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Aggregation Bias, Compositional Change, and the Border Effect

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Abstract: Most studies of the border effect rely on highly aggregated trade data. Little attention has been paid to the consequences of such high levels of aggregation on the estimated size, and economic interpretation, of the border effect. Using three-digit commodity flows among sub-national units, and adjusting the estimation procedure to account for the prevalence of zeroes in the commodity-level data, I find that standard techniques substantially overstate the border effect. Controlling for this bias, I find that the border effect falls from 21.67 to 5.71 in this data set. Further evidence of the importance of compositional change comes from a subsequent estimate: that nearly 40% percent of the remaining border-induced trade reduction occurs because commodities drop out of the traded bundle. Because most existing theoretical gravity model do not predict (and so cannot explain) such changes in the composition of trade, the results cast substantial doubt on the interpretive value of standard models.

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One of the better known empirical findings of recent years is the McCallum(1995) discovery that the gravity-adjusted volume of trade among Canadian provinces exceeds that of Canada-U.S. trade by more than a factor of twenty. This result is worrisome because standard structural models suggest that such trade reductions can imply tariff equivalent *ad valorem* border costs of well over 100%. Because such sizable costs imply important welfare consequences, the findings have attracted considerable attention in the empirical trade literature.

The attention given border-induced changes in the expected level of trade has obscured an important fact – that borders, distance and other gravity variables affect the composition, not just the size, of interregional trade bundles. Two sources of potential bias are put forward to explain how structural interpretations derived from reduced-form regression coefficients are likely to overstate the significance of border costs. First, aggregation over multiple commodities introduces a covariance term that can plausibly lead structural interpretations of aggregate elasticity estimates to overstate the size of average border costs. Second, border-induced changes in the number of commodities in the traded bundle are shown to have a substantial impact on the measurement of gravity model coefficients.

Using a special tabulation of the 1993 U.S. Commodity Flow Survey I show that aggregation bias produces a substantial overstatement of the border effect. After estimating border coefficients in commodity-specific regressions, I calculate that the aggregate border effect facing U.S. commodity shipments to Canada falls from 21.67 to 5.71. Nearly 40% of the remaining border effect can be tied to border-induced reductions in the number of traded commodities, a finding that is incompatible with structural gravity models. The results suggest that existing structural interpretations of reduced form regression coefficients estimated in aggregate data have been given far too much credence.

The paper is organized as follows. The first section provides a short explanation of the problem and demonstrates two ways in which aggregation over commodities produces an overstatement of the border effect. The second section describes an underused data set that allows a systematic investigation of aggregation bias. The third section outlines the estimation procedure, and demonstrates that it is an important feature of the data. The fourth section concludes.

Section 1. The problem

The success of the gravity model in predicting aggregate trade volumes warrants the considerable attention it has been given in the border effect literature.[1] In their quest to better understand the implications of border effects, trade economists have devoted considerable time to the derivation of formal models that make gravity-type predictions. They have spent considerably less time understanding how cross-commodity aggregation might affect econometric estimation at the aggregate level. The lack of attention given aggregation issues is unfortunate, for the economic meaning of border effects likely depends upon the distribution of trade frictions across commodities with different economic fundamentals.

In this paper, I ask whether geographic trade costs like border frictions induce significant changes in the composition of the traded bundle. Such changes can occur because commodities differ in their sensitivity to borders. Compositional changes can also occur because borders induce commodities drop out of the traded bundle. Border-induced compositional changes are important for two reasons: 1) they can bias estimates of the aggregate reduction in bilateral trade, and 2) the economic interpretation given a particular border-induced reduction in aggregate trade depends heavily on assumptions about the compositional stability of the traded bundle.

Three recent papers in the gravity literature are relevant to the discussion below. Hillberry and Hummels (2000) suggest that the border induces changes in the composition, not simply the level, of trade, and offer a formal test of the proposition. This paper offers two more tests of the compositional stability hypothesis. Evidence documented below also shows a preponderance of zero observations in commodity-level trade. As Haveman and Hummels (2001) point out, zero observations are inconsistent with existing structural gravity models of trade. Zero observations are explained by models such as Romer (1995), which posit a fixed cost of entering each market.[2]

All these papers suggest the possibility that borders might induce compositional changes in the interregional trade bundle. Such compositional changes are significant to the discussion because standard interpretations of gravity model coefficients assume no such changes exist. Structural models attach severe consequences to large changes in the level of bilateral trade, but

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[1] The literature using the gravity model to explore the exploring the significance of international borders in trade is considerable. Readers are referred to Helliwell (1998) for a review of the early literature on the topic, and to Anderson and Smith (2001) for discussion of more recent work in the area.

[2] Evans (2001) models a fixed cost of selling outside one's borders, and shows that controlling for such costs reduces the implied ad valorem equivalent of border costs. Here I consider the effects of destination specific fixed costs. Unlike Evans, we offer no formal model, as the emphasis is on aggregation bias.

do not allow compositional changes to affect the level of trade. If compositional changes are found to be prevalent in the data, it would appear that estimates of aggregate trade reductions 1) overstate the level of trade reduction due to the border and 2) misinterpret the economic consequences of trade reductions that do exist.

The standard approach to estimating border effects

McCallum-like border effects are derived from border dummy coefficients that are estimated in a log-linear version of the standard gravity equation. In levels, the gravity model is expressed in the following manner:

1) $$T_{ij} = f\left(X_{ij}\right)e^{b_H * HOME}u_{ij}$$

where T_{ij} is the aggregate volume of region i exports to region j, $f(X_{ij})$ is the conditional expected value of trade given some vector of gravity variables X_{ij}, β_H is the coefficient on a dummy variable (HOME) that takes the value of one for domestic flows and zero for cross-border flows, and u_{ij} is a log-normal error term. McCallum and others estimate $\hat{b}_H$ > 3 in data comparing interprovincial trade with province-state trade. Given the structure of (1), such estimates imply that gravity-adjusted external trade exceeds internal trade by a factor of more than 20. This 20-fold reduction in the expected cross-border trade volume is known as "the border effect."

Much of the concern about such estimate stems from the interpretation of b_H within the context of structural economic models designed to predict gravity-like flows. Models by Anderson(1979), Krugman(1980) and Deardorff(1998) suggest that b_H should be interpreted as the product of an elasticity of substitution, σ, and an ad valorem border cost, τ.[3]

2) $$b_H = s\,t$$

Mainstream interpretations of the border effect apply outside estimates of σ to (2), and make inferences about border costs.[4] Since most estimates of σ lie between 2 and 10, estimates of $\hat{b}_H$ > 3 imply ad valorem border costs of between 30 and 150%. If such costs exist, they are substantial cause for concern.

[3] The Krugman model differs slightly from the other two in that products are differentiated by firm, rather than by region.
[4] Obstfeld and Rogoff (2000) is a prominent example.

