25,188$ in total. 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.

geneity. In section 4.5, we systematically alter our estimation sample to understand how sample composition effects change border effect estimates. In section 4.6, we aggregate the 48 U.S. states into larger spatial units. We show in section 4.7 that quantitatively, border effect heterogeneity is substantially more important than heterogeneity related to multilateral resistance effects. Finally, in section 4.8 we provide numerical examples and simulations of our model.

4.3 Estimating common border effects

In columns 1 and 2 of Table 1, we replicate well-known results on the domestic border effect, estimated with a domestic border dummy. We only use trade flows within the U.S. International trade flows are not included. As our estimating equation we use the log-linear version of gravity equation (1). 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 1 we only use data for 1993. In column 2 we add the data for 1997, 2002 and 2007. Our estimate of $\widehat{\gamma} = -1.48$ in column 2 is the same as Wolf's baseline coefficient.[30]

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 ($\exp(-1.48) = 0.23$). Assuming a value for the elasticity of substitution of $\sigma = 5$, we can translate this into a tariff equivalent of the domestic border of 45 percent.[31] As we show in section 3.1.2, 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), according to expression (13) the underlying tariff equivalent would be even higher. Put differently, the $\widehat{\gamma}$ estimate only captures the domestic border barrier net of internal trade costs.

In columns 3 and 4 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 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 country fixed effects instead of exporter and importer fixed effects.[32] As the output

[30] 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.

[31] For $\ln\left(t_{ij}^{1-\sigma}\right) = -1.48$, it follows $t_{ij} = 1.45$. 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.

[32] That is, we use fixed effects that are state-specific (in the case of U.S. states) and country-specific

regressors are collinear with these fixed effects, they are dropped from the estimation. In column 3 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 ($\exp(-1.25) = 0.29$). The corresponding tariff equivalent is 37 percent. When we pool the data over the years 1993, 1997, 2002 and 2007 in column 4, 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.

Overall, we have replicated domestic and international 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).[33]

4.4 Estimating individual border effects

We run the same regression specifications with panel data as in columns 2 and 4 of Table 1, but now allowing the domestic and international border coefficients to vary across states. That is, we estimate individual, state-specific border effects. This approach is consistent with the theory in sections 3.1.4 and 3.2.2, respectively. Expressions (15) and (21) predict that for larger states, the border coefficients should be closer to zero due to spatial attenuation.

4.4.1 Individual domestic border effects

We first estimate domestic border dummy coefficients for the 48 U.S. states in our sample. We obtain the corresponding γ_k coefficients by using trade cost function (16) in otherwise standard gravity estimation. As equation (15) 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.

(in the case of foreign countries) but that do not distinguish between being an exporter or an importer.

[33] 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.

How can we obtain a measure of internal trade costs that is consistent with the theory? Equation (7) describes how t_{ii}^L depends on the number of aggregated micro regions n and the micro frictions t_{ii}^S and t^S. But since these micro frictions are unobservable, instead we resort to gravity equation (5) to obtain a theory-consistent measure of internal trade costs.[34] 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 $\ln\left(t_{ii}\right)$ with $\ln\left(y^L y^L / x_{ii}^L\right)$.[35]

As an illustration, in Figure 1 we plot the domestic border coefficients γ_k against our proxy of internal trade costs. Two main observations can be made. First, there is a large degree of heterogeneity across the estimates. While the mean of coefficients is -1.32 and thus close to the point estimates reported in columns 1 and 2 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 (not plotted in the figure).

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.[36] 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 (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.[37] At the other extreme, a few economically large states such as New Jersey and California are associated with positive border coefficients.[38] These results underline the importance of spatial

[34] We refer to section 4.8 where we discuss internal trade costs in more detail.

[35] The proxy $y^L y^L / x_{ii}^L$ roughly corresponds to a combination of two factors: a measure of openness (y^L / x_{ii}^L) multiplied by a measure of size (y^L). The proxy can be understood in the context of equation (7). That expression shows that internal trade costs of a macro region or state, t_{ii}^L, are a weighted average of the frictions within and between the underlying micro regions, t_{ii}^S and t^S. The weights are given by $1/n$ and $(n-1)/n$. Openness can be seen as capturing t_{ii}^S and t^S in that the larger these frictions are for a given state all else being equal, the harder it is to trade within that state, and therefore trade will be diverted towards other states. In the data, this leads to an increase in openness, i.e., x_{ii}^L goes down relative to y^L. In addition, size is reflected by a larger number of micro regions within a state, i.e., a larger value for n. Thus, more weight is shifted towards t^S such that internal costs go up. In the data, a bigger n is captured by an increase in y^L. See section 4.8 for examples.

[36] We also refer to section 4.8 where we provide numerical simulations confirming the positive relationship between individual coefficients and internal costs.

[37] 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.

[38] The coefficients for California, Illinois, Minnesota, Nevada, New Jersey and Virginia are positive and significant at the five percent level. In the theory in section 3.1, the upper bound for state-specific domestic border coefficients is actually zero. In equation (7) t_{ii}^L approaches t^S for $n \to \infty$, which is the same as $t_{1,2}^L$ through equation (10). Therefore, in equation (16) it follows $\gamma_k = 0$ 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 15).

attenuation effects.[39] In section 5 we discuss to what extent domestic border effects might be interpreted as statistical artefacts.

4.4.2 Individual international border effects

We also estimate individual coefficients for the international border dummies. We obtain these β_k estimates by using trade cost function (22) in otherwise standard gravity estimation, substituting bilateral distance for δ_{ij}.[40] 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 of larger economic size.

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. As with the domestic border coefficients, 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.[41] The coefficients are tightly estimated with an average standard error of 0.13. 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). The substantial difference between the above tariff equivalents can therefore be attributed to spatial aggregation as a primary driving force behind border effect estimates (see section 5 for a discussion).

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

[39] 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 1.

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

[41] 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.

when we estimate common border effects, our estimates should be sensitive to the distribution of state economic size in the sample. 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 domestic 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 -1.47. 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 4 illustrate the domestic border coefficients. As predicted by our theory, we yield the following pattern: the more big states we drop from the sample, the larger the coefficients tend to become in absolute value. Although their movement is not strictly monotonic, the downward trend is reasonably clear.

The grey diamonds in Figure 4 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 domestic border coefficients move upwards towards zero. Overall in Figure 4, we obtain coefficients ranging from around -2 to -0.5.

In Figure 5, we repeat the rolling regressions for the international border effect, starting out with the same regression as in column 3 of Table 1 where the obtained a coefficient of -1.25. We find the same pattern as in Figure 4. 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, and vice versa. The coefficients roughly fall in the range from -3.5 to 0.[42]

Therefore, in summary we find strong sample composition effects in Figures 4 and 5. 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 to U.S. Census divisions

The individual border effects illustrated in Figures 1-3 demonstrate that larger states tend to exhibit smaller border effects in absolute magnitude. We now trace this relation-

[42] 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.

ship 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.

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 6 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.

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 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 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 distance coefficients are very similar between Tables 1 and 2.

Overall, 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 1-3.

As a final note, we comment on the estimation method. Although the point estimates naturally change when we use 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 1-3, consistent with our theory. For the domestic border coefficients in Figure 1 we find a correlation of 97 percent between coefficients obtained with PPML and those obtained with OLS. The corresponding correlation for the international border coefficients in Figures 2-3 is 75 percent. Furthermore, the relationship between coefficients in Tables 1 and 2 is the same with PPML.

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.[43] 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 B.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 3 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 4 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 4 of Table 1, we estimate this border barrier based on the logarithmic version of the 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.[44] We then remove the U.S. international border and recompute the associated general equilibrium.[45]

Panel 1 presents the logarithmic differences between the counterfactual and initial

[43] 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.

