

A Solution to the Missing Globalization Puzzle by Non-CES Preferences*

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Abstract

One channel of welfare-improving globalization is through the increasing integration of trade. Although this is attributed to decreasing effects of distance across countries, the work-horse models of gravity fail to capture it, the so-called the missing globalization or the distance puzzle. This paper shows that this puzzle may be due to the restricting assumption of constant elasticity of substitution (CES) preferences working behind the gravity models. We test the validity of this assumption for different trade intervals and show that it is violated due to the distance elasticity of trade decreasing with the amount of trade. Accordingly, we consider a type of non-CES utility function, namely constant absolute risk version (CARA), and analytically show that the negative relation between trade and distance elasticity of trade is captured by CARA preferences. We estimate the gravity equation implied by CARA preferences, empirically confirm the endogenous relation between trade and distance elasticity of trade, and show that the distance puzzle is solved under CARA preferences. According to the data set used, CARA preferences are also econometrically selected over CES preferences based on their goodness of fit.

JEL Classification F12, F13, F14

Key Words: Distance Puzzle; Non-CES Preferences; CARA Preferences.

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1 Introduction

The international trade literature characterizes welfare-improving globalization as the increasing integration of trade. This integration is mostly attributed to the decreasing effects of distance over time, due to decreasing freight costs over time as shown in Figure 1.¹ Puzzlingly, however, evidence of long-distance trade integration is nowhere to be found in the estimates of the distance elasticity derived from standard workhorse models of international trade (a.k.a. "gravity" models). As is now well-documented (see, e.g., Disdier and Head, 2008), gravity estimates of the elasticity of trade with respect to distance have continually and regularly been found to be non-decreasing (or even increasing) over time. In other words, despite vast improvements in transportation and communication technologies over the latter half of the twentieth century, standard gravity regressions still find that these innovations have done nothing to make long-distance trade more feasible relative to trade over shorter distances. This has been referred to in the literature as the "missing globalization" puzzle (Coe et al., 2007) or "distance puzzle." Since the estimates of the distance elasticity may also be capturing other unobservable trends in trade costs such as falling costs of long-distance commercial flights (as in Yilmazkuday and Yilmazkuday, 2016), long-distance phone calls or internet (as in Clarke and Wallsten, 2006), and the spread of the English language (as in Ku and Zussman, 2010), the presence of the distance puzzle is even more surprising.

Accordingly, many studies in the literature have attempted to find a solution to this puzzle. In order to explain the severity of the puzzle, Buch et al. (2004) have argued that the effects

¹Figure 1 shows ad valorem freight rates for air and ocean transportation individually; however, it does not provide any information regarding their share in global trade. In particular, if the share of air transportation were increasing over time, the weighted average of these two ad valorem freight rates would be increasing. Nevertheless, considering the low share of air transportation in global trade as indicated by Hummels (2007) and Hummels and Schaur (2013), one can safely claim that the weighted average of these two ad valorem freight rates are also decreasing over time.

of globalization are captured by the constant in gravity regressions, Portes and Rey (2005) have introduced information barriers, Brun et al. (2005) have considered an augmented trade barrier function, Engel (2002) have focused on the role of nontradables sectors, Estevadeordal et al. (2003) have considered possible increases in marginal costs of transportation with respect to of production, Berthelon and Freund (2008) have investigated the role of composition of trade among industries, Felbermayr and Kohler (2006) have taken into account zero-trade observations, Head et al. (2009) have included fixed effects in their regressions to account for trading propensities of entrants, Yotov (2012) has considered the increase in international economic integration relative to the integration of internal markets, and Yilmazkuday (2014a) has considered the internal location of production of exporters.² Although some of these studies have found decreasing coefficients of distance over time, they have drawbacks of either requiring additional data sets (of which construction is achieved by alternative proxies) or finding minor reductions in the distance elasticity of trade compared to the expectations arising from Figure 1. Moreover, despite finding a possible solution through an augmented trade barrier function, Brun et al. (2005) have shown that the puzzle remains when their sample is split according to the income level of countries, suggesting that distance elasticity of trade may be determined endogenously (i.e., changes with the amount of trade).

Using a standard data set in the gravity literature in the context of a demand-side model, this paper first confirms that there is a distance puzzle by showing that the distance elasticity of trade (in absolute terms) is increasing over time when constant elasticity of substitution (CES) preferences are considered, which would be case in the context of a supply-side model as well if a CES production function is employed as in Redding and Venables (2004). This result is robust to the consideration of different measures of distance (e.g., distance between capital cities, most agglomerated cities, or

²See also Disdier and Head (2008) for a meta analysis covering earlier studies on the effects of distance on bilateral trade.

population weighted measures) as well as the consideration of distance intervals as in Eaton and Kortum (2002). We claim that this result may be due to the structure of CES preferences literally implying a *constant* elasticity of substitution and a log-linear gravity relation between trade and distance. In particular, if distance elasticity of trade is endogenously determined (i.e., changes with the amount of trade, as implied by Brun et al., 2005), this would violate the assumption of CES and thus lead to biased empirical results. We test this hypothesis by differentiating the distance elasticity of trade across different trade intervals (e.g., distance elasticity of trade regarding trade smaller and larger than the median trade) for each year individually. This is a similar approach taken by Head and Mayer (2013) who have shown that the distance puzzle is less pronounced as the expected level of trade rises. Independent of the number of intervals considered, our results show that the (absolute value of) distance elasticity of trade systematically decreases with the amount of trade for each individual year. Therefore, the assumption of CES is violated for each year in our sample, and this may result in biased estimates of the distance elasticity of trade leading to the distance puzzle. Hence, an alternative modeling approach is required that will lead to endogenously determined distance elasticity of trade that decreases (in absolute value) with respect to the amount of trade. In the existing literature, alternative explanations to similar results have been achieved by studies such as by Head and Mayer (2013) who argue that distance effects may be rising because of a combination of changing participation in trade and a non-constant trade cost elasticity; in this paper, we focus on a similar approach by using the implications of a demand-side investigation.³

Accordingly, we introduce a type of non-CES preferences, namely constant absolute risk aver-

³Also see Dutt et al. (2004) who argue that the distance puzzle can be explained by the fact that the growth of world trade is due to the growth of the trade among countries that used to trade with each other historically. Larch et al. (2015) argue that on top of the changing participation in trade, ignoring the heterogeneity of exporter firms may result in an omitted variable bias.

sion (CARA), to investigate an alternative structural relation between trade and distance, namely a lin-log gravity-type relationship, which is obtained by endogenously determined elasticity of substitution as the name *non-CES* literally implies.⁴ The key innovation is that under CARA preferences, the distance elasticity of trade is shown to be endogenously determined and decreasing with the quantity traded, which is exactly what we are looking for. We test the lin-log gravity relation implied by CARA preferences using exactly the same data set that we use for CES preferences and show that the distance puzzle is solved under CARA preferences because of the negative effects of distance decreasing over the sample period. On top of solving the distance puzzle, we also show that CARA preferences are econometrically selected over CES preferences based on their goodness of fit.

Compared to the recent literature, this paper is closest to the study by Novy (2013) who shows that translog utility functions lead to endogenously determined distance elasticity of trade, as in this paper. Nevertheless, this paper deviates from Novy's analysis by considering the implications of endogenously determined distance elasticities of trade on the distance puzzle (i.e., the effects of distance on trade over time) using a panel data between 1970 and 2005, while Novy has a static model/investigation using cross-sectional data for the year 2000. The rest of the paper is organized as follows. The next section introduces the data. Section 3 investigates the relation between distance and trade under CES preferences, confirms the existence of the distance puzzle, and searches for possible reasons behind it. Section 4 introduces non-CES preferences and solves the distance puzzle. Section 5 compares the explanatory power of the regressions based on CES and non-CES preferences. Section 6 achieved further robustness analyses. Section 7 concludes. The

⁴CARA preferences have been introduced to the literature as a source of endogenous elasticities of substitution by Behrens and Murata (2007). Several other papers, including Behrens and Murata (2012a,b), Behrens et al. (2014), Yilmazkuday (2014b, 2015, 2016), have considered these preferences under different contexts.

Appendix depicts data sources and provide the technical details of certain derivations.

2 Data

In order to be consistent with the existing literature and the sample period in Figure 1 showing the reduction in trade costs over time, we use the trade data set of Rose and Spiegel (2011) that covers the annual *real* FOB exports between 1970 and 2005 for 196 territories and localities (that we call "countries" in general).⁵ The exact data sources for each variable used in the regressions are provided in the Appendix.

Since this paper is based on the distance puzzle, the distance variable requires additional attention. The distance variable in Rose and Spiegel (2011) is the great circle distance that has been constructed using the location of countries given in CIA World Factbook. We use this distance measure as our benchmark measure.

For robustness, following Eaton and Kortum (2002), we also consider a non-parametric approach by replacing the great circle distance measure by six dummies corresponding to distance intervals of [0,375), [375,750), [750,1500), [1500,3000), [3000,6000), [6000,maximum) in miles (that we call Distance Interval #1–#6, respectively).

For further robustness, we also consider four bilateral distance indicators in the economic geography database of CEPII (Centre d'études prospectives et d'informations internationales).⁶ In this paper, "Distance Measure #1" is the great circle distance calculated using latitudes and longitudes of the most important cities/agglomerations (in terms of population), "Distance Measure #2" is the great circle distance calculated using latitudes and longitudes of the capital cities, and, finally,

⁵We start the investigation in 1970 since it is the starting year of data collection for several countries in the sample.

⁶See Mayer and Zignago (2011).

"Distance Measure #3" and "Distance Measure #4" are the great circle distance measures that are the population-weighted according to the cities/agglomerations in the source and destination countries.

3 The Distance Puzzle: CES Preferences

This section depicts the distance puzzle when CES preferences are considered. Accordingly, we consider a model characterized by destination countries consuming/optimizing imports from a finite number of exporters. Each exporter maximizes its profits by following a pricing-to-market strategy. Since we do not have/use any production data, to keep the model as simple as possible, we only focus on the trade implications of having a CES utility function.

3.1 Importers under CES Preferences

A typical importer in destination country d has the following CES utility $U_{d,t}$ out of consuming goods coming from different source countries, each denoted by s :

$$U_{d,t} = \sum_s \chi_{d,t}^s (q_{d,t}^s)^{1-\theta}$$

where $q_{d,t}^s$ is the quantity of products imported from country s , $\theta > 0$ represents a parameter (to be connected to the distance elasticity of trade, below), and $\chi_{d,t}^s$ represents a source-destination-time specific taste parameter.⁷ Maximizing utility subject to the budget constraint given by $\sum_s p_{d,t}^s q_{d,t}^s = E_{d,t}$ (where $E_{d,t}$ is the total expenditure of destination country d at time t) results in the following demand function:

$$q_{d,t}^s = E_{d,t} \left(\frac{\chi_{d,t}^s}{p_{d,t}^s} \right)^{\frac{1}{\theta}} \left(\sum_{s'} \frac{(\chi_{d,t}^{s'})^{\frac{1}{\theta}}}{(p_{d,t}^{s'})^{\frac{1-\theta}{\theta}}} \right)^{-1} \quad (1)$$

⁷In particular, this utility implies constant relative risk aversion. Behrens and Murata (2007) have shown the correspondence between CRRA and CES preferences; we confirm this relation, below, as well.