Aggregation bias within structural models

While the intuition in single sector models is straightforward, it is not immediately clear from the literature how most authors would relate the estimates of the aggregate border elasticity (henceforth b_H^{Agg}) to the structural parameters at the commodity level. Given the lack of attention paid to composition issues, it is tempting to conclude that b_H^{Agg} is thought to be common across commodities. After all, if the composition of trade is unchanged at the border, commodity specific border elasticities, β_H^k, would have to satisfy the condition:

3) $b_H^k = b_H^{Agg}, \quad \forall k .$

This is an impossibly strict condition, and one that is easily rejected by the data.

A more charitable interpretation is that authors who interpret b_H^{Agg} as a function of σ and τ mean to imply that the reduced form coefficient can be interpreted, on average, as the product of means of the two structural parameters. That is

4) $b_h^{Agg} = \bar{s}\,\bar{t}$,

where $\bar{s}$ and $\bar{t}$ are cross-commodity averages of commodity-specific structural parameters s^k and t^k.

On closer inspection, we find that the interpretation of b_H^{Agg} is slightly more complicated than (4) suggests, and that there are plausible reasons for (4) to overstate the true value of $\bar{s}$ and $\bar{t}$. The aggregate reduced form estimate b_H^{Agg} can be written as a trade-weighted share of the commodity-specific reduced form parameters:

5) $b_H^{Agg} = \sum_k t_k b_H^k$

where t_k is the conditional commodity k share of total trade at the border. Structural interpretations used above suggest that (5) can be interpreted as

6) $b_H^{Agg} = \bar{s}\,\bar{t}\left(\sum_k t_k \frac{s_k t_k}{\bar{s}\,\bar{t}} \right)$

where the term in brackets is a weighted covariance of σ^k and τ^k. If the bracketed term equals one, equation (4) is the appropriate interpretation of b_H^{Agg} .

There are, however, good reasons to believe that σ^k and τ^k are positively correlated. Commodities with large σ's are those where import surges are most likely. It is quite likely that government policies set up to protect domestic industry from import surges have raised the implicit cost of trade in those commodities. Commodities that are highly substitutable across sources, like steel and chemicals, appear frequently in anti-dumping and countervailing duty actions. Recent U.S.-Canadian trade disputes over lumber, live cattle, and salmon are indicative of the propensity for highly substitutable goods to receive endogenous protection.[5] If a commodity's propensity for import surges induces implicit or explicit protection in that commodity, σ and τ are correlated, and structural interpretations of b_H^{Agg} based on (4) will overstate $\bar{s}$ and $\bar{t}$.

The implications of aggregation over observations with zero commodity-level trade

The potential aggregation bias described above takes the structural models at face value. However, the use of aggregate data misses an important indictment of structural models, the large number of bilateral observations in which a given commodity goes untraded. The prevalence of zero observations in the disaggregated data suggest that the traded bundle changes over space in an important fashion – commodities drop out of the bundle. Such stark changes in composition can introduce an upward bias in estimates of β_H^{Agg}.

The implications of cross-commodity aggregation in the presence of zero observations can be made quite stark in a simple numerical example relating compositional changes to distance.[6] Suppose region i produces and exports K distinct commodities. Let the propensity for region i to export commodity k to region j ($T_{ij}^{k^*}$) take a gravity-like form

$$7)\ T_{ij}^{k^*} = Y_i^k Y_j D_{ij}{}^{b^k},$$

where Y_i^k is the output (value added) in region i, sector k, Y_j region j's income, D_{ij} is the distance from region i to j, and β^k is the elasticity of trade with respect to distance. Trade in a given commodity for a given ij pair is only observed if the propensity to trade exceeds the commodity threshold, $\underline{T}^k$.

$$8)\ \begin{array}{l} If\ T_{ij}^{k^*} \geq \underline{T}^k,\ T_{ij}^k = T_{ij}^{k^*}; \\ else\ T_{ij}^k = 0. \end{array}$$

where T_{ij}^k is the observed value of commodity k shipments from i to j. Aggregate shipments for an ij pair is calculated as the sum of disaggregated shipments:

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[5] The U.S Trade Representative (2000) lists a variety of Canadian barriers against agricultural products such as wheat, dairy products eggs and poultry. These are all highly substitutable products.

[6] Distance is used to demonstrate the point because it is continuous. The point applies equally well to discrete variables like a border dummy.

$$9)\ T_{ij} = \sum_k T_{ij}^k\ .$$

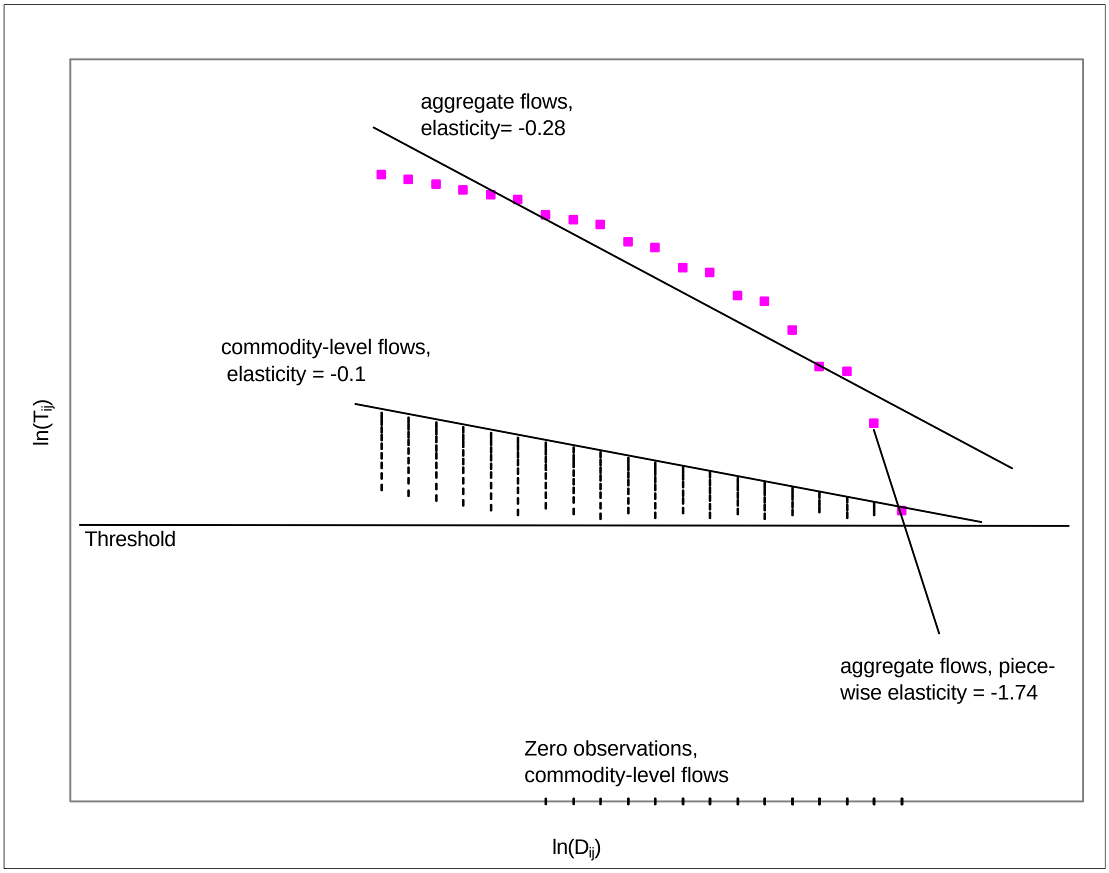
The numerical example shows that the introduction of a threshold on disaggregated interregional commodity flows can raise the aggregate estimate of b_H^{Agg} above commodity-specific values of β^k. Furthermore, changes in the composition of the bundle lead small bundles to appear more sensitive to trade costs than are large bundles.

