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How Misleading is Revealed Comparative Advantage?

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Abstract: The answer is: substantially misleading. I develop a novel decomposition to show that Revealed Comparative Advantage (RCA) consists of an index of market share, and an index of total country size. The latter accounts for 20%-30% of observed variation in RCA, even though it is unconnected with sectoral comparative advantage. Indexing RCA by a base sector and country removes this distortion, but the resulting measure still consists of two terms: a theory-consistent index of relative productivity (theoretical comparative advantage, TCA), and an index of effective market potential. Double indexed RCA only equals TCA under restrictive assumptions not met in practice: inclusion of data on intra-national trade, and trade costs that are constant across all exporters for a given importer-sector. Trade costs and market size substantially distort RCA relative to TCA: at the two-digit HS level, the distortion accounts for 60% of observed variation in RCA, while at the six-digit level it is "only" 21%. The conclusion, however, is substantively the same: RCA is a significantly distorted measure relative to a theory-consistent measure of comparative advantage based on exporter-sector characteristics. Given the ease with which TCA can now be estimated, there is little reason for applied researchers to continue using RCA.

Keywords: Gravity model; Comparative advantage; Trade policy.

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1 INTRODUCTION

The Balassa (1965) Revealed Comparative Advantage (RCA) index is commonly used by applied researchers and policy practitioners to identify sectors and products in which a country is believed to have comparative advantage. UNCTAD and the World Bank feature it prominently on their trade statistics websites,[2] while Hidalgo et al. (2007) use it as the basis of their product space literature. But to what extent does it actually provide an accurate picture of comparative advantage in practice?

A key limitation of RCA, discussed by Costinot et al. (2012), is its lack of theoretical framework. It was developed as an intuitive measure, at a time when trade data were much more scarce than they are today, and when theory had not yet developed to the point of providing detailed direction as to how to measure comparative advantage more rigorously. As those authors point out, relative to a theoretically-grounded approach to comparative advantage, RCA risks presenting results based on a mix of productivity differences—the item of interest—but also trade costs and demand differences (effective market potential).

Against that background, this paper starts from a simple question: in light of what we now know about the determinants of bilateral trade flows, what does RCA in fact measure? Or more precisely, what are the similarities and differences between RCA on the one hand and a rigorously derived, theory-based measure of comparative advantage on the other? My approach is to use a structural gravity model that incorporates Ricardian comparative advantage as a tool to analyze the deep determinants of RCA. I do so first on a theoretical level, and then empirically.

The theoretical model I use is from Costinot et al. (2012). Those authors develop a multi-sector generalization of the Eaton and Kortum (2002) Ricardian model. They show that under the model's assumptions, an index of exporter-sector fixed effects can be interpreted in terms of "revealed" productivity differences across countries and sectors, which is the essence of comparative advantage. By estimating those fixed effects using a structural gravity model framework, they can easily separate out the effects of trade costs and demand-side influences. They argue that their approach is superior to that of Balassa (1965) because it is grounded in standard trade theory, and because it emphasizes pairwise comparisons across countries and sectors rather than comparison with an arbitrary baseline.

I first analyze the standard RCA measure by taking logarithms and rearranging terms. Whereas it is typically understood as an index of relative market shares, I show that it can equally well be interpreted as an index of market share and an index of country size. While market share could plausibly be related to the sector-level determinants of comparative advantage, aggregate country size is an extraneous factor. Taking this decomposition to the data shows unambiguously that a substantial proportion of the observed variation in RCA is in fact due to differences in country size alone, which means that it is a dubious measure of comparative advantage at the exporter-sector level. To drive the point home, I highlight examples of countries in the data that have very similar shares of the world export market in a particular sector, but radically different RCA scores due to their aggregate size.

In a second stage of the analysis, I use indexing to remove RCA's aggregate country size term: I express it relative to a baseline sector and a baseline country. To go further, I then need to substitute expressions for the structural determinants of bilateral trade from the gravity model of Costinot et al. (2012). I rearrange the result to show that RCA directly includes the theory-based comparative

[2] https://unctadstat.unctad.org/EN/RcaRadar.html; https://tcdata360.worldbank.org/indicators/h62a3e8cc?country=BRA&indicator=40085&viz=line_chart&years=1988,2016.

advantage index those authors develop, but also another term related to effective market demand—as they intuit, a function of demand side factors and trade costs. Empirically, this term is important: in HS two- and four-digit datasets, it accounts for the majority of observed variation in double indexed RCA; at the six-digit level, its influence is weaker, but still substantial enough to cause serious distortions from a practical perspective. Again, I illustrate the problems with RCA by showing cases in which countries with very similar scores on the Costinot et al. (2012) theory-consistent comparative advantage index have radically different RCA scores; indeed, in some cases, the ordering of countries is even reversed.

While my analysis draws on the particular Ricardian model of Costinot et al. (2012), the insight is in fact far more general. My core derivations in Section 2 are only based on a standard structural gravity model that expresses bilateral trade flows as a function of an exporter-sector specific factor, an importer-specific factor, a bilateral trade costs factor, and an error term. As such, the most general interpretation of my findings is that RCA is in fact inconsistent with *any* model in which comparative advantage is an exporter-sector specific factor. From an intuitive point of view, that description covers most plausible models of comparative advantage, not just the specific Ricardian version in Costinot et al. (2012). For instance, the factor proportions model of Romalis (2004) sees comparative advantage as an interaction between factor intensity and factor abundance, which in a multi-country and multi-sector framework means that comparative advantage is a function of an exporter-sector factor. Similarly, the Ricardian framework of Chor (2010) models comparative advantage in the same way. So my key result, while based on one specific model incorporating comparative advantage, in fact shows that RCA is a distorted measure of comparative advantage in a wide variety of settings. The generality of this result calls into serious question the use of RCA in empirical work and policy advice.

I am not the first to argue that RCA is an imperfect measure. Costinot et al. (2012), for example, clearly make the argument. Similarly, French (2017) highlights that RCA is problematic from a revealed productivity perspective, although related measures arguably remain useful for understanding different aspects of comparative advantage. The contribution of my paper is to show for the first term the direct relationship between the theory-based indicator of Costinot et al. (2012) and RCA, and to quantify to the extent to which RCA is distorted relative to this theoretical benchmark in standard trade datasets. I also highlight a special case in which RCA corresponds exactly to the theoretical benchmark: if it is calculated using data on intra- as well as international trade flows, and if trade costs for an importer-sector do not vary across exporters. Neither condition is met in practice, of course.

The paper proceeds as follows. The next section presents my decomposition approach to RCA, starting with the standard measure, then moving to a consideration of indexed versions. Section 3 undertakes an empirical analysis using UN Comtrade data at different levels of disaggregation. Finally, Section 4 concludes, discusses directions for further research, and considers the implications of these findings for applied researchers and in policy settings.

2 Decomposing RCA: Analytical Results

My approach to analyzing RCA relies on a logarithmic decomposition. For presentational purposes, it is helpful to start with the standard RCA measure, as it takes the simplest form. The general approach can then easily be repeated with variations of that measure.