According to the demand function, after assuming that individual source countries have negligible impact on the destination price aggregates, the (absolute value of) the elasticity of substitution between the products imported from source countries s and s' can be obtained as follows:

$$\sigma_{d,t}^s(q_{d,t}^s, q_{d,t}^{s'}) = \frac{d \ln \left(\frac{q_{d,t}^s}{q_{d,t}^{s'}} \right)}{d \ln \left(\frac{dU_{d,t}}{dq_{d,t}^{s'}} \middle/ \frac{dU_{d,t}}{dq_{d,t}^s} \right)} = \frac{1}{\theta} \quad (2)$$

which confirms that our utility function corresponds to CES preferences.

3.2 Exporters under CES Preferences

Considering the demand function given by Equation 1, each source/exporter country s follows a pricing-to-market strategy by maximizing the profit out of sales to the destination/importer country d :

$$\pi_{d,t}^s = q_{d,t}^s (p_{d,t}^s - c_{d,t}^s)$$

where $c_{d,t}^s$ is the source-destination specific marginal cost in country s at time t . We further assume that overall marginal costs are given by:

$$c_{d,t}^s = w_t^s \tau_{d,t}^s \quad (3)$$

where w_t^s represents the marginal cost of production at the source country (that is common across destinations), and $\tau_{d,t}^s$ represents (gross) multiplicative trade costs that are source-destination specific. The profit maximization problem results in the following pricing strategy under CES preferences:

$$p_{d,t}^s = c_{d,t}^s \mu_{d,t}^s = \frac{c_{d,t}^s}{1 - \theta} \quad (4)$$

where (gross) markups denoted by $\mu_{d,t}^s = \frac{1}{1 - \theta}$ are constant across destination countries and time (i.e., $\mu_{d,t}^s = \mu$ for all s, d, t).

3.3 Distance Elasticity of Trade under CES Preferences

Following the empirical international trade literature, trade costs are connected to distance according to the following specification:

$$\tau_{d,t}^s = (D_d^s)^{\kappa_t} \phi_{d,t}^s \quad (5)$$

where D_d^s is the distance between source country s and destination country d , κ_t is the distance elasticity of trade costs, and $\phi_{d,t}^s$ represents trade costs that are not related to distance. If we substitute this expression into Equation 1 using Equations 3 and 4, we can obtain the following expression for the distance elasticity of trade under CES preferences:

$$\delta_{d,t}^s = \frac{\partial q_{d,t}^s}{\partial D_d^s} \frac{D_d^s}{q_{d,t}^s} = -\frac{\kappa_t}{\theta} \quad (6)$$

which is only time varying (i.e., $\delta_{d,t}^s = \delta_t$ for all s, d) but does not depend on the quantity traded due to the homotheticity implication of CES preferences.

Note that the distance elasticity of trade δ_t under CES preferences is a function of two parameters, the elasticity of substitution $\frac{1}{\theta}$ and the distance elasticity of trade costs κ_t . The elasticity of substitution $\frac{1}{\theta}$ is assumed to be constant over time to be literally consistent with the definition of CES; if the elasticity of substitution is thought to be time varying (e.g., as in Archanskaia and Daudin, 2012), then this should be modeled properly (i.e., the elasticity of substitution should be endogenized) in order to avoid explaining everything with parameter heterogeneity, which may lead to biased results.⁸ Therefore, the time varying nature of δ_t is purely determined by κ_t under CES preferences. Within this context, recall that trade costs $\tau_{d,t}^s$ are decreasing over time according to Figure 1, and since distance D_d^s is a measure that is time invariant, it is expected that κ_t and thus

⁸Parameter heterogeneity leads to biased results when elasticities are in fact determined endogenously, because parameter heterogeneity can only capture the specific part of the data under consideration rather than providing a framework that can be used for any counterfactual analysis. One solution to this problem is to make the elasticities endogenous in an analytical way, as we achieve in this paper through non-CES preferences, below.

(the absolute value of) δ_t would be decreasing over time as well. We test this expectation in the next subsection.

3.4 Estimation under CES Preferences

Combining Equations 1, 3, 4 and 5 results in the following log-linear expression for trade (which is in real terms, consistent with our trade data) after taking log of both sides:

$$\begin{aligned}
 \log q_{d,t}^s = & - \underbrace{\frac{\kappa_t}{\theta} \log D_d^s}_{\text{Time Varying Distance Effects}} - \underbrace{\frac{\log w_t^s}{\theta}}_{\text{Source and Time Fixed Effects}} - \underbrace{\frac{\log \phi_{d,t}^s}{\theta}}_{\text{Other Trade Costs}} \\
 & + \underbrace{\log \left(E_{d,t} \left(\sum_{s'} \frac{(\chi_{d,t}^{s'})^{\frac{1}{\theta}}}{(p_{d,t}^{s'})^{\frac{1-\theta}{\theta}}} \right)^{-1} \left(\frac{1}{1-\theta} \right)^{-\frac{1}{\theta}} \right)}_{\text{Destination and Time Fixed Effects}} + \underbrace{\frac{\log \chi_{d,t}^s}{\theta}}_{\text{Residuals}}
 \end{aligned} \tag{7}$$

where the existence of source-and-time and destination-and-time fixed effects would capture the implications of many general equilibrium models as shown in studies such as by Arkolakis et al. (2012). Such fixed effects would also control for any intermediate input trade as in studies such as by Redding and Venables (2004); i.e., when intermediate-input production is represented by an Armington-CES production function, a very similar expression as in Equation 7 can be obtained through optimization. Therefore, a demand-side derivation through CES preferences (as employed in this paper) is not the only approach to have such a regression analysis; a supply-side derivation through a CES production function would have very similar implications under certain assumptions.

In order to be consistent with the gravity literature, we proxy trade costs that are not related

to distance between source and destination countries (i.e., $\log(\phi_{d,t}^s)$) according to:

$$\log(\phi_{d,t}^s) = bo_{d,t}^s + la_{d,t}^s + pl_{d,t}^s + is_{d,t}^s + coc_{d,t}^s + sn_{d,t}^s + ec_{d,t}^s + cuc_{d,t}^s + cu_{d,t}^s + rta_{d,t}^s \quad (8)$$

where $bo_{d,t}^s$ is the effect of sharing a land border, $la_{d,t}^s$ is the effect of sharing a language, $pl_{d,t}^s$ is the effect of the log product of land areas, $is_{d,t}^s$ is effect of the number of island countries in pair, $coc_{d,t}^s$ is the effect of being colonized by the same country, $sn_{d,t}^s$ is the effect of s and d being the a part of a same nation, $ec_{d,t}^s$ is the effect of s or d being ever colonized by the other one, $cuc_{d,t}^s$ is the effect of s and d currently being in a colonial relationship, $cu_{d,t}^s$ is the effect of using the same currency, and $rta_{d,t}^s$ is the effect of s and d having a regional trade agreement. On top of these variables, since we have source-and-time fixed effects together with destination-and-time fixed effects (capturing time varying country-specific effects such as GDP, population, multilateral resistance terms, etc.), Equation 7 is a typical log-linear gravity equation.

We estimate Equation 7 for each time period individually.⁹ We consider alternative distance measures for robustness as discussed in the data section. We start with using the great circle distance calculated according the coordinates given in CIA World Factbook (as in Rose and Spiegel, 2011). The estimated distance elasticities of trade over time (i.e., δ_t 's) are given in Figure 2a where the negative effects of distance have increased about 50% over the sample period. According to Equation 6 and the following discussion, this corresponds to increasing κ_t 's over time, which is against the expectations of decreasing κ_t 's over time because of having decreasing trade costs over

⁹Since taste parameters act as residuals, such a strategy corresponds to having independent taste shocks across years. Employing taste parameters as residuals brings two restrictions both of which have no conflicts with the model and the results in this paper: (i) the sum of $\log \chi_{d,t}^s$'s is zero (i.e., the multiplication of $\chi_{d,t}^s$'s is one) in each year; (ii) $\log \chi_{d,t}^s$'s are orthogonal to the other right hand side variables (i.e., taste parameters will capture the pattern of trade that cannot be explained by gravity-type variables) for each year. Such a strategy is not new to this paper: Hillberry et al. (2005) and Yilmazkuday (2012) have also used this strategy in different contexts.

time according to Figure 1. This is what the literature has called the distance puzzle.

Since this result (i.e., the distance puzzle) may be due to the distance measure that we have, following Eaton and Kortum (2002), we also consider a non-parametric approach by replacing the great circle distance measure by six dummies corresponding to distance intervals of $[0,375)$, $[375,750)$, $[750,1500)$, $[1500,3000)$, $[3000,6000)$, $[6000,\text{maximum})$ in miles. Due to using other dummies (i.e., other fixed effects in the regression), only five of the coefficients in front of these dummies can be identified. The results are given in Figures 2b-2f. As is evident, for all distance intervals, we again observe the distance puzzle, because the negative effects of distance have increased over the sample period.

Finally, we also consider several other alternative distance measures obtained from CEPII (as explained in the data section). The results are given in Figure 3 for four different distance measures where we again see increasing negative effects of distance over time. Therefore, independent of the distance measure used, we have confirmed that there is a distance puzzle when CES preferences are considered, because the decreasing trade costs (according to Figure 1) are not reflected by the decreasing negative effects of distance.

3.5 Trade Intervals and Distance Elasticity of Trade

We think that the distance puzzle may be due to the structure of CES preferences literally implying a *constant* elasticity of substitution (i.e., $\frac{1}{\theta}$ in Equation 2) and thus a log-linear relation between trade and distance (in Equation 7) with a coefficient of distance changing only through time (i.e., $\frac{\kappa_t}{\theta}$ is time specific). In other words, what if the elasticity of substitution $\frac{1}{\theta}$ is not constant and changes with the amount of trade (i.e., it is endogenously determined)? In such a case, this would be reflected in the estimated distance elasticity of trade $\frac{\kappa_t}{\theta}$ as well, and $\frac{\kappa_t}{\theta}$ would change with the amount of trade, given κ_t . We test this hypothesis for each time period individually (to control for

time varying κ_t 's). In particular, for each time period, we split the trade data into equal intervals (e.g., trade smaller and larger than median trade) and test whether the estimated coefficients in front of distance change for different trade intervals according to the following modified version of Equation 7:

$$\begin{aligned}
 \log q_{d,t}^s = & - \underbrace{\sum_i \frac{\kappa_t}{\theta} \log D_d^s(i)}_{\text{Time Varying Distance Effects}} - \underbrace{\frac{\log w_t^s}{\theta}}_{\text{Source and Time Fixed Effects}} - \underbrace{\frac{\log \phi_{d,t}^s}{\theta}}_{\text{Other Trade Costs}} \\
 & + \underbrace{\log \left(E_{d,t} \left(\sum_{s'} \frac{(\chi_{d,t}^{s'})^{\frac{1}{\theta}}}{(p_{d,t}^{s'})^{\frac{1-\theta}{\theta}}} \right)^{-1} \left(\frac{1}{1-\theta} \right)^{-\frac{1}{\theta}} \right)}_{\text{Destination and Time Fixed Effects}} + \underbrace{\frac{\log \chi_{d,t}^s}{\theta}}_{\text{Residuals}}
 \end{aligned} \tag{9}$$

where $D_d^s(i)$ corresponds to distance between source and destination countries if the trade between these countries is within the trade interval i considered, and all other variables remain the same. We again estimate this equation for each time period individually. For robustness, we consider alternative trade intervals as well.