Chart 1 plots the log of commodity specific and aggregate trade flows against log distance for a given numerical example.[7] The black dots show the log level of commodity shipments from a single region i to 20 equally sized regions that lie at different distances from the source. All commodities are equally responsive to distance, β_H^k = -0.1. The threshold $\underline{T}^k$ is constant across commodities, and commodities drop out of the bundle as distance increases. The effects of compositional change can be seen in the trajectory of the gray dots, which show the distance/value relationship for the aggregate trade flow, T_{ij}. The aggregate elasticity of trade with respect to distance is –0.28. b_H^{Agg} is falling with distance, reaching –17.4 when the number of traded commodities falls from one to two.

There are two significant points to note about the relationships expressed in Chart 1. First, the aggregate elasticity of trade with respect to distance substantially exceeds its commodity-specific counterparts because the threshold induces commodities to drop out of the aggregate traded bundle. In this example, the aggregate distance elasticity exceeds the commodity specific elasticity by a factor of 2.8. Inferences drawn from the aggregate estimate would overstate the importance of disaggregated elasticities. Second, the bias of the aggregate elasticity grows as the size of the bundle falls. In the last segment of the chart, as the number of commodities in the bundle falls from 2 to 1, the aggregate elasticity rises sharply in absolute magnitude.

[7] In the example, J = 20, K=9, β^k = -0.1, D_{ij} ranges from 100 to 220,000, and Y_i^k ranges from 20 to 36. For simplicity of exposition, we assume that Y_j=1 is common across regions.

Chart 1. Aggregation bias in the presence of commodity-specific thresholds for bilateral trade



Consider the implications for estimation of U.S.-Canada border effects. It is a well-known feature of the data that the aggregate bilateral trade volumes fall sharply with distance.[8] Chart 1 suggests that this is consistent with a story asserting that the number of commodities in the traded bundle falls with distance. Most bilateral state-province pairs are at considerable distance from one another.[9] If large distances between state-province pairs mean that relatively few commodities would be shipped anyway, small border costs might induce large estimated border dummy elasticities by knocking commodities out of an already small bundle. Seen this way, it is not clear that 1) the aggregate trade reduction is appropriately inferred from $\boldsymbol{b}_H^{Agg}$, or 2) such estimates necessarily imply that the severe welfare consequences predicted by theoretical models of gravity-based trade. [10]

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[8] McCallum finds a distance elasticity of –1.42 in the Canadian data.
[9] The mean province-state distance, measured in highway miles between largest cities in the 48 contiguous U.S. states and the seven border provinces is 1604 miles.
[10] Put another way, the border effect measures the value of New Mexico's shipments to Ontario relative to that of New Mexico's shipments to Pennsylvania. If long distances lead New Mexico to ship relatively few products to Pennsylvania, and one or two fewer commodities to Ontario, analysis based on aggregate data

Section 2. Data

The data used in the econometric analysis that follows are from a special tabulation of the 1993 Commodity Flow Survey (CFS). The CFS was designed to estimate and report shipment characteristics of freight movements among U.S. states. The value of shipments for origin destination pairs was derived from surveys of a stratified sample of establishments in the United States. Publicly available CFS data report bilateral commodity flows for internal U.S. shipments at the two-digit commodity level. The special tabulation, which remains confidential and could only be used on Census Bureau grounds, breaks out shipments at three-digit commodity level detail,[11] and separates exports from the domestic bound shipments. Export shipments are reported for state of origin and port of exit at the three-digit level of commodity of detail.

It is this information that serves as the basic input into the data used below. In order to allow comparisons between internal and external shipments, I aggregated across ports of exit to produce estimates of the bilateral commodity flows between states-of-origin and provinces-of-entry. Because only land-based exports can be reliably assigned to a specific province of entry, only shipments traveling by truck and/or rail were used in the regression analysis below.

Two important caveats should precede the use of this data. First, the Census Bureau never intended to report export figures in 1993 CFS, so the export data are a by-product of the data collection effort. As a result, the procedures used to extrapolate survey data to produce aggregate estimates of total shipments were not designed to fit the value of export shipments recorded in official trade figures. Second, the tabulation did not report the country of destination for export data, so construction of the state-to-province-of-entry flows relied on inferences based on the location of the port of exit.[12] Exports traveling through U.S. ports of exit other than those on the immediate contiguous border could not be assigned to Canada because the destination country was not obvious. It is quite likely that some Canada-bound shipments were missed.

Put together, these two limitations lead the special tabulation to produce a substantial underestimate of total U.S. exports to Canada. Official U.S. figures report approximately $92 billion in 1993 cross-border goods trade. The value reported in CFS figures cannot be reported, but understates official trade figures by a factor of 2.

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might produce a large estimated border effect. If Pennsylvania can do without most New Mexican products, it is not clear that Ontario receiving one or two fewer should be of any great concern.

[11] Commodities are classified in according to the Standard Transported Commodity Classification (STCC) a commodity classification that is quite closely concorded with the US SIC.

[12] Each port of exit was assigned to the province directly across the border in Canada. Ports of exit were assigned to provinces by the author, not the Census Bureau.

The degree to which the special tabulation (and the author's assignment of cross-border shipments as exports to particular provinces) understates the actual trade volume would be quite distressing were it the purpose of this paper to provide a definitive measure of an aggregate border effect and to interpret it. However, our purpose is to demonstrate that the aggregation of data across sectors can contribute to estimation bias. Because the data are internally consistent (that is, state-province flows at the commodity level sum to the aggregate level state-province flows), they are suitable for our purpose. The analysis requires internally consistent data measuring both internal and cross-border flows at the disaggregated commodity level. The special tabulation used here appears to be the only available data set that encompasses that set of needs.