2.1 Standard RCA: Market Share and Country Size

The Balassa (1965) RCA index claims that if a country specializes in a good relative to the world share, then it has a revealed comparative advantage in it. It therefore expresses the share of a good in a country's export bundle relative to its share in the world export bundle:

$$(1)\ RCA_{i_0}^{k_0} = \frac{\sum_{j=1,\neq i_0}^{N} X_{i_0 j}^{k_0}}{\sum_{j=1,\neq i_0}^{N} \sum_{k=1}^{G} X_{i_0 j}^{k}} \Bigg/ \frac{\sum_{i=1}^{N} \sum_{j=1,\neq i}^{N} X_{ij}^{k_0}}{\sum_{i=1}^{N} \sum_{j=1,\neq i}^{N} \sum_{k=1}^{G} X_{ij}^{k}}$$

Where $X_{i_0 j}^{k_0}$ is exports of product k0 by country i0 to country j, in a world of N countries with G sectors. The summation operators exclude the cases of i=j, as the standard RCA measure is calculated using data on international trade only, and does not take account of goods that are produced and consumed in the same country (domestic shipments, or intra-national trade). Country io has comparative advantage in good k0 if the numerator is greater than the denominator.

Equation (1) immediately suggests that comparative advantage follows from a comparison of market shares: if the market share of product k0 in country i0's exports is greater than its market share in world exports, then country i0 has a comparative advantage in that good. This straightforward interpretation is no doubt an important factor behind the intuitive appeal and widespread use of RCA in applied research and policy analysis.

But a simple rearrangement of terms in logarithms shows that the measure can equally well be understood in another, less straightforward, way:

$$(2)\ \log RCA_{i_0}^{k_0} = \underbrace{\log\left(\frac{\sum_{j=1,\neq i_0}^{N} X_{i_0 j}^{k_0}}{\sum_{i=1}^{N} \sum_{j=1,\neq i}^{N} X_{ij}^{k_0}}\right)}_{market\ share} - \underbrace{\log\left(\frac{\sum_{j=1,\neq i_0}^{N} \sum_{k=1}^{G} X_{i_0 j}^{k}}{\sum_{i=1}^{N} \sum_{j=1,\neq i}^{N} \sum_{k=1}^{G} X_{ij}^{k}}\right)}_{country\ size}$$

Equation (2) shows that the standard RCA measure in logarithms consists of two components. The first is a different index of market share, namely country i0's share of global exports of product k0. The second is an index of country size, which expresses the ratio of country i0's total exports of all products relative to total world exports of all products.

The decomposition is insightful because it shows that the market share interpretation of RCA is not without complication. It makes clear, for example, that countries with the same share of global exports (equal first terms) can potentially have radically different RCA scores if they are of different sizes in terms of their weight in total global trade (different second terms). Specifically, the sign of the second term shows that for a given level of market share for the product of interest, RCA will systematically report higher scores for smaller countries. While export market share could plausibly be related to comparative advantage in the product of interest—a point I discuss more rigorously below—there is no reason to believe that aggregate country size should also matter. Specifically, it does not sit well with basic intuition for a measure of comparative advantage to be size dependent—yet equation (2) makes clear that this is the case for the standard Balassa (1965) RCA measure. In Section 3, I go through empirical examples where this effect plays out in a dramatic fashion, and show systematically how country size is an important determinant of country-sector level RCA scores.

2.2 Indexed RCA: Comparative Export Performance

The form of equation (2) immediately suggests a simple approach to removing the size bias: indexing by a baseline product k1. Equation (3) shows, however, that this approach only partially solves the problem:

$$(3)\ \log\left(\frac{RCA_{i_0}^{k_0}}{RCA_{i_0}^{k_1}}\right) = \underbrace{\log\left(\frac{\sum_{j=1,\neq i_0}^{N} X_{i_0 j}^{k_0}}{\sum_{i=1}^{N}\sum_{j=1,\neq i}^{N} X_{ij}^{k_0}}\right)}_{market\ share\ k0} - \underbrace{\log\left(\frac{\sum_{j=1,\neq i_0}^{N} X_{i_0 j}^{k_1}}{\sum_{i=1}^{N}\sum_{j=1,\neq i}^{N} X_{ij}^{k_1}}\right)}_{market\ share\ k1}$$

$$= \underbrace{\log\left(\frac{\sum_{j=1,\neq i_0}^{N} X_{i_0 j}^{k_0}}{\sum_{j=1,\neq i_0}^{N} X_{i_0 j}^{k_1}}\right)}_{country\ sectoral\ exports} - \underbrace{\log\left(\frac{\sum_{i=1}^{N}\sum_{j=1,\neq i}^{N} X_{ij}^{k_0}}{\sum_{i=1}^{N}\sum_{j=1,\neq i}^{N} X_{ij}^{k_1}}\right)}_{total\ sectoral\ exports}$$

While equation (3) does not have the country size term from equation (2), it nonetheless contains two conceptually distinct elements. The first is an index of country-sector level exports, that is, the logarithm of the ratio of country i0's exports of product k0 to its exports of product k1. Intuitively, it would again be possible to make a case that this term could be related to some understanding of comparative advantage, in the sense that countries specialize—and therefore export relatively more—in sectors in which they have comparative advantage. But the second term again has little to do with even this broad brush approach to comparative advantage: it is simply an index of total world exports of product k0 relative to total world exports of product k1. So there is again a size distortion, but this time at the sectoral level. This relative measure of RCA using a baseline product still gives systematically higher scores, but this time not based on country size, but rather sector size: smaller sectors in the sense of lower total world exports receive higher scores than larger sectors, even for a constant country-level ratio of sectoral exports. Again, this effect is undesirable in a metric of comparative advantage. Section 3 goes into detail on the empirics of this effect, using examples and a systematic assessment of the degree of importance of the second term.

But it is possible to take the indexing approach one step further, by using both a base product and a base country:

$$(4)\ \log\left(\frac{RCA_{i_0}^{k_0}}{RCA_{i_0}^{k_1}} \Big/ \frac{RCA_{i_1}^{k_0}}{RCA_{i_1}^{k_1}}\right) = \log\left(\frac{\sum_{j=1,\neq i_0}^{N} X_{i_0 j}^{k_0}}{\sum_{j=1,\neq i_0}^{N} X_{i_0 j}^{k_1}}\right) - \log\left(\frac{\sum_{j=1,\neq i_1}^{N} X_{i_1 j}^{k_0}}{\sum_{j=1,\neq i_1}^{N} X_{i_1 j}^{k_1}}\right)$$

This approach eliminates the second term in equation (3). But it shows that double indexed RCA computed in this way is simply the difference in the ratio of sectoral exports in the country of interest and the baseline country. That is, it is the difference between the ratio of exports in the sector of interest in each country divided by exports in the baseline sector. The intuitive link between this decomposition and comparative advantage is weaker than for equations (1) through (3). The interest of equation (4) is rather that it highlights the somewhat arbitrary nature of RCA, even when size distortions are removed. However, it is impossible to see what concrete links there might be between the right hand side of equation (4) and comparative advantage as rigorously understood without recourse to theory. The next subsection turns to that task.