[44] 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.

[45] 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.

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.[46] 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 4.4.2. 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.[47]

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 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 section 3.1 we assume 100 symmetric micro regions with equal incomes.[48] We set values of $t_{ii}^S = 1$ for internal trade costs within micro regions and

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

[47] 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 3 nevertheless.

[48] This is equivalent to assuming equal endowments.

$t^S = 1.2$ for bilateral trade costs between micro regions. We assume $\sigma = 5$. As outlined in section 3.1.2, 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 4.

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 4 report each case. We compute the implied internal trade costs of the macro regions with the help of equation (7). As the corresponding row in Table 4 shows, aggregation increases internal trade costs.

Table 4 also reports the corresponding common border coefficients estimated in OLS regressions. As our analytical solution in equation (13) 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 nonlinear 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 4. If we then estimate heterogeneous border effects as outlined in section 3.1.4, we obtain the same coefficient values for the macro regions as those reported in the respective columns of Table 4. This result 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 4 imply that these sample composition effects can be quantitatively substantial.

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 in equation (13). 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 4 but with macro regions of different sizes.

More specifically, we retain the same values of t_{ii}^S 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 measure the number of micro regions for other states proportionately. Equation (7) 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 section 3.1). 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 7 we plot those simulated coefficients against the ones obtained based on actual trade flows between U.S. states (see Figure 1). The correlation between the two sets of coefficients in Figure 7 stands at 48 percent. We therefore conclude that the simple underlying model with symmetric micro regions works reasonably well 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.

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). Surface area determines the number of micro regions per state. We set this number equal to 1 for Rhode Island, which is the smallest state by area. All other states consist of a proportionately larger number of micro regions, rounded to the closest integer. For instance, Delaware consists of two micro regions and Connecticut of four. Texas as the largest state by area in our sample consists of 174 micro regions. We introduce asymmetry by exploiting different population densities across states. Specifically, population density becomes our measure of n in equation (7), set equal to 1 for Wyoming as the state with the lowest population density. We retain the underlying frictions within micro regions, t_{ii}^S and t^S, using the same baseline values as above. As in equation (10), bilateral trade costs are also kept at t^S. As above, population weights determine states' income shares.

This setting means that for a given surface area, 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 in that area and thus the higher number of bilateral relationships (see equation 7). 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 8 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 clearly a 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 7. 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. Features such as mountainous terrain could also be incorporated.

5 Discussion

The aim of much of the empirical literature on border effects is to identify the parameters γ (for the domestic border effect) and β (for the international border effect). However, as we have shown in the context of equations (16) and (22), these parameters cannot be identified empirically in standard gravity regressions.[49] The reason is that their estimates are subject to spatial attenuation effects.

For the domestic border effect, in our model there is a friction t^S between states. Yet, as soon as we aggregate across space, we obtain domestic border effects that are closer to zero compared to the actual friction. This upward bias is driven by the spatial attenuation effect put forward in our analysis. That is, the more we aggregate, the more the estimated domestic border dummy coefficients are pushed upwards towards zero.

We add a note on the interpretation of domestic border effects. While there is a

[49] 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.

friction t^S between states, it 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. It would therefore be wrong to interpret those coefficients as reflecting frictions solely associated with state borders. In that sense, the domestic border effect in our model can be seen as a pure statistical artefact (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.[50] For economically irrelevant entities (such as ZIP codes or U.S. Census divisions) it is hard to see domestic border effects as anything else than statistical artefacts.

For the international border effect, there is a friction specific to crossing an international border as long as we have $\beta < 0$.[51] This friction generally cannot be identified from traditional gravity estimation. Equation (20) shows how β could be estimated once α_i and α_j have been constructed. But from equation (18) it is clear that α_i and α_j will depend on the choice of spatial unit for a micro region (be it a U.S. Census tract or some other unit – embodied in n_i and n_j) and the distance friction δ. They will also depend on the choice for the underlying topography (be it a circle or an alternative spatial structure). Recovering the β friction would thus depend on structural assumptions.[52]

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 their estimated border effects. The main result of the theory is that aggregation leads to border effect heterogeneity: larger regions or countries are associated

[50] 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.

[51] If $\beta = 0$, the international border friction does not exist. But as equation (21) demonstrates, estimation based on aggregate data would still yield heterogeneous coefficients. In our model those would be *positive*.

[52] See Coşar, Grieco and Tintelnot (2015) for evidence based on micro data from the wind turbine industry.

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 relative trade costs of trading within as opposed to 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. Moreover, it allows us to estimate these effects individually by state.

As predicted by our theoretical framework, we find that the larger the state, the smaller its domestic border effect and the smaller its international border effect. In addition, both border effects decline in magnitude when states are aggregated into larger U.S. Census divisions. 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 estimated in the literature. To the extent that there exist frictions of crossing domestic or international borders at the micro level of firms and households, standard gravity estimation based on aggregate trade flows is unable to recover them. We surmise that structural estimation or natural experiments involving micro data may be the way forward to achieve that objective.

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Appendix A: The domestic border effect

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

A.1 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 (4), we start with the more general version

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

where Π^S denotes outward multilateral resistance. We then show why the specification in equation (4) 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

$$\left(P_i^S\right)^{1-\sigma} = \sum_{j=1}^{R} \frac{y_j^S}{y^W}\left(\frac{t_{ji}^S}{\Pi_j^S}\right)^{1-\sigma},$$

where R is the number of micro regions. Due to symmetry we have $t_{ji}^S = t_{ij}^S = t^S$ for all $j \neq i$ as well as $y_j^S/y^W = 1/R$, $P_j^S = P^S$ and $\Pi_j^S = \Pi^S$, and therefore

$$\left(P^S\right)^{1-\sigma} = \frac{1}{R}\left(\frac{t_{ii}^S}{\Pi^S}\right)^{1-\sigma} + \frac{R-1}{R}\left(\frac{t^S}{\Pi^S}\right)^{1-\sigma}, \tag{23}$$

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

$$\left(\Pi^S P^S\right)^{1-\sigma} = \frac{1}{R}\left(t_{ii}^S\right)^{1-\sigma} + \frac{R-1}{R}\left(t^S\right)^{1-\sigma} \tag{24}$$

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 (23), we can then write the micro price index from the perspective of a remaining micro region as

$$\left(P^S\right)^{1-\sigma} = \frac{1}{R}\left(\frac{t_{ii}^S}{\Pi^S}\right)^{1-\sigma} + \frac{R-1-n}{R}\left(\frac{t^S}{\Pi^S}\right)^{1-\sigma} + \frac{n}{R}\left(\frac{t^S}{\Pi^L}\right)^{1-\sigma}, \tag{25}$$

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

$$\left(\Pi^S P^S\right)^{1-\sigma} = \frac{1}{R}\left(t_{ii}^S\right)^{1-\sigma} + \frac{R-1-n}{R}\left(t^S\right)^{1-\sigma} + \frac{n}{R}\left(\frac{t^S \Pi^S}{\Pi^L}\right)^{1-\sigma}. \tag{26}$$

We set equations (24) and (26) equal to obtain

$$\Pi^S = \Pi^L. \tag{27}$$

From a gravity equation at the macro level similar to (5) 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 (6) that again allows for separate outward and inward price indices to replace x_{ii}^L as well as $y^L = n y^S$ to obtain

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

For brevity, we define

$$\lambda^{1-\sigma} \equiv \frac{\left(t_{ii}^L\right)^{1-\sigma}}{\frac{1}{n}\left(t_{ii}^S\right)^{1-\sigma} + \frac{n-1}{n}\left(t^S\right)^{1-\sigma}} \tag{28}$$

and use the result in equation (27) to obtain

$$\left(P^L\right)^{1-\sigma} = \left(\lambda P^S\right)^{1-\sigma}. \tag{29}$$

Analogous to (25), 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 (27) 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 (27) and (29) 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 (24) equal to the last expression and eliminate t_{ii}^L by using (28). We yield

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

which implies $\lambda^{1-\sigma} = 1$. Note that $\lambda^{1-\sigma} = 1$ also implies the expression in equation (7) for internal trade costs in the macro region.