Section 3. Econometric procedure and results

This section outlines the methodology used to determine the extent of aggregation bias associated with threshold effects in estimates of the U.S.-Canadian border effect. The methodology is to estimate a two-part econometric model that determines the manner in which the border affects 1) the conditional probability that trade occurs ($E(Pr(T_{ij}^{k})>0)$), and 2) the size of trade volume, given that trade occurs ($E(T_{ij}^{k})|_{T_{ij}^{k}>0}$). Coefficient estimates from the two part model estimation are used as an input into Monte Carlo exercises that determine the degree to which the border reduces trade by 1) eliminating trade between bilateral pairs, and 2) reducing trade among bilateral pairs that trade.

Two-part regression model:

The econometric exercise is meant to determine the degree to which standard gravity variables affect 1) the probability that trade among two regions occur, and 2) the size of trade, given that trade does occur. When the presence of zero observations has been addressed in the gravity literature, authors have typically used sample selection models of the type proposed by Heckman (1976) or Tobin (1958). Leung and Yu (1996) show that sample selection models can produce biased coefficient estimates when the number of zero observations is large. The two-part model of Cragg (1971), which is not sensitive to such biases, is used below because there are a large number of zeroes in the disaggregated data.[13]

[13] Even after removing zero observations that occur because the origin state did not produce the commodity, zero observations constitute more than 50% of the observations in 60 of 142 commodities.

The two-part model uses separate and independently estimated equations to estimate the answers to the two-part question. The first is a binomial probit model that estimates the conditional probability that trade occurs. The estimating equation is as follows:

$$10)\ I_{ij}^{k} = a_0 + a_1 \ln Y_i^k + a_2 \ln Y_j + a_3 \ln D_{ij} + a_H HOME + u_{ij}^k$$

where I_{ij}^k is an indicator that takes the value of 1 if trade occurs and 0 if it does not. Y_i^k is the value of industry k output in region i,[14] Y_j is the value of GDP in region j.[15]

A similar specification is used to estimate the effect that standard gravity variables have on bilateral trade volume. The same variables go into a specification that relates the log value of trade to the same variables listed above.

$$11)\ \ln T_{ij}^{k} = b_0 + b_1 \ln Y_i^k + b_2 \ln Y_j + b_3 \ln D_{ij} + b_H HOME + e_{ij}^k$$

Equation 11 is applied only to the observations with non-zero reported trade volumes, and is estimated as a truncated regression model.[16] The truncated regression model is used for purposes of intellectual coherence, but does not affect the results, which do not differ significantly from OLS regressions using non-zero flow data.

Estimation at the commodity-specific level allows a determination of the border's effect on commodity-specific flows. Commodity-specific coefficient estimates allow the regression to control for other sources of bias, such as the implied restriction $\hat{b}_1^k = 1, \forall k$, which is necessary if adding up constraints ($\sum_k E\left(T_{ij}^k\right) = E\left(T_{ij}\right)$) are to hold.[17]

Table 1 reports regression results for both parts of the model, and selected commodities of general interest – Field Crops (STCC 011) and Motor Vehicles and Equipment (STCC 371).[18] All variables enter with the expected sign, and most all are highly significant. Taken alone, the border coefficient in the truncated regression (3.07), would imply a border effect of about

[14] As is typical, the aggregate gravity regression uses aggregate state GDP in the regressions of aggregate trade flows.

[15] Control dummy variables denoting instate shipments and shipments to adjacent states and provinces are also included. Because CFS data include shipments by wholesalers, there is a strong likelihood of excess shipment density in local shipments. The included controls reduce the importance of local shipments in determining the other coefficients.

[16] The truncated model accounts for the fact that the sample does not include any zero observations. The maximum likelihood procedure treats $\ln(T_{ij}^K)$ as bounded at zero, a constraint that affects the assumed distribution of ε_{ij}^k, which cannot be so large and negative as to imply a negative value for $\ln(T_{ij}^k)$.

[17] The specification above does not control for the production location effect, as proposed by Hummels (1999). Hummels' technique requires a large number of fixed effect dummy variables, which are difficult to integrate into binomial probit model.

[18] Commodity-specific estimates of the border coefficients all 142 commodities are reported in appendix A.

21.54.[19] Likewise, naïve estimates of the commodity-specific effects would imply border effects of exp(0.59) = 1.80 in Field Crops and exp(1.33) = 3.78 in Motor Vehicles and Equipment.

Table 1. Regression results

	Aggregate flows		STCC 011 – Field Crops		STCC 371-Motor vehicles or equipment	
	probit	truncated regression	probit	truncated regression	probit	truncated regression
constant	-27.73* (5.01)	-30.81* (0.80)	-22.28* (1.47)	-0.07 (2.77)	-22.01* (1.88)	-22.85* (1.57)
lnYik	0.66* (0.11)	1.03* (0.02)	0.63* (0.05)	0.05 (0.10)	0.47* (0.03)	0.85* (0.03)
lnYj	0.88* (0.16)	1.11* (0.02)	0.48* (0.32)	0.61* (0.06)	0.74* (0.06)	1.10* (0.05)
ln Dij	-1.22* (0.27)	-0.92* (0.03)	-0.62* (0.06)	-0.34* (0.10)	-0.92* (0.10)	-1.00* (0.08)
HOME	2.62* (0.32)	3.07* (0.06)	1.01* (0.11)	0.59 (0.31)	2.45* (0.14)	1.33* (0.24)
$\hat{s}_e$	1	1.07	1	2.05	1	1.88
observations	2640	2590	2200	1088	1925	1545
Pseudo-R^2	0.98		0.75		0.91	

Of course, the results in Table 1 also make it clear that the truncated regression results alone are insufficient for calculating border effects. The HOME dummy coefficient is significantly positive in all three binomial probit regressions. A naïve calculation using only the results of the truncated regression does not account for the missing trade that does not occur because the border inhibits province-state pairs from trading. An alternative method for calculating border effects is required.

Monte Carlo estimates of the border effect

Because equations (10) and (11) are estimated independently, the border effect cannot be inferred directly from the home dummy coefficients. The border has two effects on bilateral trade: 1) it reduces the probability that trade occurs, and 2) it reduces the volume of trade, given that trade occurs. What is needed is a measurement that determines the relative contribution of each border coefficient to the overall border effect. The size of the two effects can only be measured by predicting bilateral trade volumes, and measuring the degree to which removing the border would affect both the probability that trade occurred and the volume of trade where it occurs.