The results are given in Figure 4 where, for each year, the estimated value of the distance elasticity of trade changes significantly across alternative trade intervals; in particular, for each year, the (absolute value of) distance elasticity of trade decreases with the amount of trade. Therefore, for each year, the distance elasticity of trade is endogenously determined and thus the assumption of CES is violated.¹⁰ If the main assumption of having CES preferences is violated for each year (i.e., a cross-sectional violation of the CES assumption), we would like to investigate whether relaxing

¹⁰It is important to emphasize that the time path of the estimated elasticities in the graphs of Figure 5 does not provide any information for the distance puzzle itself, because comparing the distance elasticity of trade for different trade intervals over time does not have any economic intuition. Nevertheless, the cross-section evidence for each time period (i.e., the absolute value of distance elasticity of trade decreasing with the amount of trade) is the key here.

this assumption has any implications for the distance puzzle, which we achieve next.

4 Solving the Puzzle: Non-CES Preferences

This section solves the distance puzzle by relaxing the assumption of CES preferences. In particular, as shown in the previous section, having CES preferences imply homotheticity so that the elasticity measures and implied markups do not depend on the quantity traded. However, Figures 4a-4d show that the distance elasticity of trade change significantly when quantity traded changes. Moreover, the recent literature has shown the importance of variable markups in understanding the welfare gains from trade.¹¹ Accordingly, in order to have implications consistent with Figures 4a-4d and the recent literature on variable markups, we relax the assumption of CES such that the (absolute value of) distance elasticity of trade will decrease with the amount of trade. We achieve this by considering a type of non-CES preferences, namely CARA, to investigate an alternative implied structural relation between trade and distance, namely a lin-log relationship, which is obtained by endogenously determined elasticity of substitution as the name *non-CES* literally implies.

As in the CES case, consider a model characterized by destination countries consuming/optimizing imports from a finite number of exporters. Each exporter maximizes its profits by following a pricing-to-market strategy. Since we do not have/use any production data, to keep the model as simple as possible, we only focus on the trade implications of having a CARA utility function.

¹¹See Arkolakis et al. (2015) and the citations therein.

4.1 Importers under Non-CES Preferences

A typical importer in destination country d has the following CARA utility $U_{d,t}$ out of consuming goods coming from different source countries, each denoted by s :

$$U_{d,t} = \sum_s \chi_{d,t}^s (1 - e^{-\theta q_{d,t}^s})$$

where $q_{d,t}^s$ is the quantity of products imported from country s , $\theta > 0$ represents a parameter (to be connected to the distance elasticity of trade, below), and $\chi_{d,t}^s$ represents a source-destination-time specific taste parameter. Maximizing utility subject to the budget constraint given by $\sum_s p_{d,t}^s q_{d,t}^s = E_{d,t}$ (where $E_{d,t}$ is again the total expenditure of destination country d at time t) results in the following demand function:

$$q_{d,t}^s = \left(\frac{E_{d,t} - \frac{1}{\theta} \sum_{s'} \log \left(\frac{p_{d,t}^s \chi_{d,t}^{s'}}{p_{d,t}^{s'} \chi_{d,t}^s} \right) p_{d,t}^{s'}}{\sum_{s'} p_{d,t}^{s'}} \right) \quad (10)$$

According to the demand function, after assuming that individual source countries have negligible impact on the destination price aggregates, the (absolute value of) the elasticity of substitution between the products imported from source countries s and s' can be obtained as follows:

$$\sigma_{d,t}^s (q_{d,t}^s, q_{d,t}^{s'}) = \frac{d \log \left(\frac{q_{d,t}^s}{q_{d,t}^{s'}} \right)}{d \log \left(\frac{dU_{d,t}}{dq_{d,t}^{s'}} \Big/ \frac{dU_{d,t}}{dq_{d,t}^s} \right)} = \frac{1}{\theta q_{d,t}^s} \quad (11)$$

which confirms that the elasticity of substitution $\sigma_{d,t}^s$ changes with quantity $q_{d,t}^s$; therefore, CARA corresponds to (a type of) non-CES preferences.

4.2 Exporters under Non-CES Preferences

Considering the demand function given by Equation 10, each source/exporter country s follows a pricing-to-market strategy by maximizing the profit out of sales to destination/importer country d :

$$\pi_{d,t}^s = q_{d,t}^s (p_{d,t}^s - c_{d,t}^s)$$

where $c_{d,t}^s$ is the source-destination specific marginal cost in country s at time t . We again assume that overall marginal costs are given by:

$$c_{d,t}^s = w_t^s \tau_{d,t}^s \quad (12)$$

where w_t^s represents the marginal cost of production at the source country (that is common across destinations), and $\tau_{d,t}^s$ represents (gross) multiplicative trade costs that are source-destination specific. The profit maximization problem results in the following pricing strategy under CARA preferences:

$$p_{d,t}^s = c_{d,t}^s \mu_{d,t}^s = \frac{c_{d,t}^s}{1 - \theta q_{d,t}^s} \quad (13)$$

where (gross) markups denoted by $\mu_{d,t}^s = \frac{1}{1 - \theta q_{d,t}^s}$ increase with respect to the quantity sold across countries and time; i.e., markups are variable. By using the approximation of $\log(1 + x) \approx x$, especially when x is very small (which is consistent with studies such as De Loecker and Warzynski, 2012, estimating markups as low as 1.03, or Yilmazkuday, 2013, and Yilmazkuday, 2015, estimating markups about 1.04 and 1.03, respectively, under CARA preferences, each using a different data set), log markups can further be written as follows:

$$\log \mu_{d,t}^s = \log \left(\frac{1}{1 - \theta q_{d,t}^s} \right) = -\log(1 - \theta q_{d,t}^s) \approx \theta q_{d,t}^s \quad (14)$$

We will consider this approximation for the rest of the paper for simplicity (i.e., to obtain a linear trade equation that we can estimate). Nevertheless, in the Appendix, we relax this approximation and show that it does not change the results of this paper.

4.3 Distance Elasticity of Trade under Non-CES Preferences

Following the empirical international trade literature, as in the case of CES above, trade costs are connected to distance according to Equation 5. If we substitute Equation 5 into Equation 10 using

Equations 12, 13 and 14, we can obtain the following lin-log expression (of which details are given in the Appendix):

$$q_{d,t}^s = -\frac{\kappa_t}{2\theta} \log D_d^s - \frac{1}{2\theta} \log (w_t^s \phi_{d,t}^s) + \left(\frac{E_{d,t} - \frac{1}{\theta} \sum_{s'} \log \left(\frac{\chi_{d,t}^{s'}}{p_{d,t}^{s'}} \right) p_{d,t}^{s'}}{2 \sum_{s'} p_{d,t}^{s'}} \right) + \frac{\log \chi_{d,t}^s}{2\theta} \quad (15)$$

which implies the following distance elasticity of trade under CARA preferences:

$$\delta_{d,t}^s = \frac{\partial q_{d,t}^s}{\partial D_d^s} \frac{D_d^s}{q_{d,t}^s} = -\frac{\kappa_t}{2\theta q_{d,t}^s} \quad (16)$$

which change with respect to quantity traded across countries and time; i.e., the distance elasticity of trade is endogenously determined, consistent with the results in Figure 4 (as discussed, above).

4.4 Estimation under Non-CES Preferences

The lin-log expression for trade (which is in real terms, consistent with our trade data) given by Equation 15 can be rewritten as follows:

$$q_{d,t}^s = - \underbrace{\frac{\kappa_t}{2\theta} \log D_d^s}_{\text{Time Varying Distance Effects}} - \underbrace{\frac{1}{2\theta} \log w_t^s}_{\text{Source and Time Fixed Effects}} - \underbrace{\frac{1}{2\theta} \log \phi_{d,t}^s}_{\text{Other Trade Costs}} + \underbrace{\left(\frac{E_{d,t} - \frac{1}{\theta} \sum_{s'} \log \left(\frac{\chi_{d,t}^{s'}}{p_{d,t}^{s'}} \right) p_{d,t}^{s'}}{2 \sum_{s'} p_{d,t}^{s'}} \right)}_{\text{Destination and Time Fixed Effects}} + \underbrace{\frac{\log \chi_{d,t}^s}{2\theta}}_{\text{Residuals}} \quad (17)$$

where, as in the case of CES, $\log (\phi_{d,t}^s)$ is given by Equation 8. Therefore, as in Yilmazkuday (2013, 2014b, 2015), we have shown that CES preferences correspond to log-linear gravity regressions,

while CARA preferences correspond to lin-log gravity regressions. More specifically, having CES versus non-CES preferences corresponds to having trade in logs versus levels on the left hand side of the estimated gravity equations, where the right hand side variables are exactly the same.

In order to estimate Equation 17, we follow exactly the same estimation strategy and data set as in the case of CES. The estimation results for the coefficient in front of log distance (i.e., $\frac{\kappa_t}{2\theta}$'s), which is *not* equal to the distance elasticity of trade according to Equation 16, are given in Figure 5a. We first have to show that using CARA preferences gets rid of the bias we have under CES preferences as shown in Figures 4b-4d; i.e., we have to show that $\frac{\kappa_t}{2\theta}$'s do not depend on the trade intervals considered. Accordingly, for each time period, we again split the trade data into equal intervals (e.g., trade smaller and larger than median trade) and test whether the estimated coefficients in front of distance change for different trade intervals according to the following modified version of Equation 17:

$$\begin{aligned}
 q_{d,t}^s = & - \underbrace{\sum_i \frac{\kappa_t}{2\theta} \log D_d^s(i)}_{\text{Time Varying Distance Effects}} - \underbrace{\frac{1}{2\theta} \log w_t^s}_{\text{Source and Time Fixed Effects}} - \underbrace{\frac{1}{2\theta} \log \phi_{d,t}^s}_{\text{Other Trade Costs}} \\
 & + \underbrace{\left(\frac{E_{d,t} - \frac{1}{\theta} \sum_{s'} \log \left(\frac{\chi_{d,t}^{s'}}{p_{d,t}^{s'}} \right) p_{d,t}^{s'}}{2 \sum_{s'} p_{d,t}^{s'}} \right)}_{\text{Destination and Time Fixed Effects}} + \underbrace{\frac{\log \chi_{d,t}^s}{2\theta}}_{\text{Residuals}}
 \end{aligned} \tag{18}$$

where $D_d^s(i)$ again corresponds to distance between source and destination countries if the trade between these countries is within the trade interval i considered, and all other variables remain the same. We again estimate this equation for each time period individually. For robustness, we consider alternative trade intervals as well. The results are given in Figures 5b-5d, which all show

that the estimated $\frac{\kappa_t}{2\theta}$'s do not depend on the trade intervals in a systematic way. Compared to the dependence of the distance elasticity of trade (under CES preferences) to trade intervals in Figures 4b-4d, estimated $\frac{\kappa_t}{2\theta}$'s in Figures 5b-5d are much more consistent with each other across different trade intervals, especially after considering their confidence intervals (e.g., for several time periods, the confidence intervals of $\frac{\kappa_t}{2\theta}$'s overlap with each other across different trade intervals). Therefore, CARA preferences perform much better than CES preferences in terms of correcting the estimation bias due to trade intervals.