Inserting this result into (29), we find that the inward multilateral resistance price index is unaffected by the aggregation of symmetric regions, i.e., $P^L = P^S$. From (27) 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 (4) and (5) without separate outward multilateral resistance variables.

A.2 Estimating the border effect

As expressed in equation (12), 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

$$\widehat{\gamma} = \frac{\operatorname{Cov}\left(\ln\left(t_{ij}^{1-\sigma}\right), DOM_{ij}\right)}{\operatorname{Var}\left(DOM_{ij}\right)}. \tag{30}$$

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 (30) 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

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

where the last term in parentheses is the geometric average of internal trade costs in the sample. Inserting this result into (30) 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 (13).

A.3 Invariance of the border effect to normalization

A key feature of the generalized trade cost function (14) introduced in section 3.1.3 is that its implied border effect (15) is invariant to the specific normalization chosen for trade costs. For instance, suppose we choose the new normalization $t_{kl} = 1$ for trade costs between regions k and l. This normalization implies that trade costs $t_{ij}^{1-\sigma}$ for all i, j get multiplied by a constant $q \equiv 1/t_{kl}^{1-\sigma} > 0$ 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

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

where the latter equation gives the same result as in (15). Note that the traditional trade cost function (11) is also invariant to renormalization since

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

such that

$$\frac{\mathrm{d}\ln(x_{ij})}{\mathrm{d}\,DOM_{ij}} = \gamma$$

irrespective of q.

A.4 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 (14) 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 (11), 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

$$\mathrm{Cov}\left(DOM_{ij}, DOM_{ij} \ln\left(t_{ii}^{1-\sigma}t_{jj}^{1-\sigma}\right)^{\frac{1}{2}}\right) = 0. \tag{31}$$

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 (31) becomes

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

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

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

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.

A.5 A trade cost function with distance

In section 3.1 we use a model without spatial distance frictions. As a result, the trade cost function (11) 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 (35)

$$\begin{aligned}\left(t_{mm}^L\right)^{1-\sigma} &= \frac{1}{n}\left(t_{ii}^S\right)^{1-\sigma} + 2\sum_{h=1}^{n-1}\frac{n-h}{n^2}\left(t_h^S\right)^{1-\sigma} \\ &= \frac{1}{n}\left(t_{ii}^S\right)^{1-\sigma} + \exp\left(\gamma DOM_h\right)\underbrace{2\sum_{h=1}^{n-1}\frac{n-h}{n^2}\left(\delta^h\right)^{1-\sigma}}_{\left(\delta_{mm}\right)^{1-\sigma}},\end{aligned} \tag{32}$$

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 (32) is not multiplicative.

Overall, to combine bilateral and internal trade costs we set up a heterogeneous trade cost function similar to (14)

$$\ln\left(t_{ij}^{1-\sigma}\right) = \gamma DOM_{ij} + \rho\ln\left(dist_{ij}\right) + \ln\left(\alpha_i\right)^{1-\sigma} + \ln\left(\alpha_j\right)^{1-\sigma} + \left(1-DOM_{ij}\right)\ln\left(\kappa_i\kappa_j\right)^{\frac{1-\sigma}{2}}. \tag{33}$$

Trade cost function (33) 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 (14). It can be estimated as outlined in section 3.1.4 and equation (16). 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 B: The international border effect

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

B.1 Aggregate internal trade costs

Gravity holds at the macro level so that relationship (5) describes the internal trade of the macro region x^L_{mm}, where m denotes the set of n aggregated micro regions. This internal macro flow consists of the n internal flows of the original micro regions and their $n(n-1)$ bilateral flows:

$$\begin{aligned} x^L_{mm} &= \sum_{i\epsilon m} x^S_{ii} + \sum_{i\epsilon m} \sum_{j\epsilon m, j\neq i} x^S_{ij} \\ &= \sum_{i\epsilon m} x^S_{ii} + 2\sum_{h=1}^{n-1}(n-h)x^S_h, \end{aligned}$$

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

Combining the corresponding gravity relationships at the macro and micro levels, we obtain an expression similar to equation (6)

$$\underbrace{\frac{ny^S ny^S}{y^W}\left(\frac{t^L_{mm}}{P^L P^L}\right)^{1-\sigma}}_{x^L_{mm}} = \sum_{i\epsilon m} \underbrace{\frac{y^S y^S}{y^W}\left(\frac{t^S_{ii}}{P^S P^S}\right)^{1-\sigma}}_{x^S_{ii}} + 2\sum_{h=1}^{n-1}(n-h)\underbrace{\frac{y^S y^S}{y^W}\left(\frac{t^S_h}{P^S P^S}\right)^{1-\sigma}}_{x^S_h}. \quad (34)$$

Given that multilateral resistance is unaffected by aggregation, the internal trade costs of the macro region therefore follow from equation (34) as

$$\left(t^L_{mm}\right)^{1-\sigma} = \frac{1}{n}\left(t^S_{ii}\right)^{1-\sigma} + 2\sum_{h=1}^{n-1}\frac{n-h}{n^2}\left(t^S_h\right)^{1-\sigma}. \quad (35)$$

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

B.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

$$\left(P^S_i\right)^{1-\sigma} = \sum_{j=1}^{2R}\frac{y^S_j}{y^W}\left(\frac{t^S_{ji}}{P^S_j}\right)^{1-\sigma},$$

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_{ji}^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 $y_j^S/y^W = 1/(2R)$ and $P_j^S = P^S$. Therefore we can write the price index for a Home region as

$$\left(P^S\right)^{1-\sigma} = \frac{1}{2R}\left(\frac{t_{ii}^S}{P^S}\right)^{1-\sigma} + \frac{1}{2R}\sum_{j\epsilon R, j\neq i}\left(\frac{t_{ji}^S}{P^S}\right)^{1-\sigma} + \frac{1}{2}\left(\frac{t_{int}^S}{P^S}\right)^{1-\sigma}, \tag{36}$$

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

$$\left(P^S\right)^{1-\sigma} = \left(\frac{1}{2R}\left(t_{ii}^S\right)^{1-\sigma} + \frac{1}{2R}\sum_{j\epsilon R, j\neq i}\left(t_{ji}^S\right)^{1-\sigma} + \frac{1}{2}\left(t_{int}^S\right)^{1-\sigma}\right)^{\frac{1}{2}} \tag{37}$$

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 m. Analogous to (36), we can then write the micro price index from the perspective of a remaining Home micro region as

$$\left(P^S\right)^{1-\sigma} = \frac{1}{2R}\left(\frac{t_{ii}^S}{P^S}\right)^{1-\sigma} + \frac{1}{2R}\sum_{j\epsilon R, j\neq i,m}\left(\frac{t_{ji}^S}{P^S}\right)^{1-\sigma} + \frac{n}{2R}\left(\frac{t_{mi}^L}{P^L}\right)^{1-\sigma} + \frac{1}{2}\left(\frac{t_{int}^S}{P^S}\right)^{1-\sigma}, \tag{38}$$

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_{mi}^L between the macro region and the micro region. The fourth term captures the international relationships.