[19] This estimate is astonishingly different from that of Anderson and van Wincoop (2000), who estimate a border effect of 1.5 for U.S. shipments to Canada. It is likely that this difference stems from substantially

In the two-part model framework, the standard practice of extrapolating elasticities is insufficient. The border effect must be calculated as a ratio of conditional predictions of the "with border" and "without border" level of flows from states to provinces. The ratio of trade must be calculated by predicting the value of state-province commodity flows under two assumptions 1) the home dummy takes the value zero in equations (10) and (11), as it did in the data, and 2) the HOME dummy in (10) and (11) equals one, as it would if the border were fully removed. The second procedure asks, "What would the trade volume have been if provinces were part of the United States?" The ratio of the predicted "without border" trade to predicted "with border" trade is the border effect.

More formally, let the expected total state-province trade in commodity k, $E(T^k)_{SP}$, equal the sum of the predicted trade volumes for all state-province pairs:

$$12)\ E(T^k)_{SP} = \sum_i \sum_{j \in provinces} E(T_{ij}^k)\,.$$

The border effect can be found by evaluating $E(T^k)_{SP}$ at Home = 1 and HOME = 0, and calculating the ratio:

$$13)\ BE^k = \frac{E(T^k)_{SP}\ |_{HOME=1}}{E(T^k)_{SP}\ |_{HOME=0}}\,.$$

Calculating the expected trade volume for each province-state pair involves a two-step procedure. The simulation first combines coefficients from equation (10) with the data on the independent variables to determine whether or not trade occurs. For state-province pairs where $\hat{I}_{ij}^k = 1$, the simulation then combines coefficient estimates from equation (11) with the underlying data, and sums across state-province pairs to produce an estimate of $\hat{T}^k$. The calculation of $\hat{T}^k$ requires some care because $E\left(T_{ij}^k\right) > \exp\left(\ln\left(\hat{T}_{ij}^k\right)\right)$. Consistent estimation requires an acknowledgement that $\ln(\hat{T}_{ij}^k)$ is estimated with error. The problem can be circumvented by taking multiple draws of ε_{ij}^k and applying:

$$14)\ E\left(T_{ij}^k\right) = \exp\left(\ln\left(\hat{T}_{ij}^k\right) + e_{ij}^k\right).$$

different data on cross-border flows. A discussion of the differences appears in appendix B.

Because the inverse log is an asymmetric transformation, estimates of $E(T_{ij}^{k})$ are sensitive to the variance of ε_{ij}^{k}. Simply transforming $E(\ln T_{ij}^{k})$ will produce an understatement of the true $E(T_{ij}^{k})$. Consistent measures of $E(T_{ij}^{k})$ require proper treatment of the error term.

My estimates of $E(T_{ij}^{k})$ are based upon a Monte Carlo exercise that uses 100 draws of each u_{ij}^{k} and e_{ij}^{k}. Each draw produces an estimated $E(T_{ij}^{k})$, which is summed over province state pairs in a manner consistent with (3) to produce a conditional estimate of the cross-border trade volume. The mean of these 100 estimates is the estimated $E(T^{k})_{SP}$.

The new procedure raises the aggregate border effect only slightly above the estimate that the naïve procedure would produce. Using coefficients from (10) and (11) run on aggregate data, the Monte Carlo exercise estimates a border effect of 21.67. This is slightly higher than the mean estimate because it includes the portion of the border effect that arises from a positive home dummy coefficient in the probit model. By including the border effect in the probit model, the new procedure also raises border effects in the commodities of interest. The new border effect estimate is 2.73 for Field Crops (against 1.80 by the naïve estimate) and 4.12 (3.78) for Motor Vehicles and Equipment.

The alternative procedure also allows an estimate of the share of border-impeded trade that occurs because the border induces particular state-province pairs not to trade. This figure is calculated by using the Monte Carlo to evaluate the probit equation at HOME=1 and the truncated regression at HOME=0.[20] The probit share of the total trade increase is calculated as

$$15)\; s_{PR} = \frac{E(T)_{SP}^{k}\,|_{HOME=1} - E(T)_{SP}^{k}\,|_{\substack{HOME=1,\,probit\\ HOME=0,\,truncated}}}{E(T)_{SP}^{k}\,|_{HOME=1} - E(T)_{SP}^{k}\,|_{HOME=0}}\,.$$

In the aggregate data, trade between new state-province pairs represents only 0.9 percent of the total increase in trade associated with a full lifting of the border. New state-province pairs are considerably more important at the commodity level, accounting for 53.1 percent of the increased trade in Field Crops and 10.5 percent of the increase in Motor Vehicles and Equipment trade.

These results are suggestive of the problem outlined in the chart 1. In the aggregate, the border effect is estimated and interpreted as if it were a proportional reduction in each state-province pair's trade volume. The commodity-specific estimates suggest that the border actually reduces trade by reducing the number of commodities that a given regional pair trades. This is compelling evidence that borders induce sharp changes in the composition of the traded bundle.

[20] Conceptually, this is similar to the removal of the fixed costs of bilateral trade associated with borders.

Such sharp compositional changes are not predicted by standard models, and so cast doubt on their relevance for welfare calculations.

We now turn to the question of whether or not estimation at the aggregate level induces estimation bias. The commodity-specific border effects themselves suggest a strong likelihood of aggregation bias. 123 of the 142 commodities have border effects smaller than the aggregate, and the median estimate, 6.58, is far below the aggregate estimate. Evidence of the hypothesis that τ^k and σ^k are correlated is circumstantial, but there are notably large border effects in highly substitutable products like Livestock, Dairy Products, Pulp or Pulp Mill Products, and Textiles.

A more formal illustration of the effect of aggregation bias comes from a summation over the $E(T^k)_{SP}$'s that allows an aggregate border effect to be calculated from the disaggregated predictions. After a slight adjustment[21] to the commodity level figures, they can be summed to produce an estimate of with border and without border trade. Formally, the new aggregate estimate is calculated as follows:

$$16)\ BE^* = \frac{E(T^*)|_{HOME=1}}{E(T^*)|_{HOME=0}} = \frac{\sum_k E(T^k)_{SP}\ |_{HOME=1}}{\sum_k E(T^k)_{SP}\ |_{HOME=0}} = \frac{472.91\, billion}{82.84\, billion} = 5.71$$

In this data set, we find the estimate of BE* = 5.71, far lower than the border effect estimated in aggregate data, BE = 21.67.[22] These results suggest that the phenomenon noted in Chart 1 may indeed be responsible for excessively large estimates of the border effect. Further evidence that Chart 1 is relevant to the discussion comes from the calculation of new province-state pairs in trade. New pairs trade at the commodity level explains 39.67 percent of the border effect estimate BE*=5.71.