2.3 Comparative Advantage with Gravitas

To work further with equation (4), I start with a standard structural gravity model, following the notation in Head and Mayer (2014) but extended to multiple sectors:

$$(5)\ X_{ij}^{k} = S_i^k M_j^k {t^k}_{ij}^{-\theta} e_{ij}^k$$

Where: X_{ij}^{k} is exports from country i to country j in sector k; S_i^k is an exporter-sector fixed effect; M_j^k is an importer-sector fixed effect; t_{ij}^{k} is iceberg trade costs; θ is the trade elasticity; and e_{ij}^{k} is an error term satisfying standard assumptions.

Head and Mayer (2014) consider single sector models, and show that a version of equation (5) without the sector superscripts is consistent with a wide range of theoretical underpinnings. I extend their treatment by considering the multi-sector Ricardian model of Costinot et al. (2012), which can straightforwardly be expressed in terms of the components in equation (5), as shown, for example, by equation (19) is Costinot et al. (2012), where trade costs are expressed as the interaction between a country-pair fixed effect and an importer-sector specific term.

Concretely, in the Costinot et al. (2012) model, $S_i^k = {z_i^k}^{\theta}$, where z is productivity. So the exporter-sector fixed effect is "revealed productivity". In their empirical work using equation (5), Costinot et al. (2012) adopt the double indexing approach from the previous section, and compute a theory-consistent measure of comparative advantage (theoretical comparative advantage, TCA) as follows:

$$(6)\quad \frac{TCA_{i_0}^{k_0}}{TCA_{i_0}^{k_1}} \Bigg/ \frac{TCA_{i_1}^{k_0}}{TCA_{i_1}^{k_1}} = \frac{\hat{S}_{i_0}^{k_0}}{\hat{S}_{i_0}^{k_1}} \Bigg/ \frac{\hat{S}_{i_1}^{k_0}}{\hat{S}_{i_1}^{k_1}}$$

Hat notation on the right hand size of equation (6) indicates econometric estimates of the relevant terms of equation (5).

There is a close relationship between equation (6)—the theory consistent measure of comparative advantage from Costinot et al. (2012)—and equation (4)—the double indexed version of the standard RCA measure. But before showing exactly what that relationship is, it is important to establish some key facts about the estimation of equation (5).

Santos Silva and Tenreyro (2006) suggest estimating equation (5) by Poisson Pseudo-Maximum Likelihood (PPML). OLS is inconsistent in the presence of heteroskedasticity due to log-linearization, and also excludes observations where bilateral trade is equal to zero. Estimating structural gravity models by PPML is now standard practice (Santos Silva and Tenreyro, 2021), in particular since a version of PPML is now available that accommodates high dimensional fixed effects (Correia et al., 2020).

Arvis and Shepherd (2013) and Fally (2015) show that PPML estimates of equation (5) have another convenient property that is very useful in the present context: group sums of predicted trade (without the error term) that are exactly identical to group sums of observed trade (with the error term). PPML is unique among estimators from the generalized linear model family in having this "adding up" property. This property is important because RCA depends on just such group sums, so it opens up the prospect of directly substituting PPML estimates of equation (5) into equation (4) to potentially obtain a more informative decomposition. Formally, this "adding up" property means that the following holds, where hats indicate estimates obtained using PPML:

$$(7)\quad \sum_{j=1,\neq i}^{N} X_{ij}^{k} = \sum_{j=1,\neq i}^{N} \hat{X}_{ij}^{k} \equiv \hat{S}_i^k \sum_{j=1,\neq i}^{N} \widehat{M}_j^k {\hat{t}^{k}}_{ij}^{-\theta}$$

This remarkable property of PPML means that I can substitute equation (7) into equation (4), then rearrange to provide a much more meaningful decomposition of the double indexed RCA measure:

$$(8)\ \log\left(\frac{RCA_{i_0}^{k_0}}{RCA_{i_0}^{k_1}}\Bigg/\frac{RCA_{i_1}^{k_0}}{RCA_{i_1}^{k_1}}\right) = \log\left(\frac{\hat{S}_{i_0}^{k_0}\sum_{j=1,\neq i_0}^{N}\widehat{M}_j^{k_0}\hat{t}_{i_0j}^{k_0\ -\theta}}{\hat{S}_{i_0}^{k_1}\sum_{j=1,\neq i_0}^{N}\widehat{M}_j^{k_1}\hat{t}_{i_0j}^{k_1\ -\theta}}\right) - \log\left(\frac{\hat{S}_{i_1}^{k_0}\sum_{j=1,\neq i_1}^{N}\widehat{M}_j^{k_0}\hat{t}_{i_1j}^{k_0\ -\theta}}{\hat{S}_{i_1}^{k_1}\sum_{j=1,\neq i_1}^{N}\widehat{M}_j^{k_1}\hat{t}_{i_1j}^{k_1\ -\theta}}\right)$$

$$= \underbrace{\log\left(\frac{\hat{S}_{i_0}^{k_0}}{\hat{S}_{i_0}^{k_1}}\Bigg/\frac{\hat{S}_{i_1}^{k_0}}{\hat{S}_{i_1}^{k_1}}\right)}_{TCA} + \underbrace{\log\left(\frac{\sum_{j=1,\neq i_0}^{N}\widehat{M}_j^{k_0}\hat{t}_{i_0j}^{k_0\ -\theta}}{\sum_{j=1,\neq i_0}^{N}\widehat{M}_j^{k_1}\hat{t}_{i_0j}^{k_1\ -\theta}}\Bigg/\frac{\sum_{j=1,\neq i_1}^{N}\widehat{M}_j^{k_0}\hat{t}_{i_1j}^{k_0\ -\theta}}{\sum_{j=1,\neq i_1}^{N}\widehat{M}_j^{k_1}\hat{t}_{i_1j}^{k_1\ -\theta}}\right)}_{effective\ market\ potential}$$

The first term in equation (8) is exactly identical to the double indexed TCA index of Costinot et al. (2012). In other words, double indexed RCA is identical to the first of the two terms in my decomposition. The presence of the second term immediately indicates, however, that RCA is a distorted measure relative to the more rigorous TCA. Following the analysis in Head and Mayer (2014), I interpret the second term as an index of effective market potential. Each element captures the effective demand for a country's exports of a particular product. "Effective" in this context means adjusted for trade costs. So as the second term of the decomposition makes clear, RCA not only captures revealed productivity in the Costinot et al. (2012) sense, but also effective market potential, which is a mixture of country size, sectoral expenditure shares, and trade costs. The decomposition makes clear that together, these factors distort RCA relative to its theory-consistent counterpart. In Section 3, I quantify the extent to which the second term distorts RCA relative to the theoretical benchmark using standard trade data.