From gravity equation (5) at the macro level, we can solve for the macro price index as

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

We use (34) to replace x_{mm}^L as well as $y_m^L = n y_m^S$ to obtain

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

For brevity, we set

$$\lambda^{1-\sigma} \equiv \left(\frac{\left(t_{mm}^L\right)^{1-\sigma}}{\frac{1}{n}\left(t_{ii}^S\right)^{1-\sigma} + \frac{2}{n^2}\sum_{h=1}^{n-1}(n-h)\left(t_h^S\right)^{1-\sigma}}\right)^{\frac{1}{2}} \tag{39}$$

so that we have

$$\left(P^L\right)^{1-\sigma} = \left(\lambda P^S\right)^{1-\sigma}. \tag{40}$$

We insert this result back into expression (38) and solve for the micro price index as

$$\left(P^S\right)^{1-\sigma} = \left(\frac{1}{2R}\left(t_{ii}^S\right)^{1-\sigma} + \frac{1}{2R}\sum_{j\epsilon R, j\neq i,m}\left(t_{ji}^S\right)^{1-\sigma} + \frac{n}{2R}\left(\frac{t_{mi}^L}{\lambda}\right)^{1-\sigma} + \frac{1}{2}\left(t_{int}^S\right)^{1-\sigma}\right)^{\frac{1}{2}}. \quad (41)$$

Setting this result equal to expression (37), we obtain

$$n\left(\frac{t_{mi}^L}{\lambda}\right)^{1-\sigma} + \sum_{j\epsilon R, j\neq i,m}\left(t_{ji}^S\right)^{1-\sigma} = \sum_{j\epsilon R, j\neq i}\left(t_{ji}^S\right)^{1-\sigma}.$$

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

$$n\left(\frac{t_{mi}^L}{\lambda}\right)^{1-\sigma} = \sum_{j\epsilon m}\left(t_{ji}^S\right)^{1-\sigma}, \quad (42)$$

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

In equation (38) 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

$$\left(P^L\right)^{1-\sigma} = \frac{n}{2R}\left(\frac{t_{mm}^L}{P^L}\right)^{1-\sigma} + \frac{1}{2R}\sum_{j\epsilon R, j\neq m}\left(\frac{t_{jm}^L}{P^S}\right)^{1-\sigma} + \frac{1}{2}\left(\frac{t_{int}^S}{P^S}\right)^{1-\sigma},$$

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 (40) and solve for the micro price index as

$$\left(P^S\right)^{1-\sigma} = \left(\frac{1}{\lambda^{1-\sigma}}\right)^{\frac{1}{2}}\left(\frac{n}{2R}\left(\frac{t_{mm}^L}{\lambda}\right)^{1-\sigma} + \frac{1}{2R}\sum_{j\epsilon R, j\neq m}\left(t_{jm}^L\right)^{1-\sigma} + \frac{1}{2}\left(t_{int}^S\right)^{1-\sigma}\right)^{\frac{1}{2}}.$$

We set this result equal to equation (41). To replace the $\left(t_{mm}^L\right)^{1-\sigma}$ term, we use the definition of λ in equation (39). To replace the $\left(t_{mi}^L/\lambda\right)^{1-\sigma}$ term in equation (41), we use the result in (42). We also note that due to symmetry, we have $\left(t_{jm}^L\right)^{1-\sigma} = \left(t_{mj}^L\right)^{1-\sigma}$. Through equation (42) this is the same as

$$\left(t_{jm}^L\right)^{1-\sigma} = \left(t_{mj}^L\right)^{1-\sigma} = \frac{\lambda^{1-\sigma}}{n}\sum_{i\epsilon m}\left(t_{ij}^S\right)^{1-\sigma}.$$

Collecting terms and simplifying, we obtain

$$\begin{aligned} & \left(t_{ii}^{S}\right)^{1-\sigma}+\frac{2}{n}\sum_{h=1}^{n-1}(n-h)\left(t_{h}^{S}\right)^{1-\sigma}+\frac{1}{n}\sum_{j\epsilon R,j\neq m}\sum_{i\epsilon m}\left(t_{ij}^{S}\right)^{1-\sigma}+\frac{1}{\lambda^{1-\sigma}}R\left(t_{int}^{S}\right)^{1-\sigma} \\ = & \left(t_{ii}^{S}\right)^{1-\sigma}+\sum_{j\epsilon R,j\neq i}\left(t_{ji}^{S}\right)^{1-\sigma}+R\left(t_{int}^{S}\right)^{1-\sigma}. \end{aligned}$$

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

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

We also note that

$$\begin{aligned} & \frac{1}{n}\sum_{j\epsilon R,j\neq m}\sum_{i\epsilon m}\left(t_{ij}^{S}\right)^{1-\sigma}+\frac{1}{n}\sum_{j\epsilon m}\sum_{i\epsilon m,i\neq j}\left(t_{ij}^{S}\right)^{1-\sigma} \\ = & \sum_{j\epsilon R,j\neq i}\left(t_{ij}^{S}\right)^{1-\sigma}=\sum_{j\epsilon R,j\neq i}\left(t_{ji}^{S}\right)^{1-\sigma} \end{aligned}$$

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 (40) we therefore arrive at the result that the price index is unaffected by aggregation, i.e., $P^{L}=P^{S}$.

B.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

$$\operatorname{Cov}\left(INT_{ij},INT_{ij}\ln\left(\alpha_i\alpha_j\right)^{1-\sigma}\right)=0. \tag{43}$$

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 (43) 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 $\overline{A} = M/\left(K+M\right)$. 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 C: Data

This appendix describes our data sources in detail.

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.[53]

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.[54] 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.[55]

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.[56] We use the annual data from 1993, 1997, 2002, and 2007 for total merchandise exports.[57]

[53] 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.

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

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

[56] 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.

[57] 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.[58] 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.[59]

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.[60] This calculation yields adjustment factors of 0.495 for 1993, 0.508 for 1997, 0.430 for 2002, and 0.405 for 2007.[61] 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.

[58] 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.

[59] 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.

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

[61] 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.

Table 1: Domestic and international border effects

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

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. Exporter and importer fixed effects in columns 1 and 2; state and country fixed effects in columns 3 and 4; those fixed effects are time-varying in columns 2 and 4. *** significant at 1% level.

Table 2: Border effects based on U.S. Census divisions

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

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. Exporter and importer fixed effects in columns 1 and 2; division and country fixed effects in columns 3 and 4; those fixed effects are time-varying in columns 2 and 4.
*** significant at 1% level.

Table 3: 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			
	$\Delta \ln(x_{ij})$	=	$(1-\sigma) \Delta \ln(t_{ij})$	+	$(\sigma-1) \Delta \ln(P_i P_j)$	+	$\Delta \ln(y_i y_j / y^W)$		$\Delta \ln(x_{ij})$	=	$(1-\sigma) \Delta \ln(t_{ij})$	+	$(\sigma-1) \Delta \ln(P_i P_j)$	+	$\Delta \ln(y_i y_j / y^W)$	
	(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 4: 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_{ii}^{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.