All this evidence appears considerably damning of the profession's reliance on aggregate data. It appears that the conjecture illustrated in Chart 1 has considerable relevance for the interpretations of border effects. Borders affect the number of commodities that are traded. In that sense, they affect the composition of trade, not just the level. Existing theoretical models

[21] I did not have access to confidential production data. In the gravity regression all observations with suppressed state-of-origin production data were omitted from the regressions. This posed no problem for estimating BE^k. However, calculating E(T*) requires that a true estimate of the cross-border flow be calculated in each commodity (not simply a ratio of expected cross-border flows) so that the estimates can be summed across commodities. To make the adjustment, I assumed that omitted production was distributed randomly across geographic space. Under that assumption, inflating predicted trade volumes by dividing them by (1-omitted production share) will give a consistent estimate of $E(T^k)$. The "expansion ratio" reported in appendix A is the value of (1-omitted production share) used in the analysis.

[22] Recall that the data understate the true volume of U.S. exports to Canada. The true border effect is probably somewhat lower than the estimate of 5.71.

assume that each region ships a bundle of constant composition to all destinations. Such assumptions are quite likely to lead such models to overstate the welfare consequences of geographic trade frictions.

Section 4. Conclusion

Most studies of the border effect have relied on aggregate data. I show that the existence of threshold effects in commodity-level data can introduce upward aggregation bias in regressions that use aggregate data. Threshold effects are quite evident in the data, and are fully consistent with models with fixed costs of market entry.

These effects are shown to be important in estimating the border effect in U.S. Commodity Flow data. The aggregate border effect estimate of 21.67 is reduced to 5.71 when commodity level threshold effects and aggregation are taken into account. These results suggest that much of the concern about border effects may be overstated. They also suggest that we have little of relevance to learn from gravity regressions based on highly aggregated data. In particular, these results cast doubt on the reliability of inferences about structural parameters drawn from gravity model coefficients estimated in aggregate data.

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Appendix A

The table below contains estimates of commodity-specific values of the calculations outlined in the text. Columns 1 and 2 include the commodity code and a description of the commodity. Columns 3 and 4 include the regression coefficients a_H and b_H, as defined in the text. Columns 5 and 6 contain estimates of predicted trade volumes that come from the Monte Carlo simulation. Column contains the implied border effect. Column 8 defines the expansion ratio, which is defined as the value of publicly available state SIC production divided by the value of national production in the that SIC category.

STCC	description	a_H	b_H	Predicted SP trade, with border $(E(T)_{SP}\|_{Home=0})$ millions of $	Predicted SP trade, no border $(E(T)_{SP}\|_{Home=1})$ millions of $	Border effect	Share of new pairs in new trade (s_{PR})	expansion ratio
0	Aggregate flows	2.62	3.07	19014	411991	21.67	1.19	1
	sum of disaggregated commodities			82841	472912	5.71	39.67	
11	Field crops	1.01	0.59	1275	3478	2.73	1.92	1
12	Fresh fruits or tree nuts	0.97	0.17	2	26	14.06	13.87	1
13	Fresh vegetables	1.45	0.86	101	586	5.82	4.47	1
14	Livestock or livestock products	1.57	1.54	13	728	55.16	51.48	1
15	Poultry or poultry products	0.73	-0.57	52	125	2.38	2.82	1
19	Miscellaneous farm products	1.24	-0.61	251	274	1.09	1.54	1
80	Forest products	1.28	-0.5	8	63	8.14	8.54	1
90	Fresh fish or other marine animals	0.89	0.29	63	200	3.17	2.84	1
100	Metallic ores	0.49	-1.61	1891	732	0.39	1.19	1
110	Coal	1.36	0.6	104	1655	15.97	15.14	1
141	Dimension stone	0.76	0.43	4	19	4.42	3.89	1
142	Crushed or broken stone or rip rap	1.37	0.32	4	25	6.47	6.1	1
144	Gravel or sand	2.54	-0.45	2	35	16.31	16.67	1
145	Clay, ceramic or refractory minerals	1.38	0.3	7	56	8.25	7.91	1
147	Chemical or fertilizer minerals	1.73	0.55	5	120	25.14	24.42	1
149	Miscellaneous non-metallic minerals	1.33	0.27	11	68	6.22	5.91	1
19	Ordnance and accessories	1.96	1.4	57	1081	18.96	15.89	0.89
201	Meat, poultry and small game	2.39	2.26	854	12321	14.43	5.87	0.99
202	Dairy products	2.57	2.72	245	5883	24.02	9.91	1
203	Canned or preserved fruits, vegetables or seafood	2.45	1.91	1372	12256	8.93	3.21	0.98
204	Grain mill products	1.55	1.36	1503	7045	4.69	1.8	1
205	Bakery products	2.28	1.97	287	3082	10.75	4.59	0.99
206	Sugar, beet or cane	1.26	0.3	156	543	3.48	3.13	0.92
207	Confectionery or related products	1.98	1.68	90	1709	18.94	14.56	0.9
208	Beverages or flavoring extracts	1.93	2.4	289	5381	18.63	8.58	1
209	Miscellaneous food preparations or related products	1.85	1.59	1278	8738	6.84	2.92	0.95
211	Cigarettes	-	-	0	3336	infinite	100	0.49
212	Cigars	2.56	0.95	3	58	17.36	15.76	0.49
213	Chewing or smoking tobacco	-	-	0	12	infinite	100	0.49

214	Stemmed or redried tobacco	-0.27	1.41	5	13	2.65	1496.68	0.49
221	Cotton broad woven fabrics	2.62	1	82	858	10.41	8.7	0.91
222	Man-made fibre or silk broad-woven fabrics	1.96	2.14	38	695	18.52	11.02	0.97
223	Wool broad-woven fabrics	0.64	0.12	100	189	1.89	1.76	0.21
224	Narrow fabrics	1.57	1.41	140	1302	9.33	6.22	0.94
225	Knit fabrics	1.59	1.31	63	703	11.18	8.47	0.9
227	Floor coverings	2.04	1.41	294	2547	8.66	5.56	0.92
228	Thread or yarn	1.3	0.07	480	964	2.01	1.94	0.98
229	Miscellaneous textile goods	1.47	0.76	450	1316	2.92	1.78	0.9
231	Men's, youths', or boys' clothing or uniforms	3.39	1.63	296	6237	21.05	16.92	0.85
233	Women's, misses', children’s, or infants’ clothing	3.56	2.73	691	23026	33.34	18.99	0.99
235	Caps, hats, millinery or hat bodies	1.59	1.47	3	70	22.88	19.53	0.81
237	Fur goods	0.37	-4.34	109	3	0.03	1.02	0.99
238	Miscellaneous apparel or accessories	2.22	2.33	108	2682	24.76	15.5	0.88
239	Miscellaneous fabricated textile products	2.34	1.35	286	2071	7.24	4.38	1
241	Primary forest or wood raw materials	0.85	-0.29	278	305	1.1	1.35	1
242	Sawmill or planing mill products	1.33	1.07	810	2878	3.55	1.65	1
243	Millwork or prefabricated wood products or plywood or veneer	2.18	1.52	578	4031	6.98	3.4	1
244	Wooden containers	2.12	0.18	9	68	7.67	7.47	0.98
249	Miscellaneous wood products	2.48	1.53	231	1506	6.52	2.91	0.98
251	Household or office furniture	2.48	1.2	964	4217	4.38	2.06	0.99
253	Public building or related furniture	2.6	-0.7	103	189	1.83	2.34	0.78
254	Lockers, partitions, or shelving	2.59	1.87	59	759	12.96	7.5	0.95
259	Miscellaneous furniture or fixtures	2.38	2.28	8	256	33.28	24.46	0.91
261	Pulp, or pulp mill products	0.38	-1.1	341	166	0.49	1.15	0.4
262	Paper	2.65	1.72	670	5240	7.82	3.24	0.85
263	Fibreboard, paperboard or pulpboard	1.46	1.25	156	1286	8.27	5.77	0.73
264	Converted paper or paper board products	2.54	2	422	4613	10.94	4.52	0.94
265	Containers or boxes, paperboard, fibreboard, or pulpboard	2.22	2.7	87	1854	21.19	7.31	0.76
266	Building paper or building board	1.25	0.54	69	252	3.64	2.93	0.99
281	Industrial inorganic or organic chemicals	1.73	1.06	2560	9078	3.55	1.67	0.86
282	Plastic materials or synthetic fibres, resins or rubbers	2.22	1.6	963	7538	7.83	3.86	1
283	Drugs	1.82	1.94	1556	15054	9.67	3.7	0.95
284	Soap or other detergents, cleaning preparations, cosmetics and perfumes	2.3	1.79	1313	10429	7.94	2.94	0.93
285	Paints, enamels, lacquers, shellacs, or varnishes	2.43	1.49	391	2274	5.81	2.38	0.98