2.4 When Intuition and Theory Coincide: A Special Case

Notwithstanding the divergence of RCA from its theory-consistent counterpart, it is worth considering a special case of equation (8). The special case is of particular interest because it identifies conditions under which RCA corresponds exactly to TCA.

For equation (8) to collapse into the special case just outlined, the second term of the decomposition needs to vanish. The first step is therefore to define a closely related indicator RCA' that includes domestic shipments (intranational trade), which allows me to rewrite equation (8) as follows:

$$(9)\ \log\left(\frac{RCA'^{k_0}_{i_0}}{RCA'^{k_1}_{i_0}}\Bigg/\frac{RCA'^{k_0}_{i_1}}{RCA'^{k_1}_{i_1}}\right) = \underbrace{\log\left(\frac{\hat{S}_{i_0}^{k_0}}{\hat{S}_{i_0}^{k_1}}\Bigg/\frac{\hat{S}_{i_1}^{k_0}}{\hat{S}_{i_1}^{k_1}}\right)}_{TCA} + \underbrace{\log\left(\frac{\sum_{j=1}^{N}\widehat{M}_j^{k_0}\hat{t}_{i_0j}^{k_0\ -\theta}}{\sum_{j=1}^{N}\widehat{M}_j^{k_1}\hat{t}_{i_0j}^{k_1\ -\theta}}\Bigg/\frac{\sum_{j=1}^{N}\widehat{M}_j^{k_0}\hat{t}_{i_1j}^{k_0\ -\theta}}{\sum_{j=1}^{N}\widehat{M}_j^{k_1}\hat{t}_{i_1j}^{k_1\ -\theta}}\right)}_{effective\ market\ potential}$$

I then only need to apply one assumption to make the second term vanish:

1. $t_{ij}^{k} = \bar{t}^{k}{}_{j} \forall i$

Assumption 1 means that trade costs are applied on a most-favored nation basis at the importer-sector level. In other words, they are constant across all exporters for a given importer within a sector. As a result, $\hat{t}_{i_0 j}^{k_0} = \hat{t}_{i_1 j}^{k_0}$ for a given country j, and similarly for sector k1. It is straightforward to verify that this assumption leads to the numerator and denominator terms in the ratios that form the second decomposition term being equal, which means that the entire term disappears from equation (9).

This analysis is informative, because it suggests that the distortion in RCA introduced by the second term in equation (8) can be understood as separate impacts coming from the absence of intra-national trade data on the one hand, and variation in trade costs on the other. I quantify both of these effects in Section 3 using standard trade data. At the present stage, however, it is enough to conclude that RCA, even when double indexed, is a function not only of exporter-specific factors that can be understood in terms of comparative advantage rigorously defined, by also importer-specific factors like market size and expenditure shares, pair-specific factors like variable trade costs, and the inclusion or exclusion of domestic shipments (intra-national trade).

Before leaving the special case, it is important to address the issue of domestic shipments. Standard trade data do not include domestic shipments. While multi-region input-output tables do include such data, they are much more aggregate than even the two-digit level of the harmonized system, and so are rarely used in applied work on comparative advantage. But if I assume that intra-national trade is frictionless, then equation (5) allows me to use PPML estimates to compute a proxy for domestic shipments:

$$(10)\ \hat{X}_{ii}^{k} = \hat{S}_{i}^{k} \widehat{M}_{j}^{k}$$

The two fixed effects can be estimated using observations on international trade only, so there is no computational barrier to computing the proxy for intra-national trade in this way. Of course, it relies on two assumptions: one that intra-national trade is frictionless, which is standard in theoretical models; and two that estimates of the fixed effects are unbiased even though intra-national trade data are absent from the estimation procedure. These assumptions are strong, but this approach has previously been used in the literature when direct observations on intra-national trade are unavailable: e.g., Anderson et al. (2018). I adopt it below in my empirical work, because my interest is not in a precise quantification of intra-national trade, but rather in understanding qualitatively the extent to which inclusion or exclusion of such data alter the RCA computation.

2.5 A Generalization

The analysis in Section 2.3 relies on the Ricardian model of Costinot et al. (2012). In particular, the derivation of TCA as a re-indexing of exporter-sector specific factors draws explicitly on their framework. But it is important to note that the results I have stated are, in fact, much more general. That is, the distorted nature of RCA as a measure of comparative advantage is true with regard to a much broader class of theoretical models than just the Costinot et al. (2012) framework.

To see that this is true, it is sufficient to note that equation (8) is expressed in terms of the structural gravity model in equation (5). Costinot et al. (2012) is one model that is consistent with that framework, but it is by no means the only one. My derivations remain equally true for any multi-sectoral model in the structural gravity class, which, as Head and Mayer (2014) show, covers a wide range of theoretical foundations. The important point is that if bilateral trade is a function of exporter-sector, importer-sector, and bilateral factors (as well as noise), then RCA will itself always be a function of all of those factors. So as Costinot et al. (2012) note, RCA mixes supply, demand, and trade cost factors. My contribution is to highlight the extent of the distortion introduced by the mixing of those factors relative to a theoretically-grounded approach in which comparative advantage is a function of exporter-sector specific factors only.

It flows from basic intuition that comparative advantage is a supply side property that should be unrelated to demand side factors and bilateral trade costs. That is how Costinot et al. (2012) model it. But the approach is far more general than that. For instance, the factor proportions model of Romalis (2004) also conceptualizes comparative advantage as the interaction of factor abundance and factor intensity, which is an exporter-specific factor. The Ricardian model of Chor (2010) takes the same approach. The importance of this work for my analysis is that it highlights that RCA is in fact incompatible with any model in which comparative advantage is a function of exporter-specific factors. So while the Costinot et al. (2012) model serves to make the point particularly clearly, it is in fact far more general than reliance on that specific framework would seem to suggest.

3 Empirical Application: How Much does Comparative Advantage Matter for RCA?

The previous section has highlighted the difficulties with RCA relative to TCA. But it remains to be seen how important these issues are in practice. It is to that question that the present section turns, using standard UN Comtrade data at different levels of disaggregation.

3.1 Empirical Decomposition Methodology

The analysis above has shown that each type of RCA indicator can be decomposed exactly into two terms. In particular, using PPML estimates from a structural gravity model means that the final decomposition—into theoretical comparative advantage and effective market potential—is also exact. These results are informative in themselves, but they leave open the question of the extent to which each element of the decomposition contributes to the overall observed variation in the indicator. That is the question I turn to in this section.

My starting point for dealing with each of the decompositions above using observed data is a regression framework. Of course, the regressions are not interesting in themselves: because the decompositions are exact, they have R2s equal to unity, and coefficients given by theory. There is no error in the decompositions, so the regressions do not produce estimates of interest.

What is of interest, by contrast, is the proportion of observed variation in log RCA (equal to R2 in the regression with both decomposition terms) that is attributable to each of the two components. Decomposing R2 in this way, however, is not entirely straightforward. A number of approaches are possible.