Having the estimated coefficients in front of log distance (i.e., $\frac{\kappa_t}{2\theta}$'s) for all time periods, we further use them to construct the distance elasticities of trade $\delta_{d,t}^s$'s according to Equation 16 by also using trade data for $q_{d,t}^s$'s. However, the obtained $\delta_{d,t}^s$'s are source-destination-time specific because of their endogenous structure. Therefore, we have to come up with a strategy to make the estimated distance elasticity of trade under CARA preferences comparable to the estimates under CES preferences. Accordingly, we construct time-specific distance elasticities of trade for CARA preferences by considering the weighted average of estimated distance elasticities of trade that are source-destination-time specific:

$$\delta_t = \sum_{s,d} \omega_{d,t}^s \delta_{d,t}^s \quad (19)$$

where $\omega_{d,t}^s$ represents the weight measured according to the trade between countries s and d at time d with respect to the world trade for each time period:

$$\omega_{d,t}^s = \frac{q_{d,t}^s}{\sum_{s,d} q_{d,t}^s} \quad (20)$$

The estimated distance elasticities of trade over time (i.e., δ_t 's) are given in Figure 6a when CIA World Factbook (as in Rose and Spiegel, 2011) coordinates are used to create the great circle distance. As is evident, the negative effects of distance have decreased about 50% over the sample period according to CARA preferences. This is consistent with distance capturing the decreasing

negative effects of trade costs according to Figure 1; therefore, CARA preferences solve the distance puzzle.

This result is also robust to the consideration of alternative distance measures. In particular, Figures 6b-6f replicate Figures 2b-2f under CARA preferences and depict that the distance puzzle is solved when distance intervals suggested by Eaton and Kortum (2002) are used as well. Finally, in Figure 7, distance elasticities of trade δ_t 's estimated using alternative distance measures obtained from CEPII also confirm that the distance puzzle is solved under CARA preferences.

Therefore, independent of the distance measure used, we have confirmed that considering a log relation between trade and distance implied by CARA preferences solve the distance puzzle, because the decreasing trade costs (according to Figure 1) are reflected by the decreasing negative effects of distance over time.

5 Model Selection: CES versus CARA

We have so far found evidence for the distance puzzle under CES preferences and for a solution to the distance puzzle under CARA preferences. However, in econometric terms, which model is better? In order to answer this question, we need to compare the goodness of fit across these models.

One problem with this comparison is the fact that we have different dependent variables in Equations 7 and 17, namely *log* of trade and *level* of trade; therefore, the R-squared values cannot be directly compared with each other. A textbook solution to this problem (e.g., see Wooldridge, 2013, Chapter 6) can be defined as follows: (1) Estimate Equation 7, which has log of trade as the dependent variable, and calculate the fitted values. (2) Take the exponential of the fitted values. (3) Calculate the R-squared of Equation 7 that can be compared to the R-squared of Equation 17 as the square of the correlation between the level of trade and the exponential of the fitted values

found in the previous step.

This methodology results in obtaining an R-squared value for Equation 7 that can be compared with the R-squared of Equation 17. In other words, these comparable R-squared values represent the explained sum of squared over the total sum of squares for the *level* of trade (rather than the *log* of trade). These comparable R-squared values are given in Figure 8 for all the regressions that we have run so far. As is evident, in all regressions, the explanatory power of CARA preferences is above the explanatory power of CES preferences on average (across time). Therefore, CARA preferences not only solve the distance puzzle but are also econometrically selected over CES preferences according to our data set.

Finally, the R-squared values for CARA preferences (when the *level* of trade is the dependent variable) are about 0.40 on average, which may seem lower compared to the existing studies in the literature. However, it is important to emphasize that these R-squared values for CARA preferences should not be compared to the R-squared values obtained for CES preferences (when the *log* of trade is the dependent variable) in the literature. To give the reader a comparison point with respect to the literature, the raw R-squared values for CES preferences (i.e., before making them comparable to the R-squared values for CARA preferences) are about 0.71 on average, which are in line with Rose and Spiegel (2011) that we have borrowed the trade data from. Since CARA preferences are econometrically selected over CES preferences when R-squared values for the level of trade are compared in Figure 8, we can safely claim that the goodness of fit under CARA preferences are even higher compared to the typical gravity studies in the literature.

6 Further Robustness Analyses

The analysis that we have achieved so far has been based on the observations in the trade data set of Rose and Spiegel (2011) between 1970 and 2005. However, there may be two potential concerns regarding this data set. One concern is about the number of country pairs in each year. In particular, if different country pairs are used in the estimations between 1970-2005, the effects of distance may be representing different country pairs in our calculations above. In this section, as a further robustness analysis, we restrict our investigation to a balanced panel between 1970-2015, where the same country pairs are used in the estimations across years. Another concern is about the zero-trade observations that are not included in our data set. Since distance may be effective on such zero-trade observations as well, we also achieve another robustness analysis by considering such observations in this section.

6.1 Results Based on a Balanced Panel

When the data are restricted to have the very same country pairs between 1970-2005, the corresponding results are given in Figure 9, where the benchmark great circle distance is used as the measure of distance. As is evident, there is still evidence for negative effects of distance increasing about 50% over the sample period (as in Figure 2). When the results based on CARA preferences are considered in Figure 9, the negative effects have decreased over the sample period (as in Figure 6). Therefore, the results are robust to the consideration of a balanced panel. When the goodness of fit is compared across CES and CARA preferences in Figure 9 (using the very same methodology in the previous section), CARA preferences are econometrically selected on more time as in Figure 8. In sum, considering a lin-log relation between trade and distance implied by CARA preferences solve the distance puzzle using a balanced panel as well.

6.2 Results Including Zero-Trade Observations

It is straightforward to include zero-trade observations in a lin-log regression implied by CARA preferences, since the dependent variable is in levels. However, including such observations in a log-linear regression implied by CES preferences is not possible, since the log of zero is undefined. Nevertheless, the existing literature has suggested alternative estimation methodologies such as Pseudo Poisson Maximum Likelihood. (PPML) that can be used in the presence of zero-trade observations (see, Santos Silva and Tenreyro, 2006). Accordingly, although the estimation results are based on two alternative estimation strategies, we achieve our estimations by including zero-trade observations based on CARA and CES preferences and depict the results in Figure 10, where the benchmark great circle distance is used as the measure of distance.

As is evident in Figure 10a, there is still evidence for negative effects of distance increasing over time in the case of CES preferences, although this increase is not as severe as in the benchmark case of Figure 2. When CARA preferences are considered, the estimated distance elasticities in Figure 10c shows once again that there is evidence for negative effects of distance decreasing over time. Hence, considering a lin-log relation between trade and distance implied by CARA preferences solve the distance puzzle even when zero-trade observations are included in the investigation. Better goodness of fit by CARA preferences as shown in Figure 10d further supports these results.

6.3 Results Based on Country Specific Deflators

As explained in the Data Appendix, in order to convert values into quantities, FOB exports measured in US\$ are deflated by U.S. CPI under the assumption that the purchasing power parity holds across countries. Nevertheless, such an assumption may not hold in reality. Accordingly, we revisit our benchmark case (for which the great circle distance is used) by considering an alterna-

tive deflator, "Goods, Deflator/Unit Value of Exports, Index, US Dollars, Index," that has been obtained from International Financial Statistics (IFS). The results are given in Figure 11, where there is still evidence for the distance puzzle in Figure 11a when CES is used, and the puzzle is solved when CARA is used in Figure 11c. Therefore, our results are robust to the consideration of alternative deflators as well. Better goodness of fit by CARA preferences as shown in Figure 11d further supports these results.

6.4 Distribution of Non-CES Distance Elasticity Measures

In order to have a unique measure for the non-CES distance elasticity for each year, we have so far used Equations 19 and 20 to have an aggregation across country-pair specific non-CES distance elasticity measures. Nevertheless, such an aggregation may suppress important details regarding the distribution of non-CES distance elasticity measures across country pairs. Moreover, although such a weight is commonly used in the literature, it does not have any theoretical background either. Accordingly, to give the reader a better insight, the distribution of non-CES distance elasticity measures across country pairs within each year is given in Figure 12 and Figure 13, where the former is based on a balanced set of countries excluding zero-trade observations, and the latter is based on a balanced set of countries including zero-trade observations. As is evident, independent of the percentile (or average) considered, non-CES distance elasticity measures have been increasing over the sample period. Therefore, the results in this paper are also robust to the consideration of alternative aggregation methodologies in order to get a unique non-CES distance elasticity measure for each year.

6.5 Other Robustness Analyses

Since the effects of our gravity variables are time-varying in Equation 8, our results also depict trends based on the variables other than distance. Although they are not the main focus of this paper, for example, the border elasticity of trade has been increasing over time under the cases of both CES and CARA preferences; it is implied that trade relationships between immediate neighbors versus non-neighbors are intensifying over time.¹²

Finally, the rich data set of Rose and Spiegel (2011) that we employ in our regressions include gravity variables such as "the product of land areas" or "the number of island countries in pair" that are not standard in the literature as discussed in other studies such as by Head and Mayer (2013). Accordingly, we achieved alternative estimations by ignoring these additional gravity variables. Moreover, although it would be subject to the problem of omitted variable bias, we also achieved regressions by including only distance and ignoring all other gravity/control variables. In all of these alternative specifications, the results were qualitatively the same (i.e., there is evidence for distance puzzle under CES preferences, and CARA preferences successfully solve this puzzle), although there were slight quantitative differences.