286	Gum or wood chemicals	2.25	2.33	1	145	263.39	254.07	0.98
287	Agricultural chemicals	1.57	0.76	545	1858	3.41	2.28	0.88
289	Miscellaneous chemical products	1.91	1.11	1041	3644	3.5	1.48	0.98
291	Products of petroleum refining	1.49	1.47	395	1987	5.03	1.68	0.8
295	Paving or roofing materials	1.41	0.1	168	306	1.83	1.73	0.85
299	Miscellaneous coal or petroleum products	1.52	0.73	28	160	5.74	4.65	0.79
301	Rubber tires or inner tubes	2.09	-0.26	1926	2493	1.29	1.52	0.66
302	Rubber or plastic footwear	1.43	1.16	42	877	20.67	18.47	1
303	Reclaimed rubber	0.77	-1.56	5	11	2.07	2.86	1
304	Rubber or plastic hose or belting	1.07	-0.44	3	18	6.23	6.59	0.2
306	Miscellaneous fabricated rubber products	0.94	0.91	444	1425	3.21	1.72	0.23
307	Miscellaneous plastics products	2.86	2.66	559	9887	17.7	4.36	1
311	Leather	1.01	0.12	146	380	2.6	2.48	0.74
312	Industrial leather belting (SIC 3199)	-	-	0	1	infinite	100	0.82
313	Boot or shoe cut stock or findings	1.37	-0.18	4	27	6.05	6.21	0.47
314	Footwear, leather or other materials	2.6	2.32	86	3576	41.81	32.65	0.79
315	Leather gloves or mittens	-	-	0	29	infinite	100	0.55
316	Luggage or handbags, leather or other materials	0	0	0	197	infinite	100	0.41
319	Leather goods, nec	2.03	1.1	2	67	37.85	35.85	0.82
321	Flat glass	1.3	-0.33	490	606	1.24	1.52	1
322	Glass and glassware, pressed or blown	2.66	1.49	211	1354	6.43	3.01	0.83
324	Hydraulic cement	1.26	0.36	93	207	2.23	1.8	0.81
325	Structural clay products	1.75	1.43	44	295	6.67	3.49	0.93
326	Pottery or related products	1.95	0.87	96	474	4.91	3.52	0.81
327	Concrete, gypsum, or plaster products	0.99	0.95	124	416	3.35	1.77	0.99
328	Cut stone or stone products	1.62	0.38	90	304	3.37	2.92	0.67
329	Abrasive asbestos products or miscellaneous nonmetallic mineral products	1.55	0.7	514	1298	2.53	1.51	0.99
331	Steel works, rolling mill, or other reduction plant products	2.41	1.38	2253	10422	4.63	1.65	0.96
332	Iron or steel castings	2.25	1.42	210	1393	6.64	3.53	1
333	Nonferrous metal primary smelted products	1.36	2.37	68	1337	19.53	9.87	0.63
335	Nonferrous metal primary basic shapes	2.58	1.99	655	6905	10.55	4.22	0.94
336	Nonferrous metal or nonferrous metal base alloy castings	2.1	1.15	182	893	4.89	2.72	0.93
339	Miscellaneous primary metal products	1.98	0.85	297	1255	4.23	2.89	0.72
341	Metal cans	1.39	0.74	201	691	3.44	2.35	0.86
342	Cutlery, hand tools or general hardware	2.32	1.99	309	3402	11	4.67	0.94
343	Plumbing fixtures or heating apparatus	1.88	1.11	132	820	6.23	4.19	0.8