On the one hand, each decomposition consists of two terms, so it is simple to decompose observed variation in the left hand side variable into components coming from variation in each of the right hand side variables, along with their covariance. But interpretation is not always simple: if the two terms have a negative covariance, then the variance contribution of each element independently will not sum to unity.

An alternative approach is to look at semi-partial R2s, namely the increase in model R2 produced by adding each term to a model in which only the other one is included. While highly intuitive, this metric does not fully account for the different ways in which each variable can influence the final R2 value, including both direct and indirect mechanisms.

A measure that takes full account of these issues is the Shapley (1953) decomposition. The original contribution is from game theory, but Shorrocks (2013) shows that it can be used to decompose any statistic, including R2. It uses information from all possible models to calculate the total contribution of each variable to the overall model R2 (equal to unity) without taking account of path dependence. By definition, the contributions sum to unity, without the inconvenience of accounting separately for their covariance.

Using subscripts on R2 to indicate the variables included in the model, the Shapley-Shorrocks decomposition showing the total contribution to R2 of a single variable is calculated as follows:

$$R_j^2 = \sum_{T \subseteq Z \setminus x_j} \frac{k!\,(p-k-1)!}{p!} \left[R^2\left(T \cup x_j\right) - R^2(T)\right]$$

Where: R_j^2 is variable x_j's contribution to overall model R2; Z is the set of all p variables; and T is a subset of Z containing k variables but not x_j.

This is the approach I apply here. For each decomposition, I calculate the left hand side directly from observed trade data, and the right hand side either directly from observed trade data, or through a combination of observation and estimation. I then run regressions that confirm the exact nature of the decompositions developed above, and use the Shapley-Shorrocks decomposition to identify the total contribution of each of the two terms.

3.2 Data and Descriptive Statistics

In terms of data, I use a standard trade dataset to compute various versions of the RCA index, as well as the individual components identified above. I source the trade data from UN Comtrade at the six-digit HS level. I use them at that level, and also at the four- and two-digit levels, with aggregation by summing. In line with standard practice, I prefer import data to export data for quality reasons, so exports are proxied by mirrored imports. I exclude lightly traded commodities that could produce unreliable results by limiting consideration in the bilateral datasets to sectors with at least ten exporter-sector and ten importer-sector observations. Table 1 presents descriptive statistics. There is only a single variable, the value of exports, so the table presents summary data for the three levels of aggregation I use.

Table 1: Descriptive statistics.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Exports (USD 000) HS 2	643,503	30907.250	657830.600	0.000	154,000,000.000
Exports (USD 000) HS 4	2,859,993	6733.343	191467.400	0.000	99,200,000.000
Exports (USD 000) HS 6	6,052,341	2979.254	104549.600	0.000	66,300,000.000

All levels of aggregation are unbalanced panels. The two-digit dataset contains observations on 97 HS sectors for 229 exporters and 131 importers. The four-digit dataset contains observations on 1,215 HS sectors for 217 exporters and 131 importers. The six-digit dataset contains observations on 5,091 HS sectors for 211 exporters and 131 importers.

3.3 Standard RCA: Market Share vs. Country Size

In Section 2.1, I showed that the standard Balassa (1965) RCA measure can be decomposed into two elements: one captures product level market share, which is plausibly related to comparative advantage, while the other captures total country size. I compute all relevant terms using the two-, four-, and six-digit datasets.

Figure 1 presents results. Term 1 (market share) has the expected positive correlation with RCA at all three levels of disaggregation. The relationship between RCA and term 2 (country size) is weaker, but slightly negative in all cases. However, the figure shows unconditional correlations, and so does not account for covariance between the two terms. A regression confirms that R2 is unity, and the estimated coefficients have the expected magnitudes and signs in all cases, which means that the decomposition is indeed exact.

Figure 1: Correlations between standard RCA and the two decomposition terms

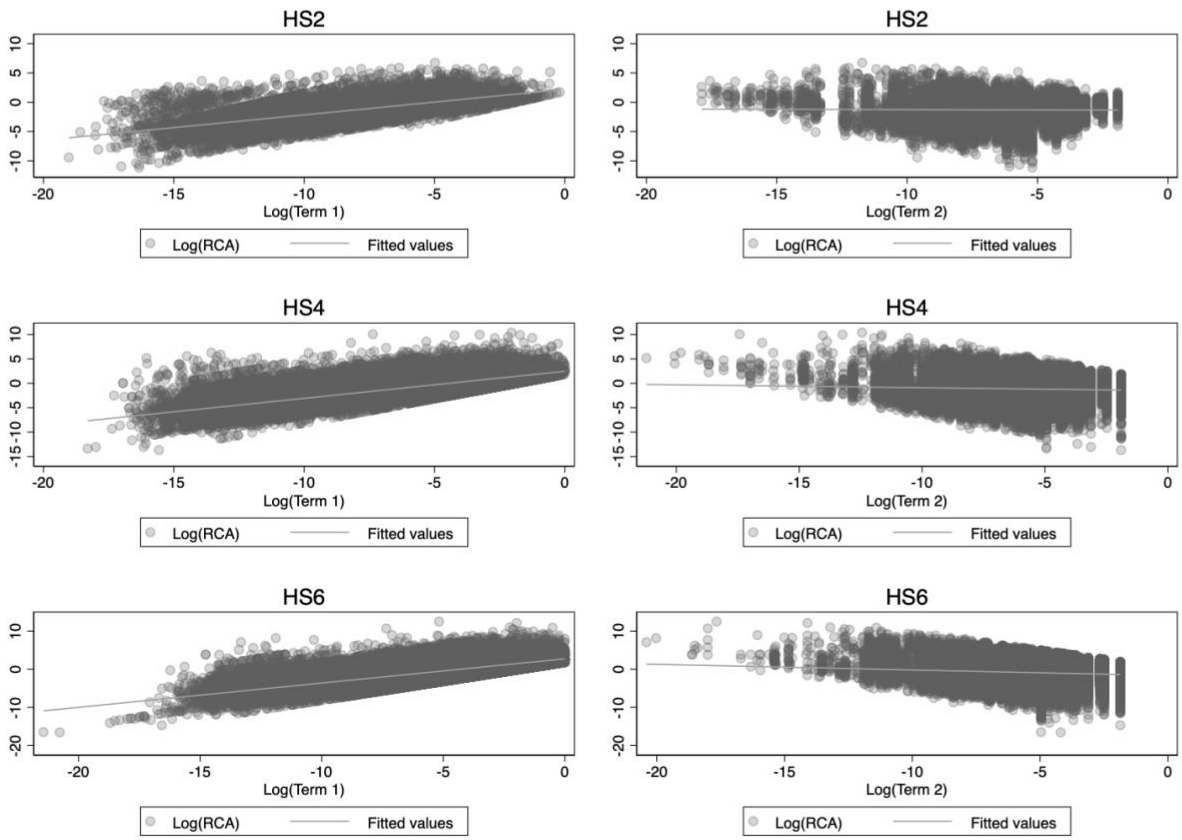


Table 2 presents Shapley-Shorrocks decompositions for the regressions using the three levels of aggregation. The first row shows that standard RCA is substantially determined by market share, and that the proportion of observed variation explained by term 1 of the decomposition increases with the level of disaggregation of the data. But the key finding is in relation to the second term, which is a raw index of country size: it accounts for between 20 and nearly 30% of the observed variation in RCA. In other words, country size is an empirically important determinant of standard RCA, in addition to export market share. The data therefore confirm the importance of the second term in the decomposition, which I argued above has undesirable characteristics from the point of view of a metric of comparative advantage.