7 Concluding Remarks

One of the characterizations of globalization is the increasing integration of trade among countries. Although this integration is mostly attributed to decreasing effects of distance between countries, the studies based on gravity-type estimations fail to capture it due to non-decreasing distance elasticities of trade estimated over time. This paper first confirms this relation (the so-called distance puzzle) using a standard gravity data set. Afterwards, we show that the failure of gravity equations may

¹²Similar results are available for other gravity variables upon request.

be due to their underlying assumption of CES preferences (implying log-linear gravity regressions), because the (absolute value of) distance elasticity of trade is shown to be decreasing with the amount of trade considered, after controlling for other explanatory variables. Therefore, the assumption of CES is violated, and this may be creating a bias through log-linear gravity regressions resulting in the distance puzzle.

Accordingly, we consider a type of non-CES preferences, namely CARA preferences, and analytically show that the (absolute value of) distance elasticity of trade decreases with the amount of trade, which is consistent with empirical findings that we mentioned in the previous paragraph. Using the very same data set, when we test the implications of CARA preferences by running the corresponding gravity regression (which is in lin-log terms this time), we empirically confirm that the (absolute value of) distance elasticity of trade decreases with the quantity traded; therefore, increasing integration of trade is associated with decreasing effects of distance on trade in a transparent and empirically convenient way. Independent of the distance measure considered, there is evidence for the reduction in the distance elasticity of trade during the sample period and thus the distance puzzle is solved by CARA preferences as an alternative to the existing literature. On top of solving the distance puzzle, CARA preferences are also econometrically selected over CES preferences according to their goodness of fit.

Although this paper has focused on log-linear and lin-log gravity equations obtained by considering the final consumption patterns of importers through a demand-side approach, very similar equations can be obtained (to be estimated) by considering the production patterns of intermediate inputs through production functions based on CES and CARA frameworks as shown by Redding and Venables (2004). Accordingly, the results in this paper can be broadly considered as the comparison of CES-based versus CARA-based gravity equations rather than just a demand-side comparison. Nevertheless, the results are not without caveats. In particular, this paper has focused

on the distance puzzle by considering multiplicative iceberg trade costs (for both CES and CARA preferences) to have comparable results with the existing literature on the distance puzzle (e.g., see Disdier and Head, 2008). Yet, in future research, the results are subject to further improvement if additive trade costs as in Irarrazabal et al. (2015) or other sources of variation in the trade-cost function as discussed by Martin (2012) would be considered with the appropriate/corresponding data.

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8 Appendix

8.1 Data Sources

We use the trade data set of Rose and Spiegel (2011) for which the data sources are given as follows:

- FOB exports are measured in US\$, taken from IMF Direction of Trade CD-ROM, deflated by US CPI for All Urban Consumers (CPI-U), all items, 1982-84=100.
- Country-specific data (on location, area, island-nation status, contiguity, language, colonizer, and independence) taken from CIA World Factbook website.
- Currency-union data taken from Glick-Rose (2002).
- Regional trade agreements taken from WTO website, http://www.wto.org/english/tratop_e/region_e/eif_e.xls
- See Rose and Spiegel (2011) for the list of countries and further details.

8.2 Approximation of Markups

This subsection shows how the main results in this paper do not depend on the approximation of markups that we have achieved in Equation 14. In particular, if we ignore this approximation, the expression for the distance elasticity of trade in Equation 16 is replaced with the following expression:

$$\delta_{d,t}^s = \frac{\partial q_{d,t}^s}{\partial D_d^s} \frac{D_d^s}{q_{d,t}^s} = - \left(\frac{\kappa_t}{\theta q_{d,t}^s} \right) \left(\frac{1 - \theta q_{d,t}^s}{2 - \theta q_{d,t}^s} \right)$$

where $\frac{\kappa_t}{\theta q_{d,t}^s}$ is just the double of $\delta_{d,t}^s$ that consider in the main text and thus what we depict in Figures 5-6. Therefore, if the markup approximation would make a difference (in the results of this

paper) through time, it is only possible through $\frac{1-\theta q_{d,t}^s}{2-\theta q_{d,t}^s}$. However, it can easily be shown that $\frac{1-\theta q_{d,t}^s}{2-\theta q_{d,t}^s}$ decreases with $q_{d,t}^s$:

$$\frac{\partial \left(\frac{1-\theta q_{d,t}^s}{2-\theta q_{d,t}^s} \right)}{\partial q_{d,t}^s} < 0$$

Therefore, as long as trade is increasing over time (which is the real case according to our data set), $\delta_{d,t}^s$ would further decrease (in absolute value), further supporting the results of this paper that considering CARA preferences solves the distance puzzle.

8.3 Derivation of Equation 15

The demand function implied by CARA preferences is given by:

$$q_{d,t}^s = \left(\frac{E_{d,t} - \frac{1}{\theta} \sum_{s'} \log \left(\frac{p_{d,t}^s \chi_{d,t}^{s'}}{p_{d,t}^{s'} \chi_{d,t}^s} \right) p_{d,t}^{s'}}{\sum_{s'} p_{d,t}^{s'}} \right)$$

where prices are given as follows:

$$p_{d,t}^s = c_{d,t}^s \mu_{d,t}^s = c_{d,t}^s \mu_{d,t}^s = w_t^s \tau_{d,t}^s \mu_{d,t}^s = w_t^s (D_d^s)^{\kappa_t} \phi_{d,t}^s \mu_{d,t}^s$$

Using $\log \mu_{d,t}^s \approx \theta q_{d,t}^s$, log prices can be written as the following approximation:

$$\log p_{d,t}^s \approx \log w_t^s + \kappa_t \log D_d^s + \log \phi_{d,t}^s + \theta q_{d,t}^s$$

Substituting this expression back into the demand function results in:

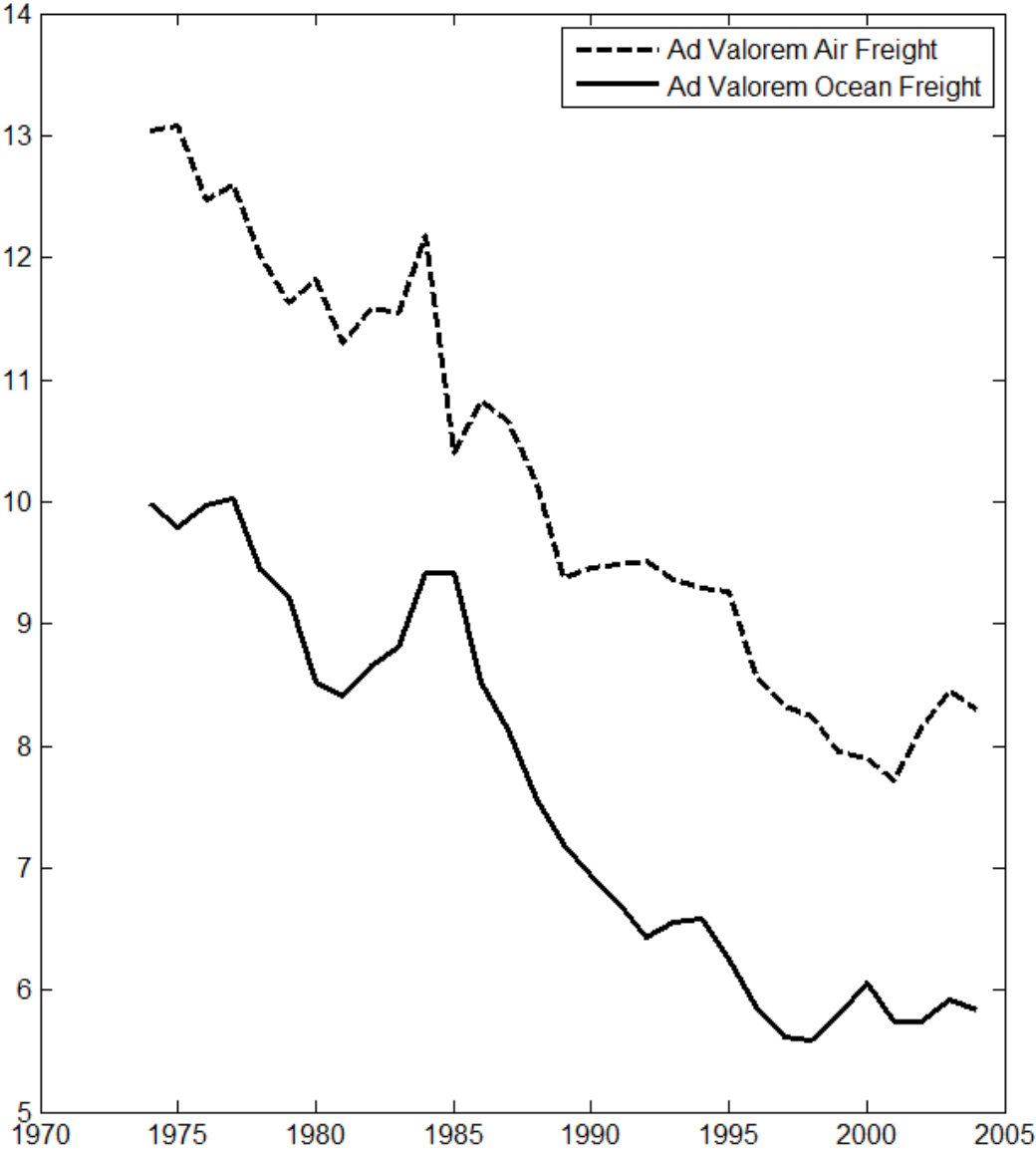
$$q_{d,t}^s = \frac{-\log w_t^s - \kappa_t \log D_d^s - \log \phi_{d,t}^s - \theta q_{d,t}^s}{\theta} + \left(\frac{E_{d,t} - \frac{1}{\theta} \sum_{s'} \log \left(\frac{\chi_{d,t}^{s'}}{p_{d,t}^{s'}} \right) p_{d,t}^{s'}}{\sum_{s'} p_{d,t}^{s'}} \right) + \frac{\log \chi_{d,t}^s}{\theta}$$

where $q_{d,t}^s$ shows up in both sides of the equation due to variable markups. When $q_{d,t}^s$ is left alone, we obtain:

$$q_{d,t}^s = -\frac{\kappa_t}{2\theta} \log D_d^s - \frac{1}{2\theta} \log (w_t^s \phi_{d,t}^s) + \left(\frac{E_{d,t} - \frac{1}{\theta} \sum_{s'} \log \left(\frac{\chi_{d,t}^{s'}}{p_{d,t}^{s'}} \right) p_{d,t}^{s'}}{2 \sum_{s'} p_{d,t}^{s'}} \right) + \frac{\log \chi_{d,t}^s}{2\theta}$$

which is Equation 15 in the text.