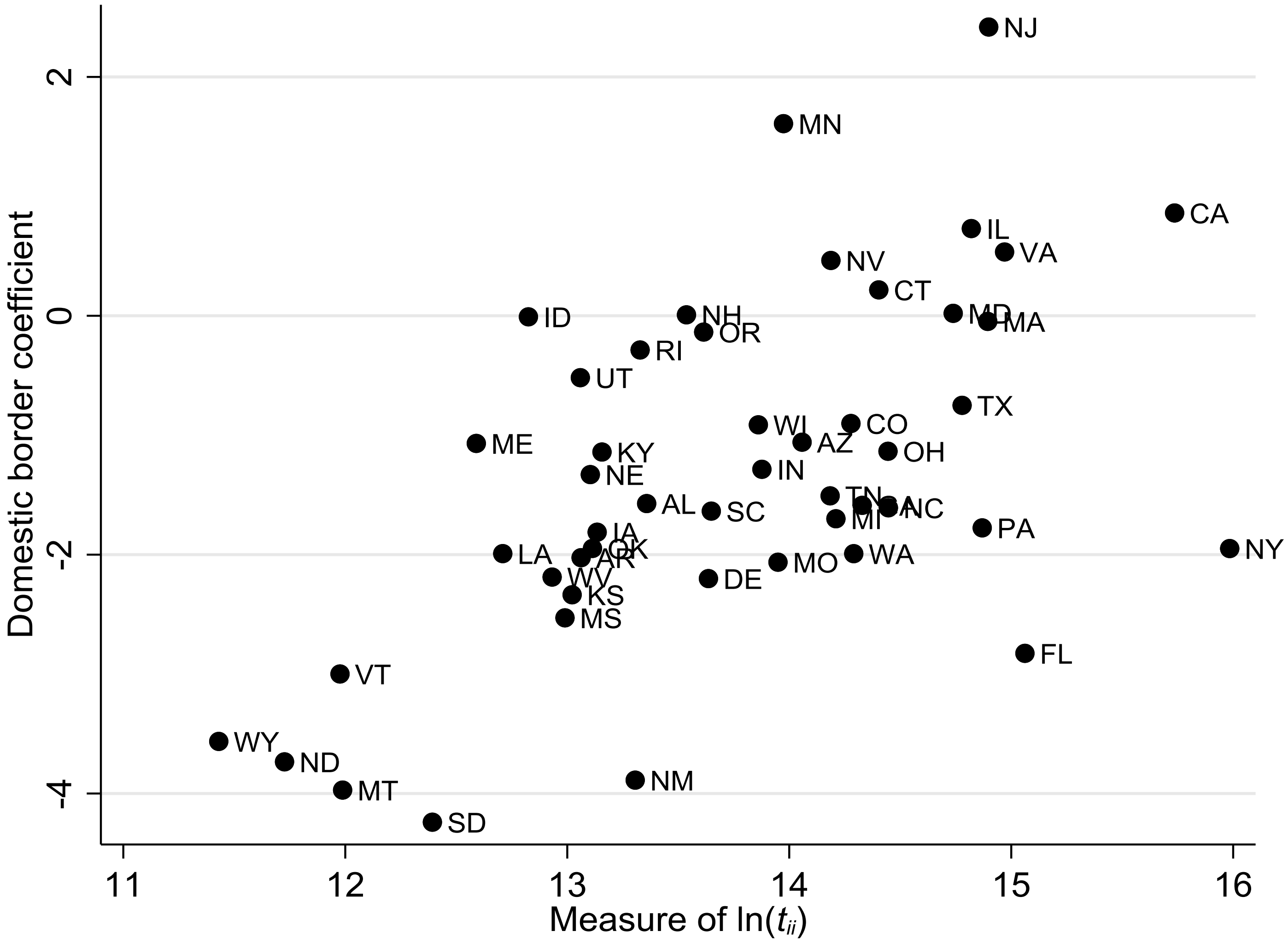

Figure 1: Plot of domestic border dummy coefficients for the 48 contiguous U.S. states against the logarithm of a model-consistent proxy for internal trade costs t_{ii}. The mean of the coefficients is -1.32. The average standard error is 0.13 (not plotted). More details are provided in the main text.

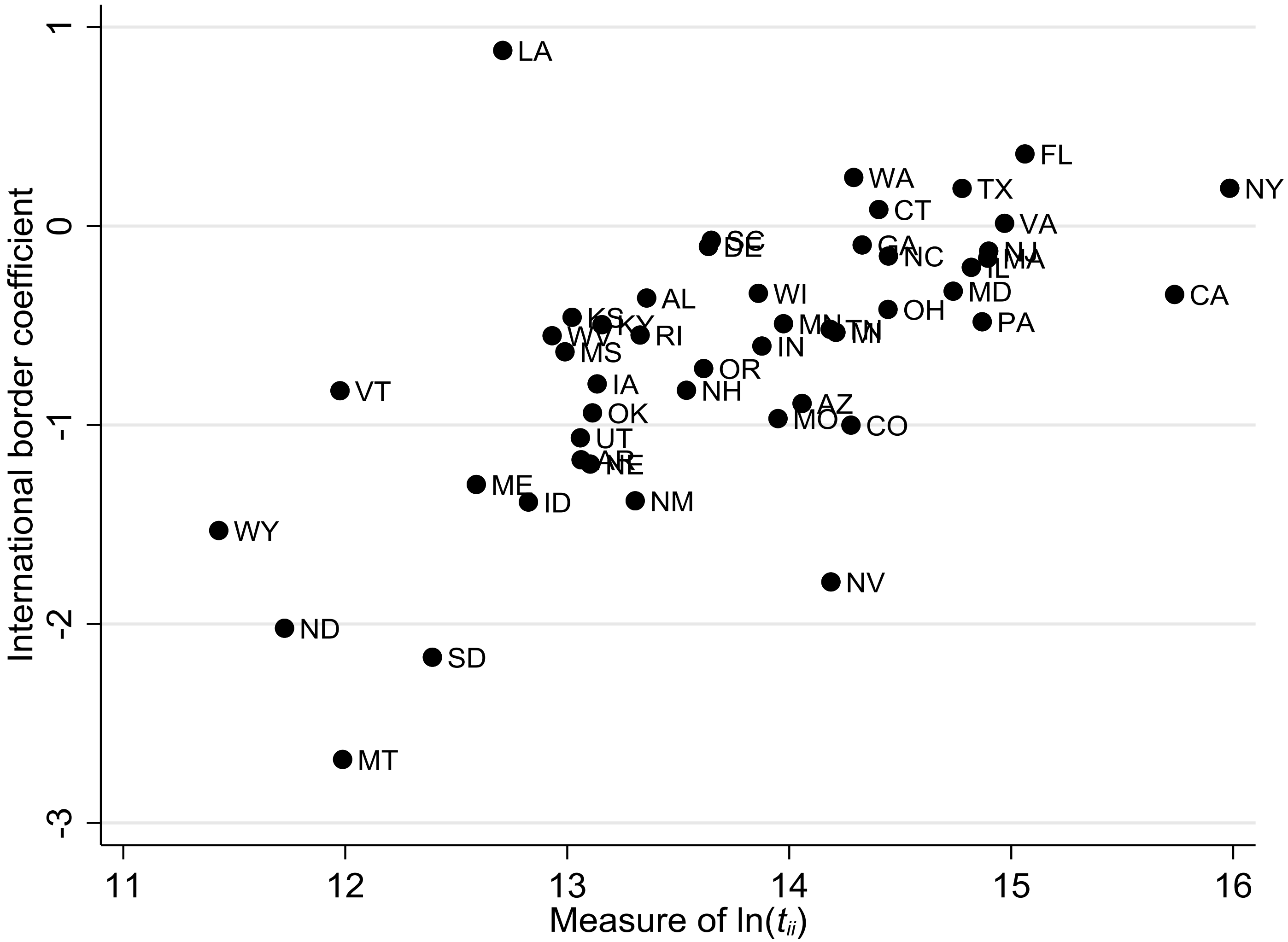

Figure 2: Plot of international border dummy coefficients for the 48 contiguous U.S. states against the logarithm of a model-consistent proxy for internal trade costs t_{ii}. The mean of the coefficients is -0.64. The average standard error is 0.13 (not plotted). More details are provided in the main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