Table 2: Shapley-Shorrocks decomposition of observed variation in standard RCA.

Element	Two-Digit	Four-Digit	Six-Digit
Market Share (Term 1)	71.486%	76.225%	78.297%

Country Size (Term 2)	28.514%	23.775%	21.703%

Some examples from the two-digit dataset suffice to make the point. Taking cereals as the first example (HS sector 10), Japan and Estonia have very similar world market shares: term1 in log terms is -7.165 for the former and -7.299 for the latter. But Japan is a much larger country than Estonia in terms of total export value, so its RCA score in logarithms is -4.008 compared with -0.063 for Estonia. RCA is often understood informally as a comparison of market shares, but this example clearly shows that countries with very similar market shares can in fact end up with radically different RCA scores.

A second example comes from the pharmaceuticals sector (HS code 30). Germany and Switzerland have very similar market shares: term one in logarithms is -2.012 for the former, and -2.035 for the latter. But Switzerland, as the smaller country, receives a much higher RCA score: 1.753 in logarithms versus Germany's 0.697. Again, the size distortion is important both conceptually and empirically: it is clearly undesirable for countries with similar export market shares to receive substantially different scores on a comparative advantage metric simply because their aggregate exports are very different. Country size in an aggregate sense has nothing to do with comparative advantage in a sectoral sense.

Examples like these show that comparing RCA scores across countries, as is frequently done in policy settings, is treacherous: the index potentially has as much or more to say about total country size than performance in a single sector of interest. The data confirm that the second term of the decomposition plays an empirically important role in determining country-sector scores on the standard RCA metric.

3.4 Double Indexed RCA: Comparative Advantage vs. Effective Market Potential

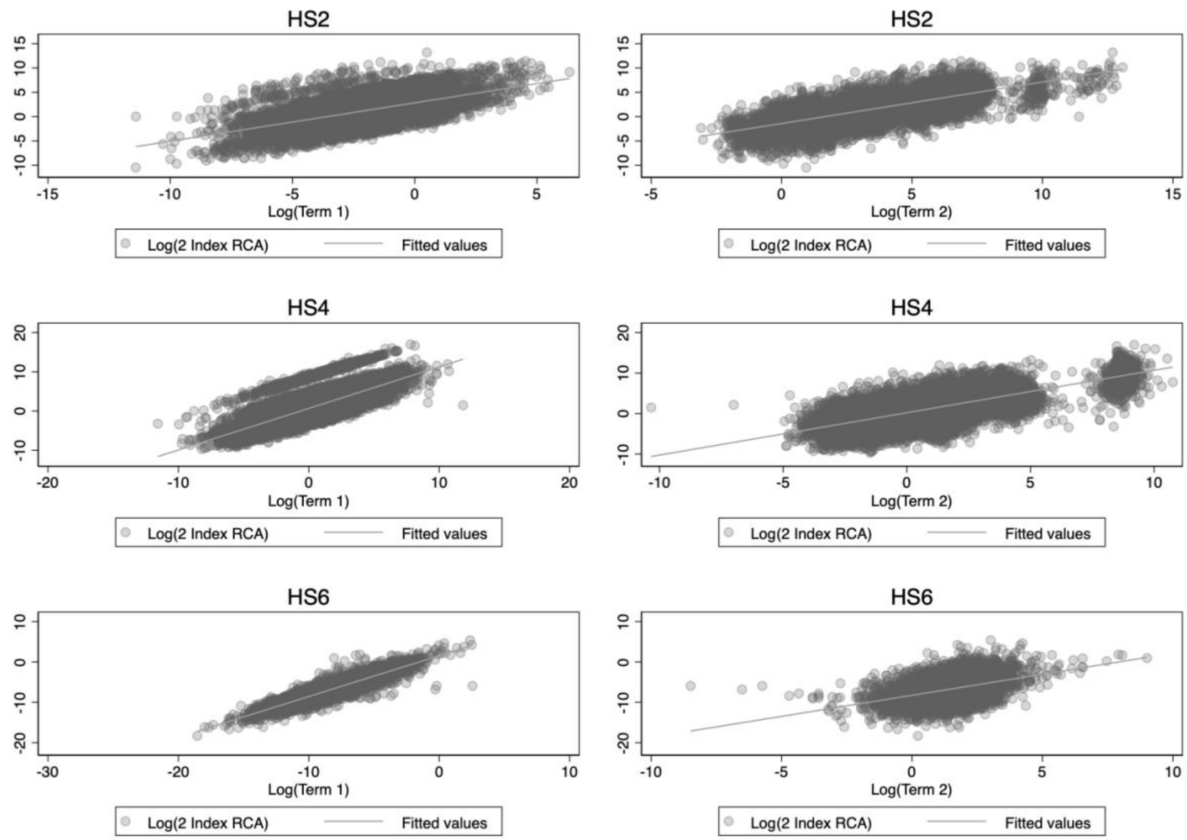
Section 2.2 showed that the size distortion in RCA can be mitigated, but not removed, by indexing. Then Section 2.3 showed that double indexing by a baseline sector and a baseline country leads to a measure with a clear interpretation in terms of theory-based comparative advantage. But even this rearrangement of the standard RCA measure still contains a distortion: while the first term is identical to the TCA measure of Costinot et al. (2012), the second term in the decomposition mixes market size and trade costs to produce an index of effective market demand. The effect of the second term is to distort RCA relative to TCA. But the extent of that distortion is an empirical question that can only be answered with reference to observed data.

I therefore calculate double-indexed RCA and the two elements of the decomposition using the three datasets at different levels of disaggregation. In this case, I need to estimate gravity models by PPML to recover the exporter-sector fixed effects that make it possible to calculate all terms in the decomposition. Thanks to the high dimensional PPML estimator of Correia et al. (2020), it is straightforward to do so. Since there are only fixed effects in the models, it is not useful to report results in the standard way. Rather, I summarize model performance briefly. The two-digit model has an R2 of 0.953, with 640,771 observations and 43,354 fixed effects. The four-digit model has an R2 of 0.938, with 2,857,440 observations and 180,371 fixed effects. Finally, the six-digit model has an R2 of 0.941, with 6,048,718 observations and 454,786 fixed effects. The Correia et al. (2020) estimator handles these large models rapidly on a standard desktop computer, so for purposes of estimating TCA—highlighted as subject to computational issues in the previous literature—there is no longer any barrier to running models at even the most disaggregated internationally harmonized level of the trade classification system.