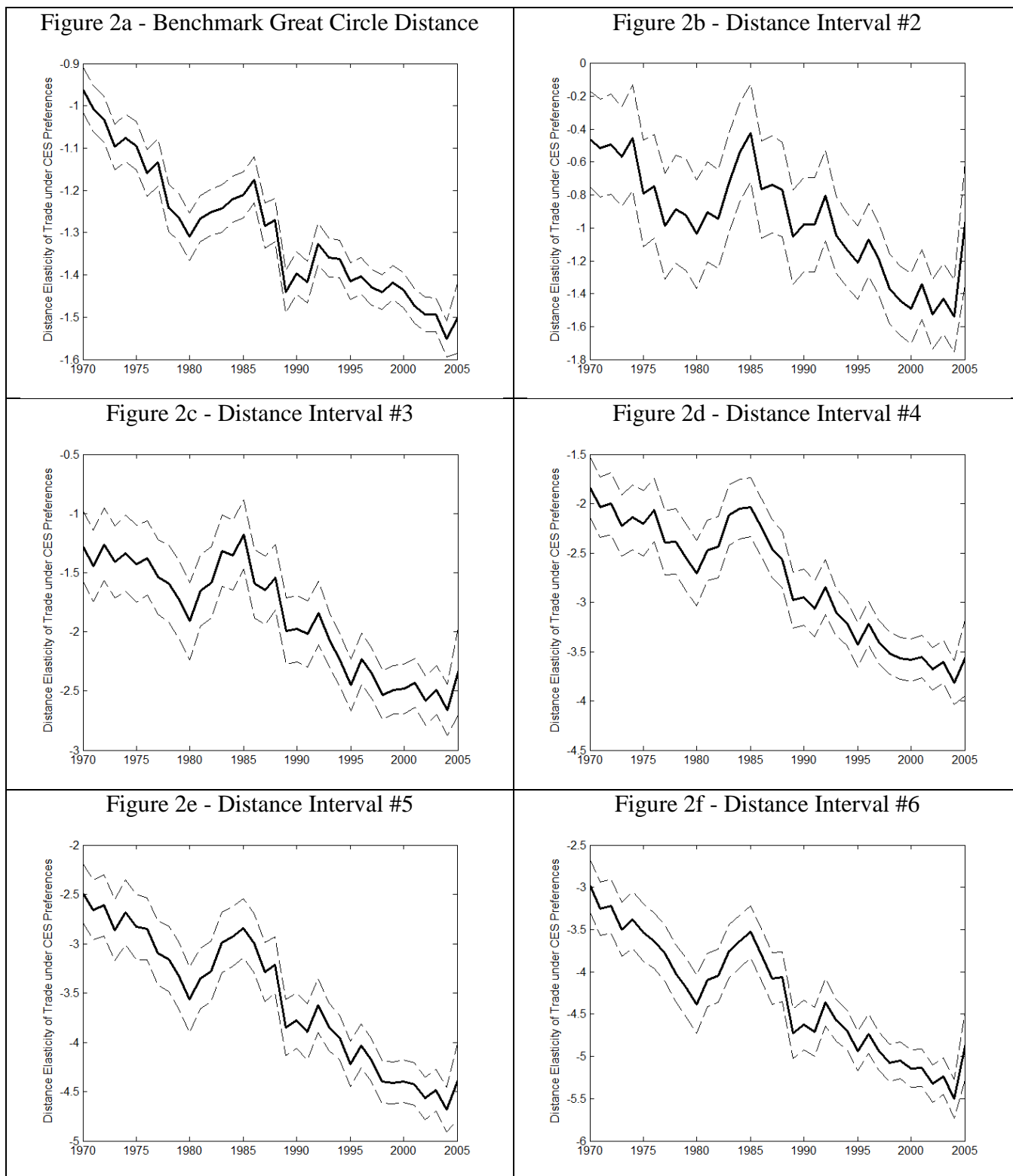
Figure 1 - Ad Valorem Freight Rates



Source: Hummels (2007).

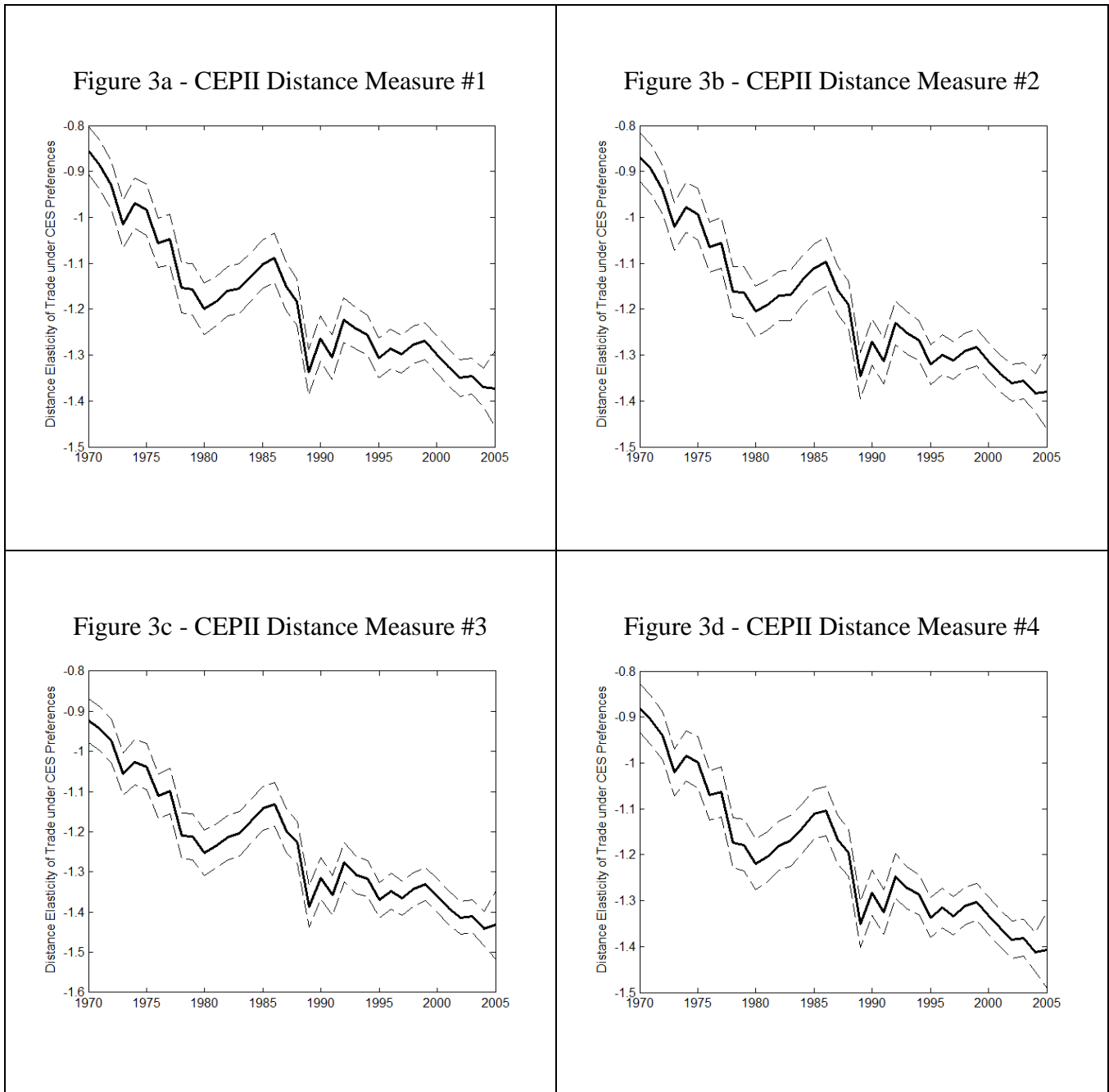
Notes: This figure is a combination of Figure 5 and Figure 6 in Hummels (2007). We depict the fitted ad valorem rates for air and ocean freight given in Hummels (2007) for the period over 1974-2004.

Figure 2 - Distance Elasticity of Trade under CES Preferences



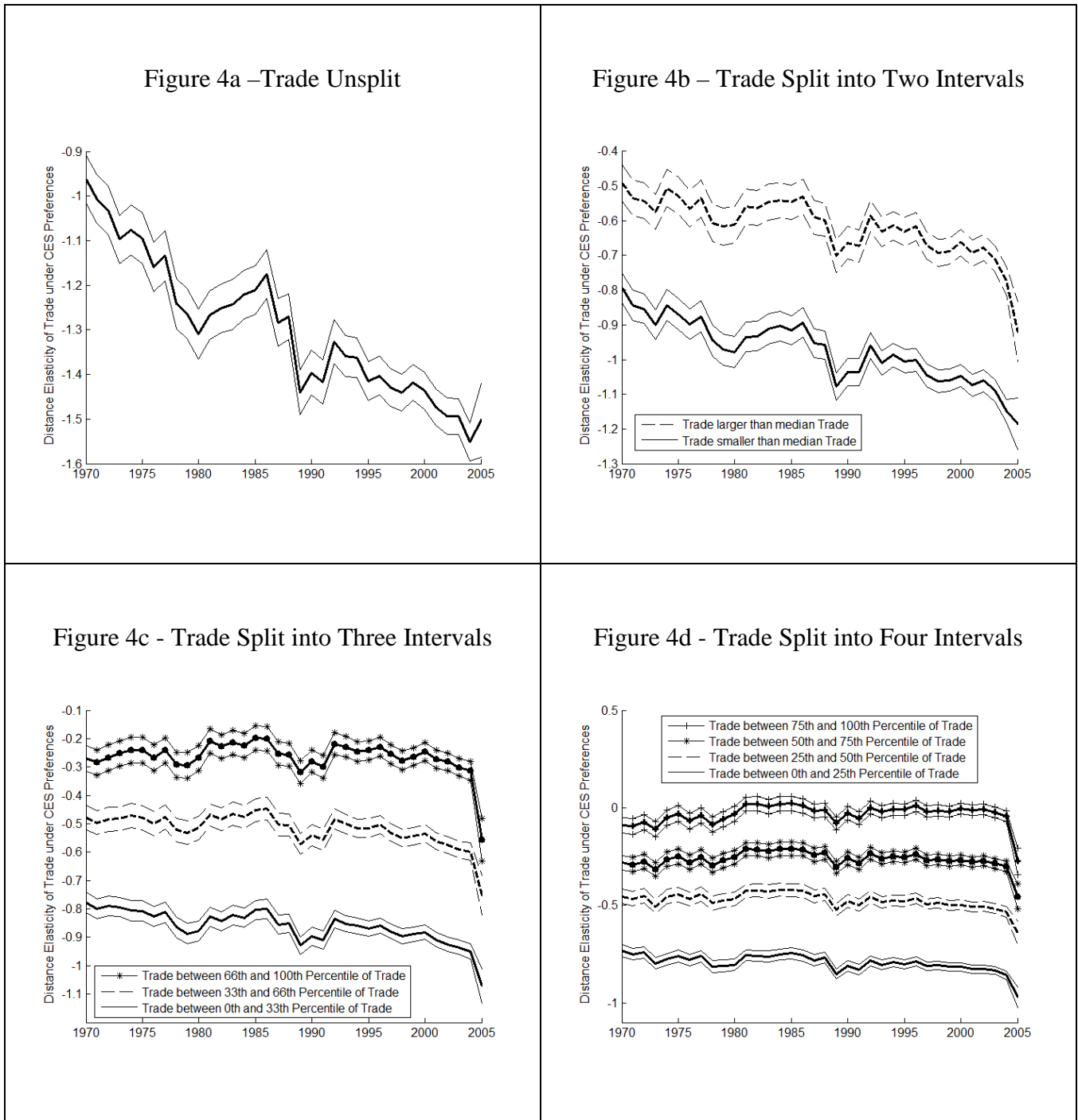
Notes: The solid lines represent the estimated distance elasticity of trade, while the dashed lines represent the 90% confidence intervals. Distance intervals #2-#5 correspond to [375,750), [750,1500), [1500,3000), [3000,6000), [6000,maximum), respectively, in miles.