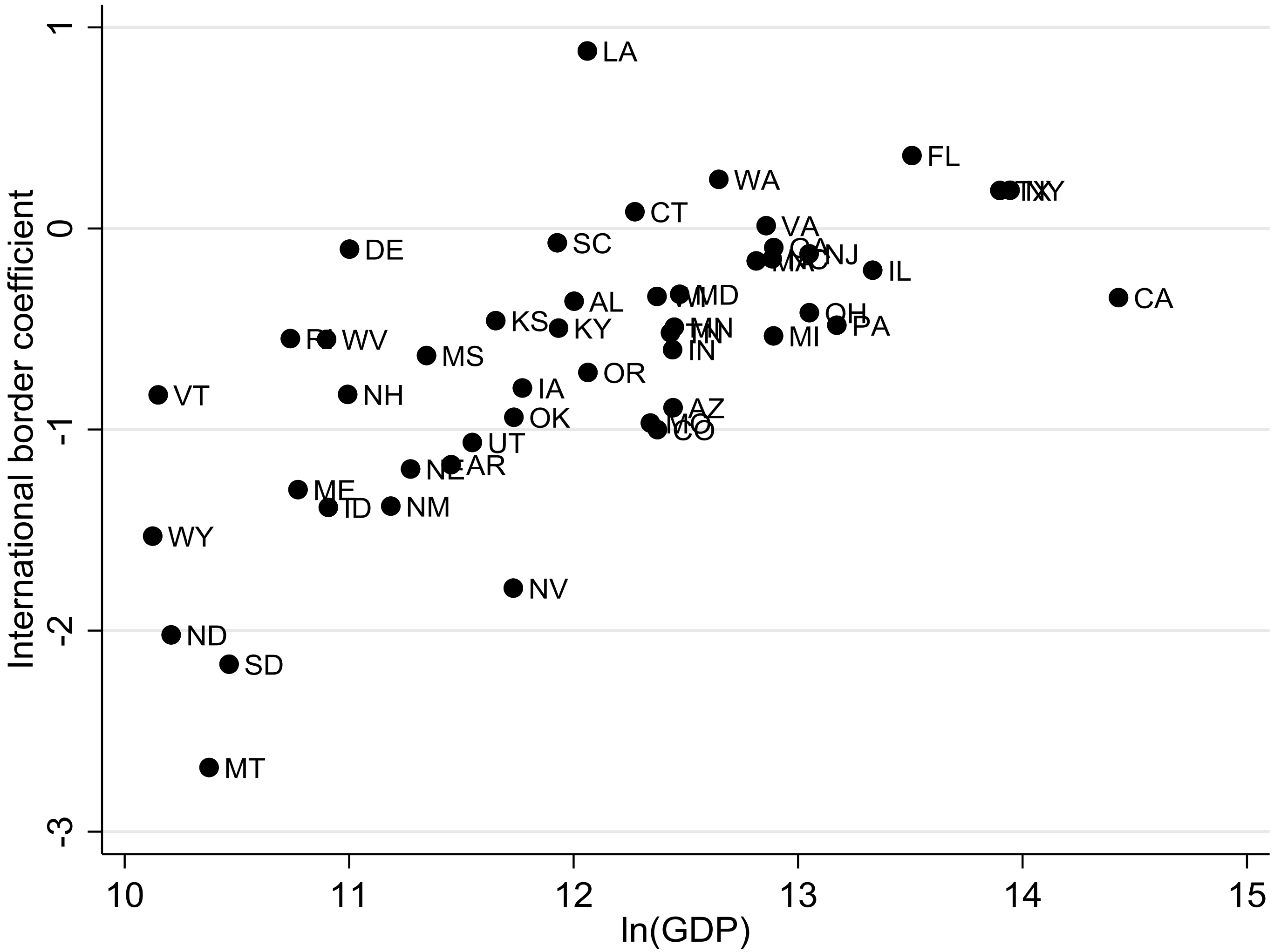

Figure 3: Plot of international border dummy coefficients for the 48 contiguous U.S. states against the logarithm of state GDP. The mean of the coefficients is -0.64. The average standard error is 0.13 (not plotted). More details are provided in the main text.

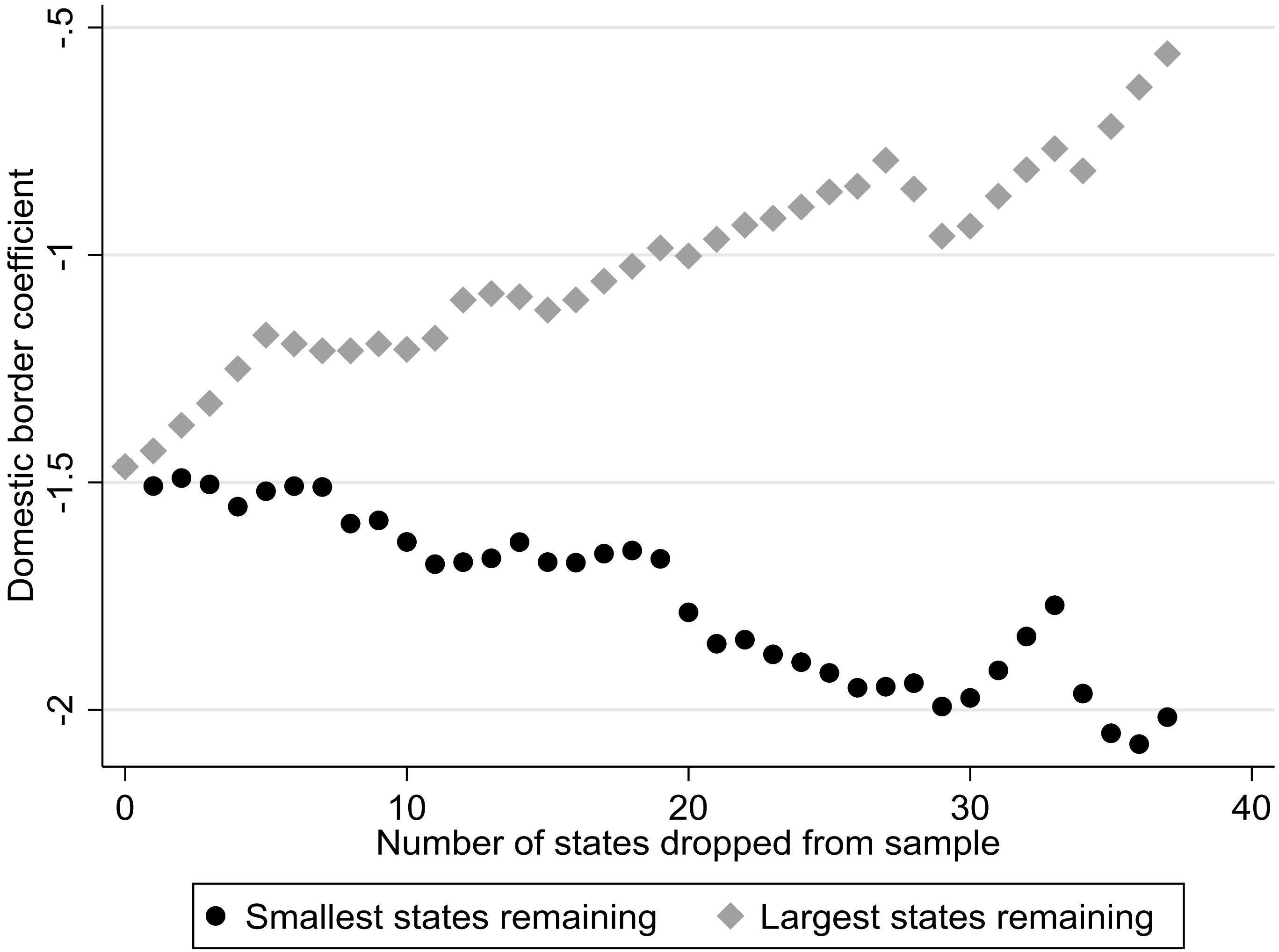

Figure 4: Plot of common domestic border dummy coefficients estimated for different samples of U.S. states. When zero states are dropped, the coefficient is -1.47 as in column 1 of Table 1. Black dots plot the coefficients obtained by successively dropping the largest remaining state from the sample 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.