Finally, to calculate relative measures I need to choose a baseline sector and country. For all three datasets, I use the USA as the baseline country. For the sector, I use cereals (HS 10) in the two-digit dataset, durum wheat (HS 1001) in the four-digit dataset, and seed of durum wheat (HS 100111) in the six-digit dataset.

Figure 2 shows that at all three levels of disaggregation, the double indexed RCA measure has the expected positive correlation with each term of the decomposition. The degree of dispersion appears relatively less as the data become more disaggregated. But these bivariate correlations, which do not take account of covariance between the two terms, suggest that the second term—which is not related to comparative advantage in a theoretical sense—potentially plays an important role in determining RCA scores even after double indexing.

Figure 2: Correlations between double indexed RCA and the two decomposition terms



This view is confirmed by a regression approach using the Shapley-Shorrocks decomposition (Table). The second term of the decomposition accounts for between 20% and 60% of the observed variation in the double indexed RCA measure. There is a clear increase in the relationship between double indexed RCA and TCA as the level of disaggregation increases. But even at the six-digit level, the role of the second decomposition term is not negligible: 20% of observed variation in RCA is a substantial proportion. While at higher levels of aggregation, the data show that factors other than TCA in fact account for the bulk of observed variation in RCA. In other words, even indexing RCA by a baseline sector and country does not bring it fully into line with TCA: the measure remains substantially distorted relative to the theoretical benchmark.

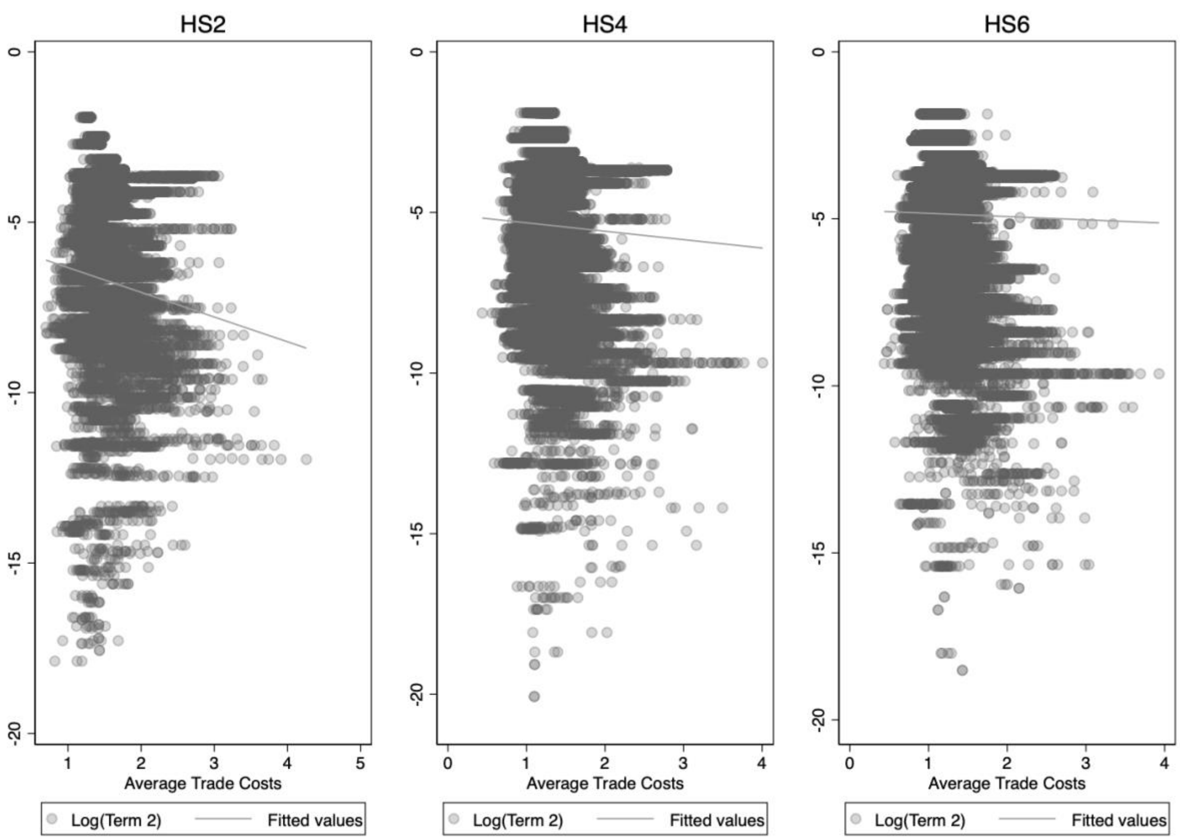
Table 3: Shapley-Shorrocks decomposition of observed variation in standard RCA.

Element	Two-Digit	Four-Digit	Six-Digit
Theoretical Comparative Advantage (Term 1)	39.608%	44.222%	78.925%

Effective Market Potential (Term 2)	60.392%	55.778%	21.075%

Connecting these results with the special case in Section 2.4 shows that the important role of the second decomposition term is due to some combination of missing domestic shipments data, and trade costs that vary by country pair. There is no straightforward way to separate out these two effects in the second term, but Figure 3 shows the correlation in each of the three datasets between simple average trade costs—derived from the country pair fixed effect divided by an indicative trade elasticity of -4.5, and exponentiated—and the second term of the decomposition. There is a clear negative association, which means that exporters facing higher trade costs tend to receive systematically lower RCA scores. However, in line with the results in Table 2, the effect is noticeably attenuated as the data are disaggregated: the correlation is stronger at the two-digit level than at the six-digit level. The conclusion, however, is that the data support an interpretation whereby country-pair specific trade costs play an important role in determining double indexed RCA scores: countries with lower trade costs tend to receive higher RCA scores.