Figure 3 - Distance Elasticity of Trade under CES Preferences - CEPII Distance Measures



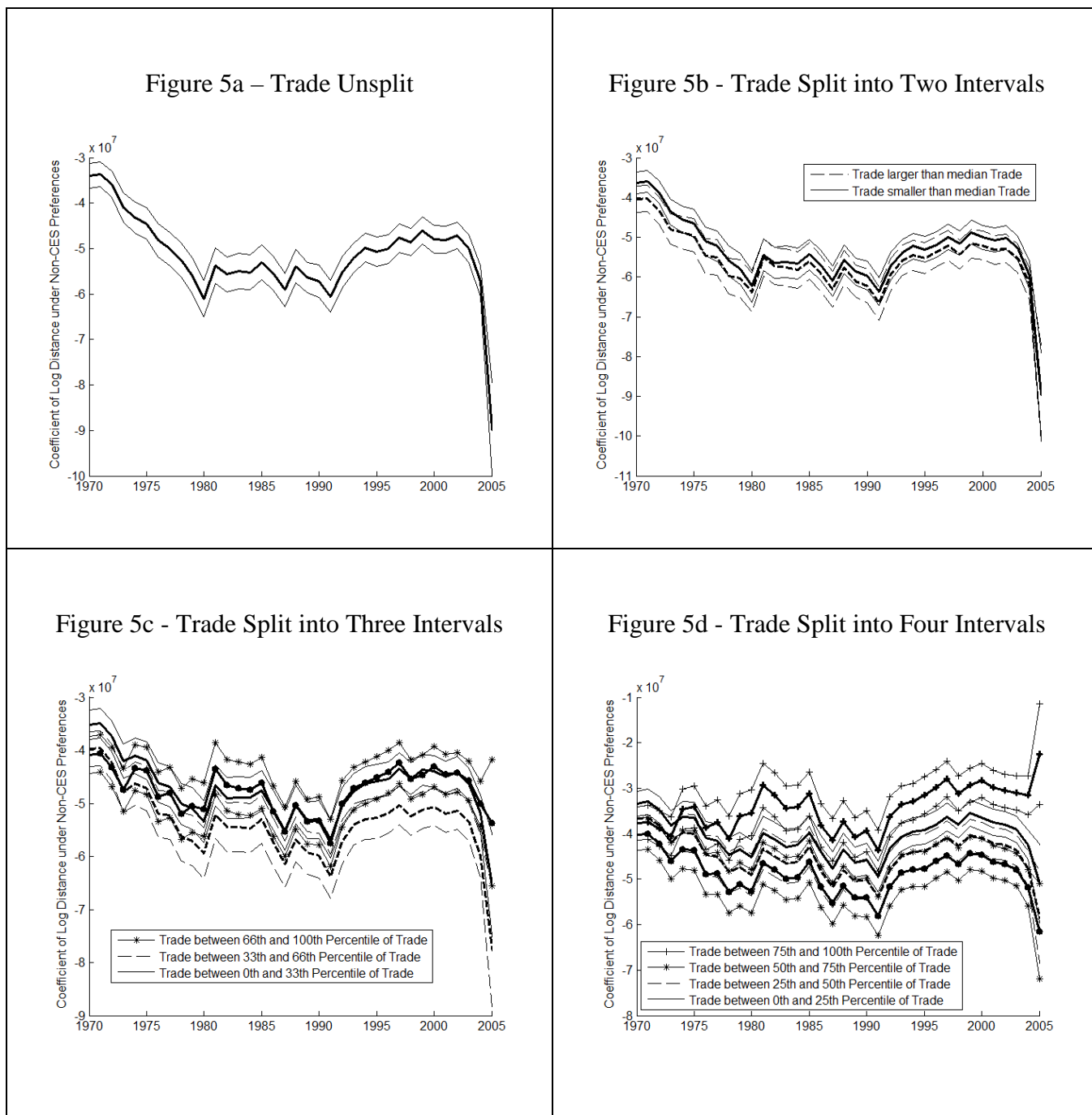
Notes: The solid lines represent the estimated distance elasticity of trade, while the dashed lines represent the 90% confidence intervals.

Figure 4 - Distance Elasticity of Trade for Different Trade Intervals under CES Preferences



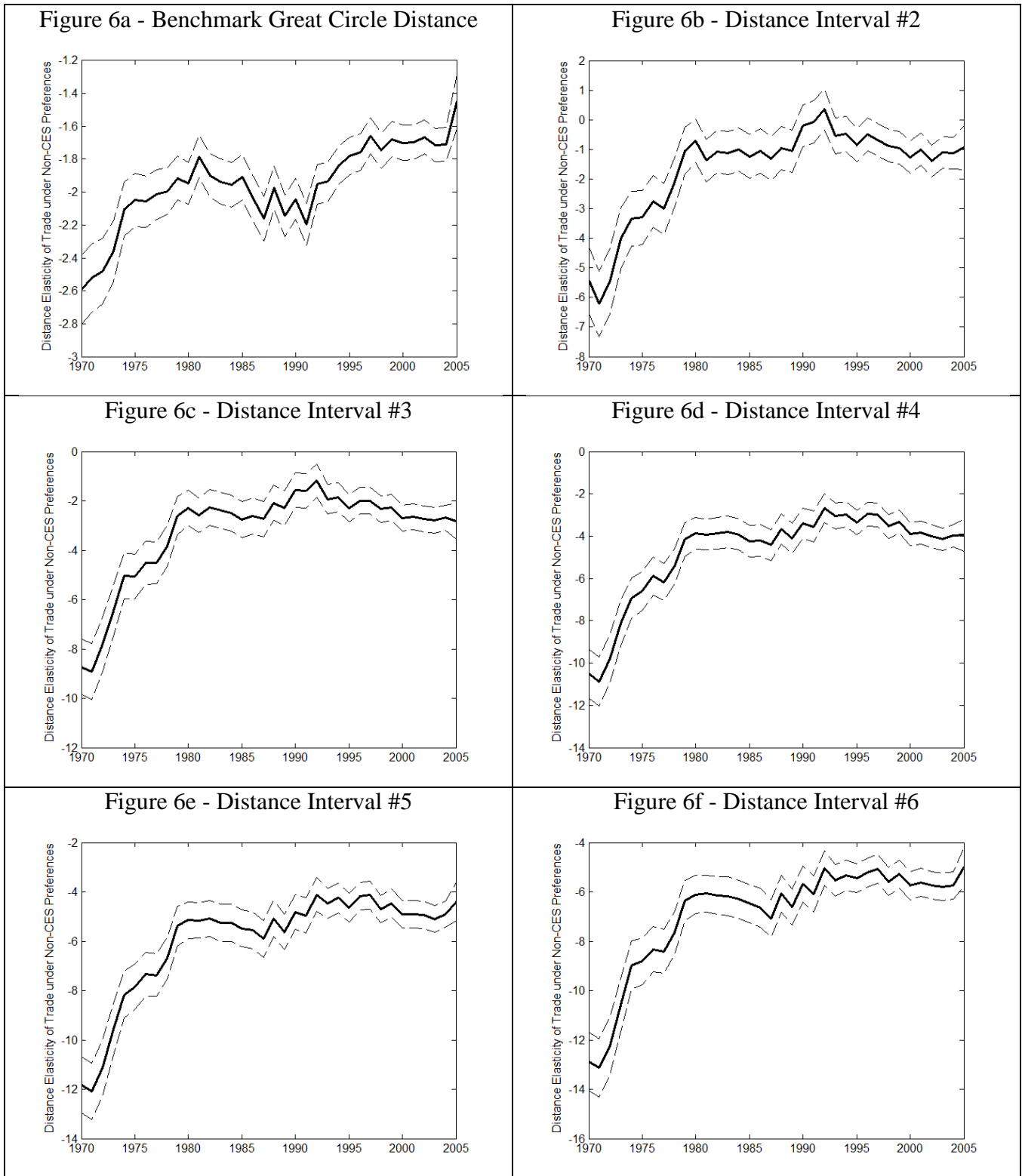
Notes: Notes: The bold lines represent the estimated distance elasticity of trade, while the light lines represent the 90% confidence intervals. The figures have been obtained using the benchmark great circle distance as indicated in the data section. The percentiles of trade have been calculated for each year individually. As is evident, the (absolute value of) distance elasticity of trade decreases with trade; this result also holds when we increase the number of intervals, although such results are not shown here for presentational simplicity.

Figure 5 - Coefficient of Log Distance for Different Trade Intervals under Non-CES Preferences