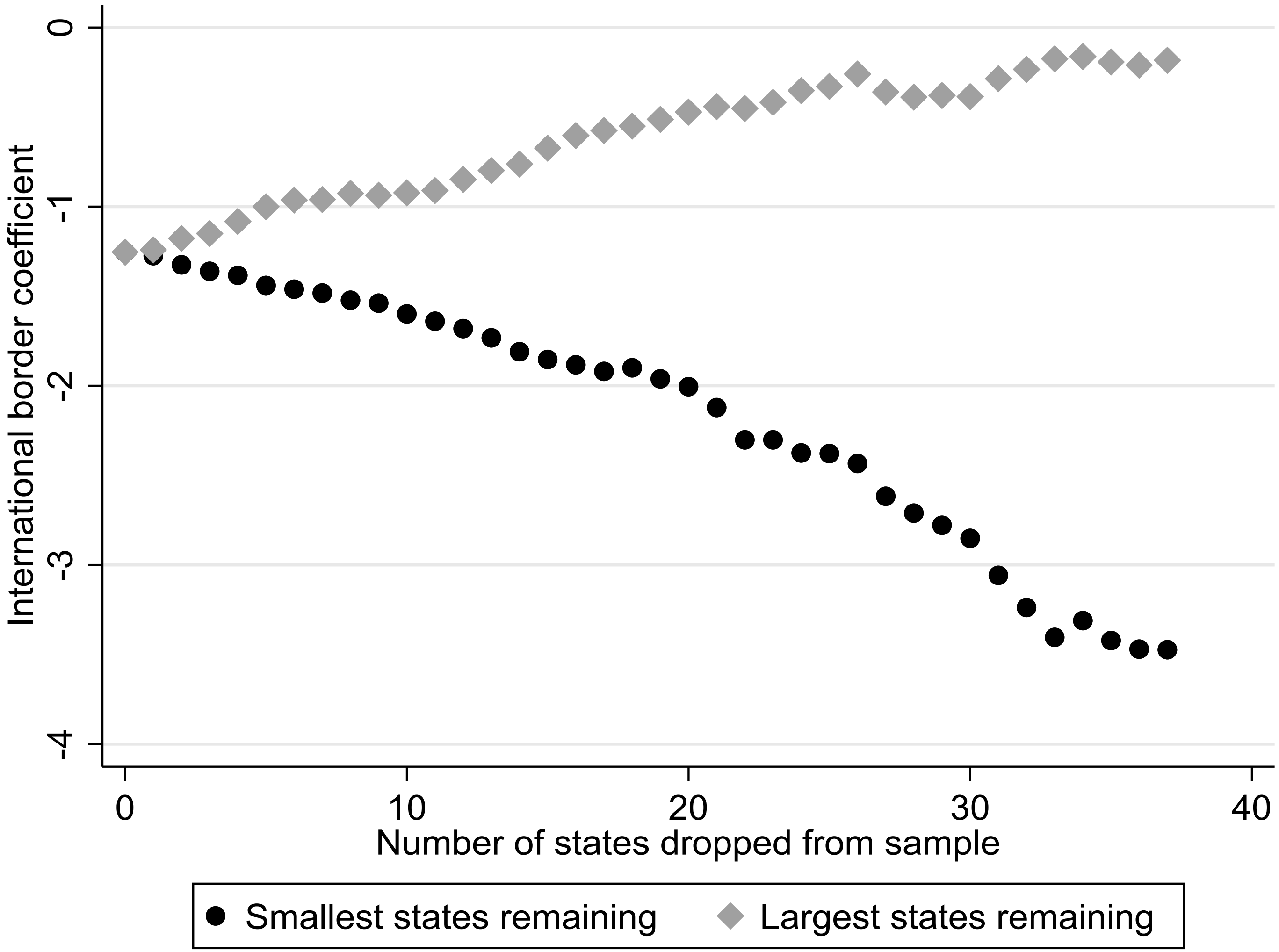

Figure 5: Plot of common international border dummy coefficients estimated for different samples of U.S. states. When zero states are dropped, the coefficient is -1.25 as in column 3 of Table 1. Black dots plot the coefficients obtained by successively dropping the largest remaining state from the sample 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.

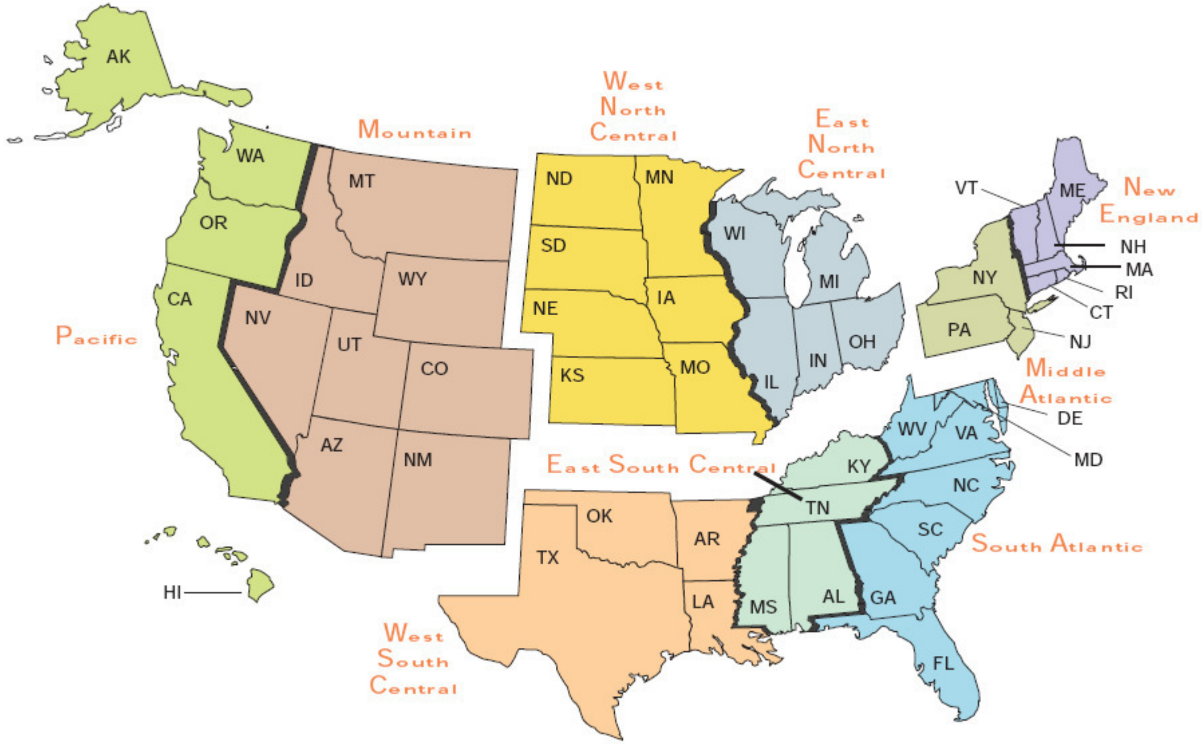

Figure 6: A map of the nine U.S. Census divisions (source: U.S. Department of Energy).