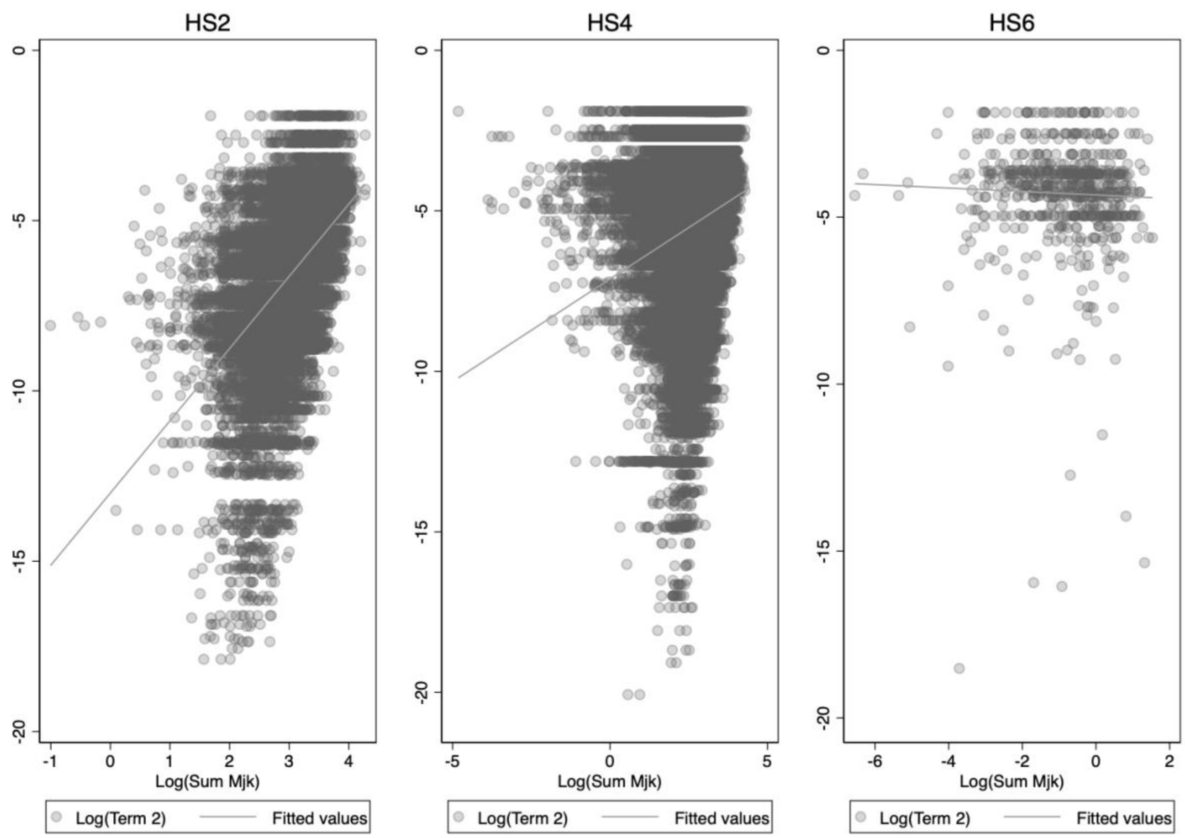
Figure 3: Correlations between the second term of the double indexed RCA decomposition and average country-pair trade costs.



Another way of looking at this issue is to consider it from the perspective of market potential, i.e. the importer-sector terms. I can take the sum for each exporter-sector combination, which is market potential without adjusting for trade costs as in the second term of the decomposition. Figure 4 shows that the association is stronger than for trade costs, although there is still evidence of diminishing importance as the data become more disaggregated; that finding is in line with the results from the

Shapley-Shorrocks decomposition in Table 2. But the key result from the figure is that there is the expected positive correlation between the second term of the decomposition and market potential as measured by the sum of the importer-sector fixed effects for each exporter-sector combination. In other words, in addition to the distortion introduce by pair specific trade costs, there is also evidence that differences in market potential also play a substantial role in distorting RCA relative to the theory-consistent benchmark.

Figure 4: Correlations between the second term of the double indexed RCA decomposition and importer-sector terms.



To get a sense of what these conclusions mean in practice, it is again useful to take some examples from the two-digit dataset.

Taking HS sector 62 (textiles and apparel), Pakistan and Sri Lanka have relatively similar values of term one in the decomposition, 3.759 and 3.848 respectively. But their RCAs are very different: for Pakistan it is 3.145, while it is and 8.342 for Sri Lanka, all in double indexed logarithmic terms. The two countries are different both in terms of the size of the domestic market, but also potentially the trade costs they face, so their second terms are very different—which is what drives the distortion in double indexed RCA relative to TCA (term 1). While there is only a small difference in the degree of comparative advantage as defined using theory, the RCA measure exaggerates that difference substantially.

A second example is from the electrical equipment sector (HS 85). Viet Nam's term one index is equal to 0.077, while that of the Philippines is 0.028. However, the former's double indexed RCA in logarithms is 1.734, compared with the latter's 7.605. In this case, the distortion in the second term of the decomposition in fact inverses the ordering of the two countries given by the theory-based comparative advantage index in the first term. The Philippines has a larger economy than Viet Nam, but it is also possible that the two countries face substantially different trade costs in key markets. Whatever the cause, the distortion in this case is major, since it reverses the ordering given by the theory-based measure. Again, the data clearly support the view that RCA is a substantially distorted measure of comparative advantage, in particular when calculations are made using relatively aggregate data.

4 CONCLUSION

RCA has a long history among applied researchers and policy practitioners. But I have shown that it sits poorly with recent theoretical and empirical work on comparative advantage. By assuming that trade flows are governed by structural gravity, I have been able to show that RCA only coincides with comparative advantage as rigorously understood under very restrictive assumptions that are never met in practice. In particular, variation in trade costs and demand side factors mean that RCA will always contain an element of distortion relative to a theory-consistent index of comparative advantage, such as the one developed by Costinot et al. (2012). More generally, RCA distorts any measure of comparative advantage that is a function of exporter-sector specific factors, which means that the result in fact applies to a broad class of trade models.

Of course, from a policy perspective, the size of that distortion matters. I use standard UN Comtrade data to show that extraneous factors—country size, trade costs, and market potential—account for 20%-60% of the observed variation in RCA, depending on the level of aggregation of the data. So the distortion relative to the theory-consistent measure is substantial, and is therefore potentially associated with misleading policy implications and advice when RCA is used. I have made that point clearly with examples of countries with similar TCA scores but radically different, and even differently ordered, RCA scores.

Thankfully, the literature already has a ready solution to hand, embodied in the first term of my decomposition of RCA. Costinot et al. (2012) provide a rigorous foundation for an index of Ricardian comparative advantage using structural gravity. All that is needed to compute the index is a consistent estimate of exporter-sector fixed effects. The gravity literature provides strong guidance on how to obtain such estimates, and the ubiquity of gravity models in applied work suggests that researchers and analysts are comfortable using them to answer a wide range of trade policy questions. It would be relatively straightforward, therefore, to abandon computing the traditional RCA measure in favor of the gravity-based comparative advantage index. As the analysis in this paper shows, even using a dataset with millions of observations and hundreds of thousands of fixed effects does not pose any particular computational problems for standard hardware and software. An important limitation on this approach, however, is that as French (2017) points out, different approaches to comparative advantage may be warranted when the perspective is not only the assessment of differences in revealed productivity, as here.

As noted at the outset, international organizations such as the World Bank and UNCTAD continue to publicize RCA in their public-facing data portals. My results suggest that doing so is a mistake. There is a strong case for international agencies to take up the work of Leromain and Orefice (2014), and systematically compute and make freely available theory-consistent comparative advantage measures.

In terms of future work, a key dimension for extending my findings here would be to generalize them in terms of the structural gravity literature beyond Costinot et al. (2012), thereby extending the findings of French (2017). That paper uses a particular Ricardian model, but given the strong symmetries found elsewhere in the gravity literature (e.g., Arkolakis et al., 2012; and Costinot and Rodriguez-Clare, 2012), it would not be surprising if multi-sector generalizations of other micro-founded gravity models yield similar interpretations. Such a finding would help deal with the concern that the theory-based index used here is dependent on particular modeling assumptions, and may, or may not, be consistent with a wider range of modeling frameworks.

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