344	Fabricated structural metal products	2.58	1.5	677	4016	5.93	2.47	1
345	Bolts, nuts, screws, rivets, washers, or other industrial fasteners	2.08	0.61	412	1120	2.72	1.88	0.95
346	Metal stampings	2.02	0.49	869	2004	2.31	1.68	1
348	Miscellaneous fabricated wire products	2.07	0.58	177	552	3.13	2.35	0.98
349	Miscellaneous fabricated metal products	2.75	1.74	596	4218	7.08	2.39	1
351	Engines or turbines	1.14	-0.08	713	1059	1.48	1.57	0.64
352	Farm machinery or equipment	1.42	0.71	838	2337	2.79	1.76	0.92
353	Construction, mining or materials handling machinery or equipment	1.88	0.89	1550	4766	3.07	1.63	0.98
354	Metalworking machinery or equipment	2.16	1.48	397	2554	6.43	3.05	0.99
355	Special industrial machinery	1.84	0.87	722	2503	3.47	2.09	0.97
356	General industrial machinery or equipment	2.36	1.54	622	3909	6.28	2.62	1
357	Office, computing or accounting machines	2.03	2.39	363	8654	23.83	13.92	0.87
358	Service industry machines	2.34	1.44	402	2467	6.13	2.9	0.96
359	Miscellaneous machinery or parts	1.66	0.66	400	1267	3.17	2.22	1
361	Electrical transmission or distribution equipment	2.88	1.7	191	2270	11.87	7.41	0.82
362	Electrical industrial apparatus	1.87	0.95	670	2680	4	2.41	0.98
363	Household appliances	3	1.79	319	4270	13.37	8.41	0.86
364	Electric lighting or wire equipment	2.79	1.94	172	2298	13.35	7.38	0.97
365	Radio or television receiving sets	1.7	1.67	671	6466	9.63	5.31	0.85
366	Communication equipment	1.61	1.32	377	2687	7.12	4.38	0.84
367	Electronic components or accessories	1.69	0.81	1339	4834	3.61	2.37	0.93
369	Miscellaneous electrical machinery, equipment, or supplies	1.73	1.15	186	1280	6.89	4.74	0.98
371	Motor vehicles or equipment	2.45	1.33	28273	116471	4.12	1.33	0.89
372	Aircraft or parts	1.55	2.2	398	7183	18.03	9.96	0.58
373	Ships or boats	1.52	0.94	265	2004	7.56	6	0.58
374	Railroad equipment	0.63	0.55	193	468	2.42	1.68	0.72
375	Motorcycles, bicycles or parts	1.07	-0.17	150	577	3.84	4	0.91
376	Guided missile or space vehicle parts, nec	-	-	0	1470	infinite	100	0.53
379	Miscellaneous transportation equipment	1.32	0.78	365	1100	3.01	1.84	0.82
381	Engineering, laboratory, or scientific instruments	1.1	0.78	182	783	4.31	3.12	0.9
382	Measuring, controlling, or indicating instruments	1.3	0.24	184	502	2.73	2.46	0.97
383	Optical instruments or lenses (SIC 3827)	1.27	2.48	2	118	57.63	46.71	0.9
384	Surgical, medical, or dental instruments or supplies	2.06	1.41	449	4146	9.24	6.13	0.98

385	Ophthalmic or opticians goods	0.96	-0.47	25	75	3.05	3.42	0.73
386	Photographic equipment or supplies	1.42	1.19	1838	10563	5.75	3.45	0.2
387	Watches, clocks, clockwork operated devices, or parts	1.31	0.83	20	139	7	5.71	0.34
391	Jewelry, silverware, or plated ware	1.68	-2.55	202	208	1.03	1.95	0.95
393	Musical instruments or parts	1.41	1.41	379	5907	15.6	12.52	0.02
394	Toys, amusements, sporting or athletic goods	2.71	1.43	383	3160	8.26	5.08	0.99
395	Pens, pencils, or other office materials, or artists' materials	1.64	1.1	22	251	11.33	9.33	0.86
396	Costume jewelry, buttons, novelties or notions	2.06	1.03	7	193	26.41	24.62	0.91
399	Miscellaneous manufactured products	2.66	1.68	839	5918	7.05	2.68	0.97

Appendix B

The estimate of the HOME coefficient (β_H=3.07) reported in the text is substantially higher than its counterpart (β_H=0.41) in Anderson and van Wincoop (2001). The results here suggest that the profession puts too much emphasis on estimates calculated with aggregate data. Nonetheless, such a sizable difference between two estimates that purport to measure the same thing is sufficiently large to merit further comment.

It appears that the difference between the results lies primarily in the use of different data documenting state-to province flows. Interstate flow data are quite similar in both studies (though Anderson and van Wincoop deflate interstate flows by 40% in order to match certain regularities of the data), while the state-to-province flows are taken from completely different sources. For state-to-province flows, this study uses the special tabulation of export flows that is described above. Anderson and van Wincoop use Canadian trade data from Statistics Canada.

Before moving to a discussion of the relative merits of the two data sources used for state-province flows, it is worth recalling the activity that is measured by the U.S. Commodity Flow Survey. The CFS was not intended as a measure of trade activity *per se*, but rather as documentation of the use of U.S. transportation networks. As such, the CFS makes no effort to track goods from place of production to final user (as trade data would). Instead, it treats each shipment as a unique flow, a data collection procedure that leads to double counting (in a trade sense) as commodities are shipped from plant to wholesale establishment and wholesale establishment to retail establishment. Furthermore, such counting techniques presumably reduce the reported distance that shipments travel, as compared with trade data (two or more short shipments instead of one long one). They may also increase the reported f.o.b. value of shipments, as the value of shipments leaving wholesale establishments also includes wholesale margins.

CFS data serve as the basic measure of domestic national activity, both in this study and in Anderson and van Wincoop.[23] It is unfortunate that no direct counterpart to the Canadian inter-provincial trade data exists. Nonetheless, the CFS provides unparalleled detail on sub-national movements in the United States. Furthermore, it provides far more commodity-level detail than even the Statistics Canada data. From Anderson and van Wincoop's perspective, the data also allow a direct comparison of border effects facing U.S. and Canadian firms. Clearly, economists should not reject the use of CFS data out of hand because they are incompatible with structural economic models of trade. Instead, the profession should develop models that might be used to better understand the information about trade conveyed in the CFS.

As noted in the text, the U.S.-Canada flow data used here (U.S. Commodity Flows to Canada) has two important limitations. First, it understates the value of trade at the border by a factor of 2. This weakness suggests that any estimate derived from this data should be cut in half, so a border effect estimate of 20 implies an actual effect on the order of 10. The second important limitation of CFS export data is that it does not report the final destination in Canada. If shipments entering Canada proceeded onward to other provinces, the data could substantially understate the distances relevant for shipments to Canada.

Anderson and van Wincoop avoid these difficulties by using the Canadian data. The Canadian data have the advantage of (presumably) matching observable cross-border flows. However, they have a substantial disadvantage, that they measure a different activity than the CFS data measure. Anderson and van Wincoop address the difference in the two data sets by scaling the CFS data so that CFS reported shipments matched the value of shipments from

[23] The public use data used by Anderson and van Wincoop include exports as domestic shipments to the state where the shipment left the U.S. transportation network. In that sense, an additional source of double counting has been removed from the data for this paper. Anderson and van Wincoop remove it in the scaling procedure described below.

manufacturing and mining establishments in the United States. The purpose of the scaling exercise was to compensate for the double counting introduced by the CFS' inclusion of wholesale activities. The scaling done by Anderson and van Wincoop presents a significant change to the level of overall U.S. activity, reducing the reported value of each state-to-state shipment by approximately 40%.

Anderson and van Wincoop explain this substantial change to the data in an appendix. Their discussion acknowledges the transformation as imperfect, but makes no reference to any economic content that might be included in such a scaling exercise. Implicitly, the scaling procedure assumes that the wholesale share of shipments is 1) common across regions (and therefore common across commodities because output bundles vary across states), and 2) insensitive to either distance or borders. The scaling procedure does nothing to address the likelihood that double-counting reduces the reported distance that goods travel, relative to the distance that would have been reported if goods had been tracked to their final destination. Given the difficulties interpreting the content of CFS data, and in contrast to Anderson and van Wincoop, I make no attempt to link the reduced-form estimates to a specific structural economic model.