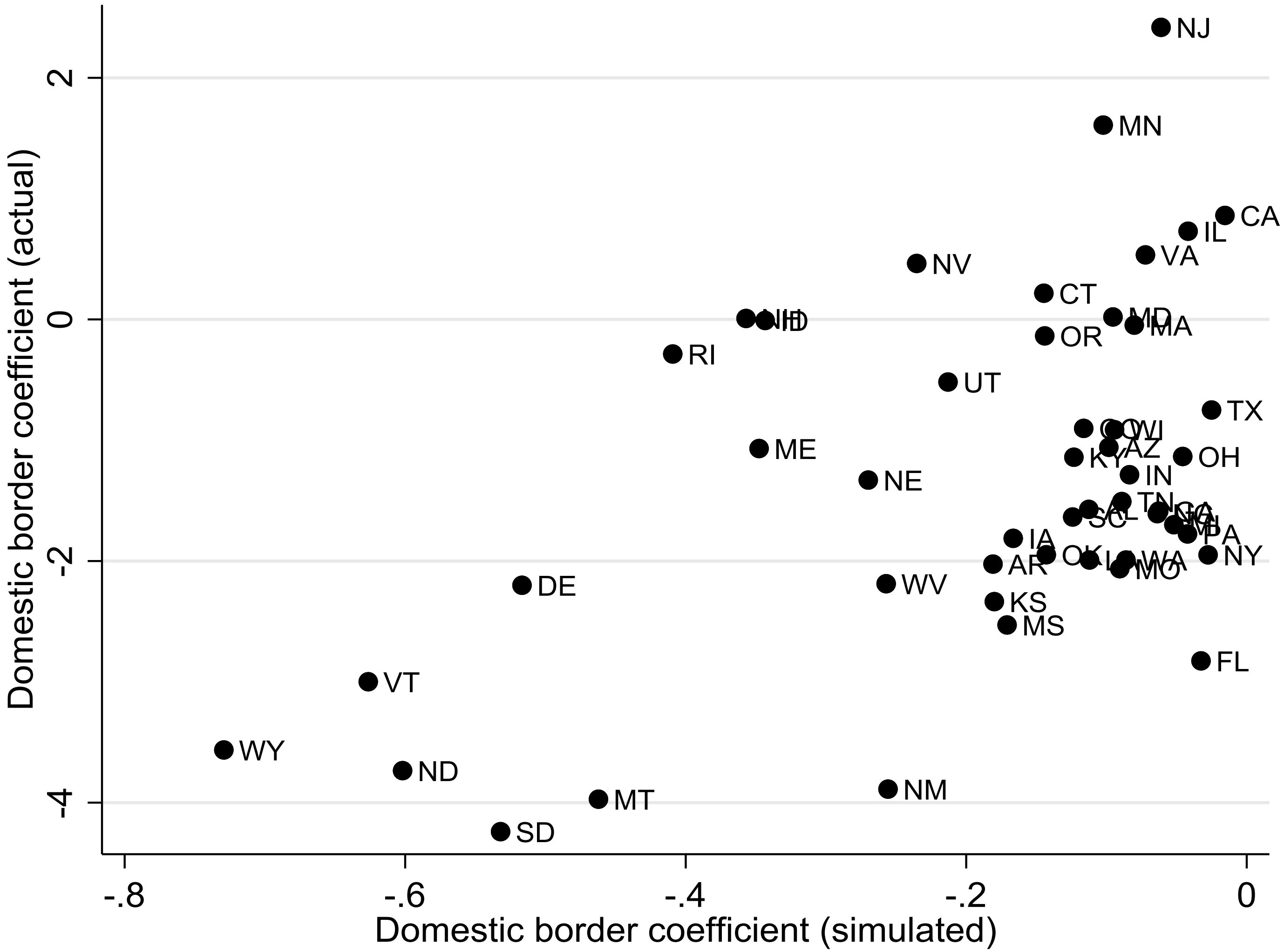

Figure 7: Plot of domestic border dummy coefficients for the 48 contiguous U.S. states based on actual data (as in Figure 1) against domestic border dummy coefficients based on simulated data. Their correlation is 48 percent. More details are provided in the main text.

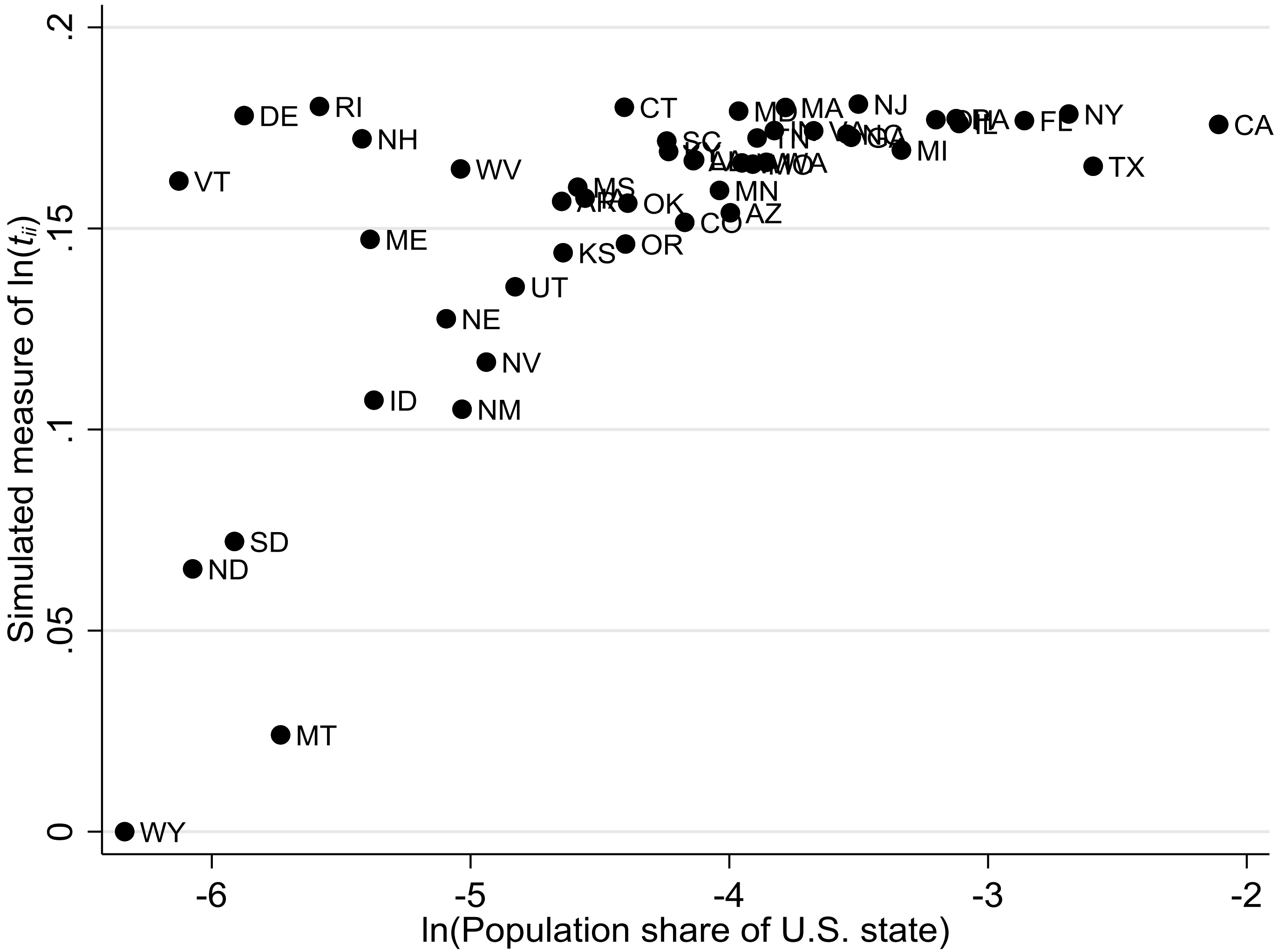

Figure 8: Plot of a simulated measure of logarithmic trade costs t_{ii} for U.S. states against population shares of U.S. states (both in logarithms).Their correlation is 63 percent. More details are provided in the main text.