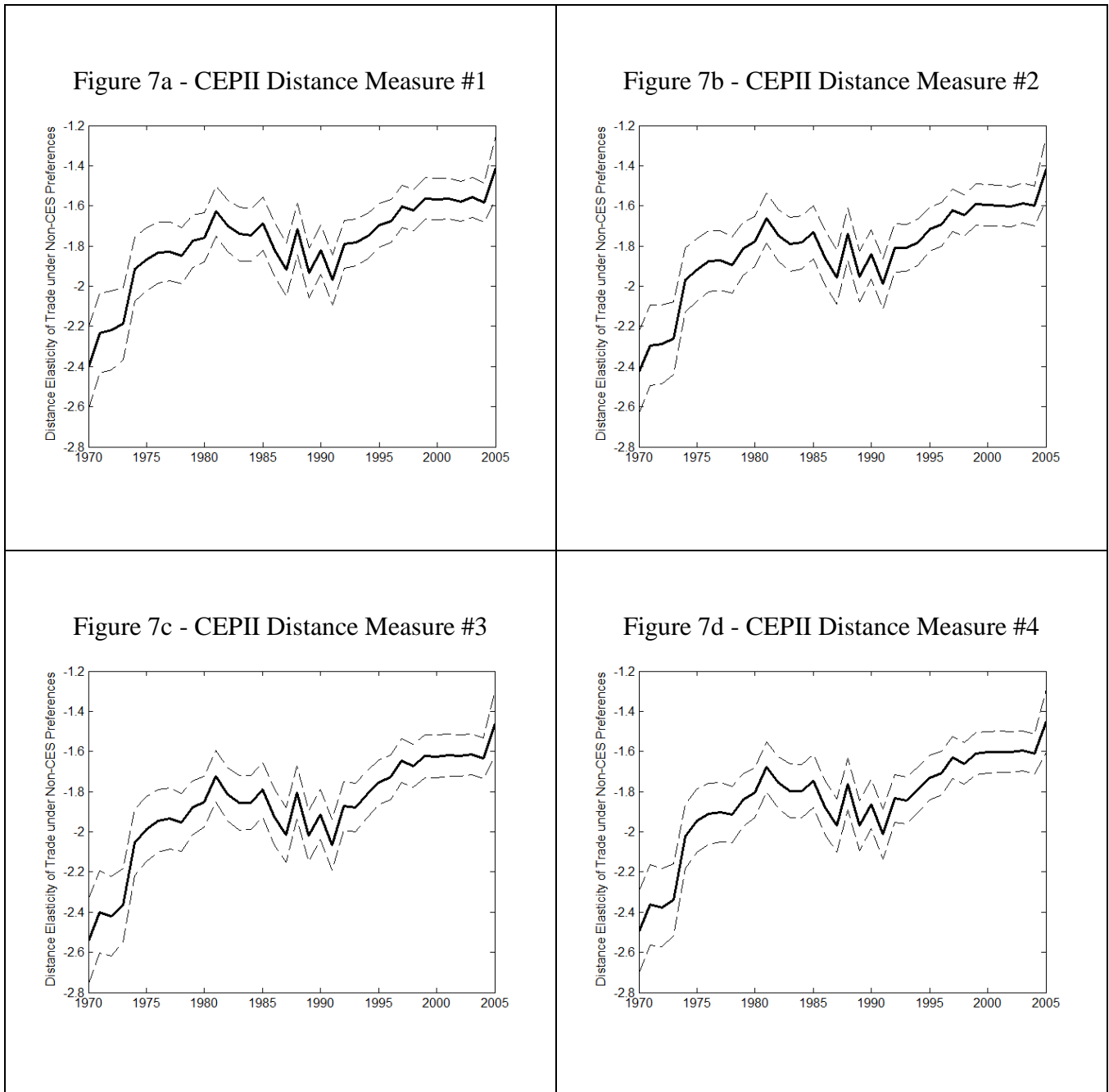
Notes: Notes: The solid lines represent the estimated distance elasticity of trade, while the dashed lines represent the 90% confidence intervals. The figures have been obtained using the benchmark great circle distance as indicated in the data section. The percentiles of trade have been calculated for each year individually.

Figure 6 - Distance Elasticity of Trade under Non-CES Preferences



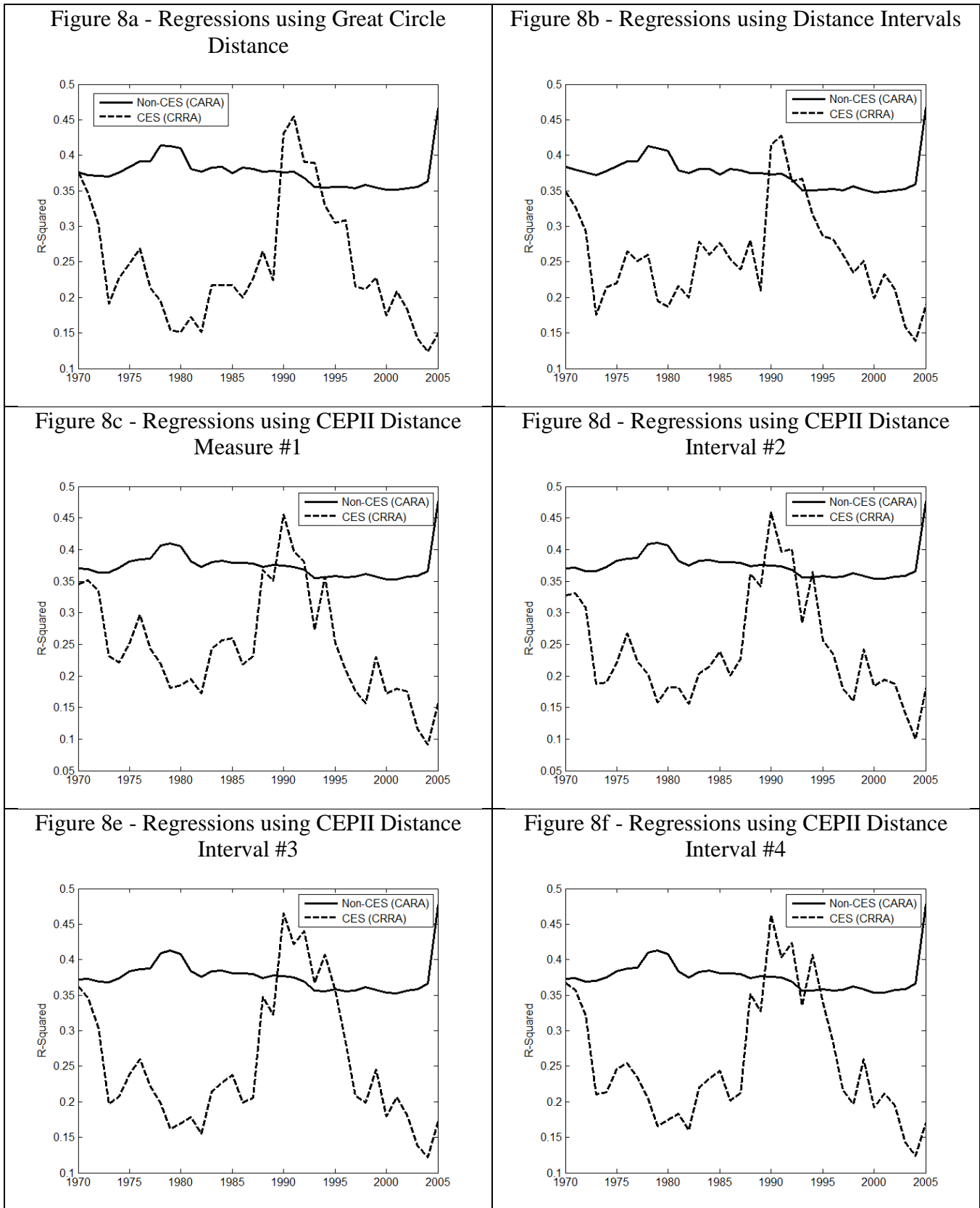
Notes: The distance elasticity of trade is country-pair specific under non-CES preferences. The solid line represents the weighted average of the estimated distance elasticities of trade under non-CES preferences, where the (time-specific) weights for each country pair have been determined according to their real trade volume. The dashed lines represent the 90% confidence interval. Distance intervals #2-#5 correspond to [375,750), [750,1500), [1500,3000), [3000,6000), [6000,maximum), respectively, in miles.

Figure 7 - Distance Elasticity of Trade under Non-CES Preferences - CEPII Distance Measures



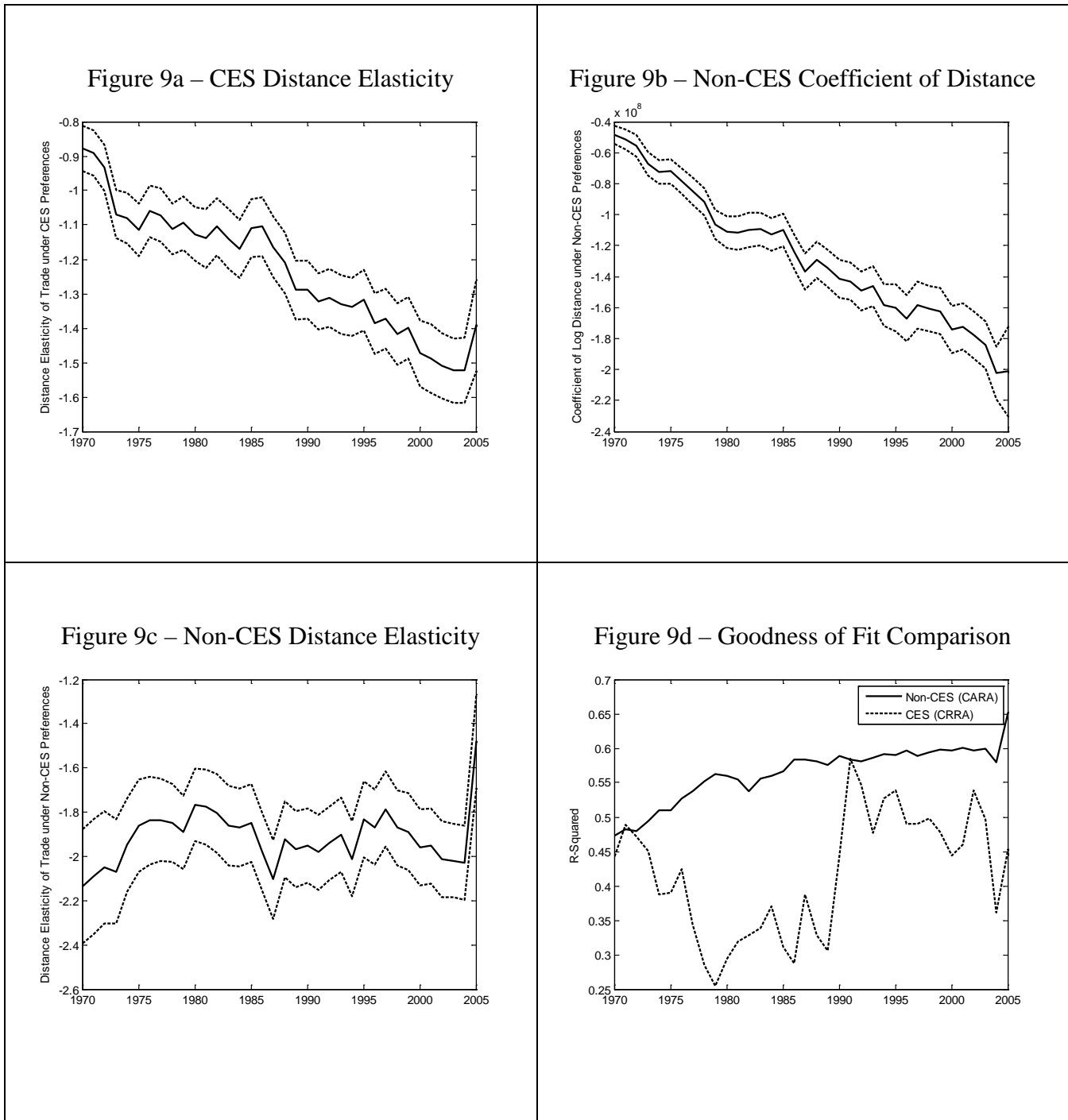
Notes: The distance elasticity of trade is country-pair specific under non-CES preferences. The solid line represents the weighted average of the estimated distance elasticities of trade under non-CES preferences, where the (time-specific) weights for each country pair have been determined according to their real trade volume. The dashed lines represent the 90% confidence interval.

Figure 8 - Goodness of Fit for the Level of Trade under CES versus Non-CES



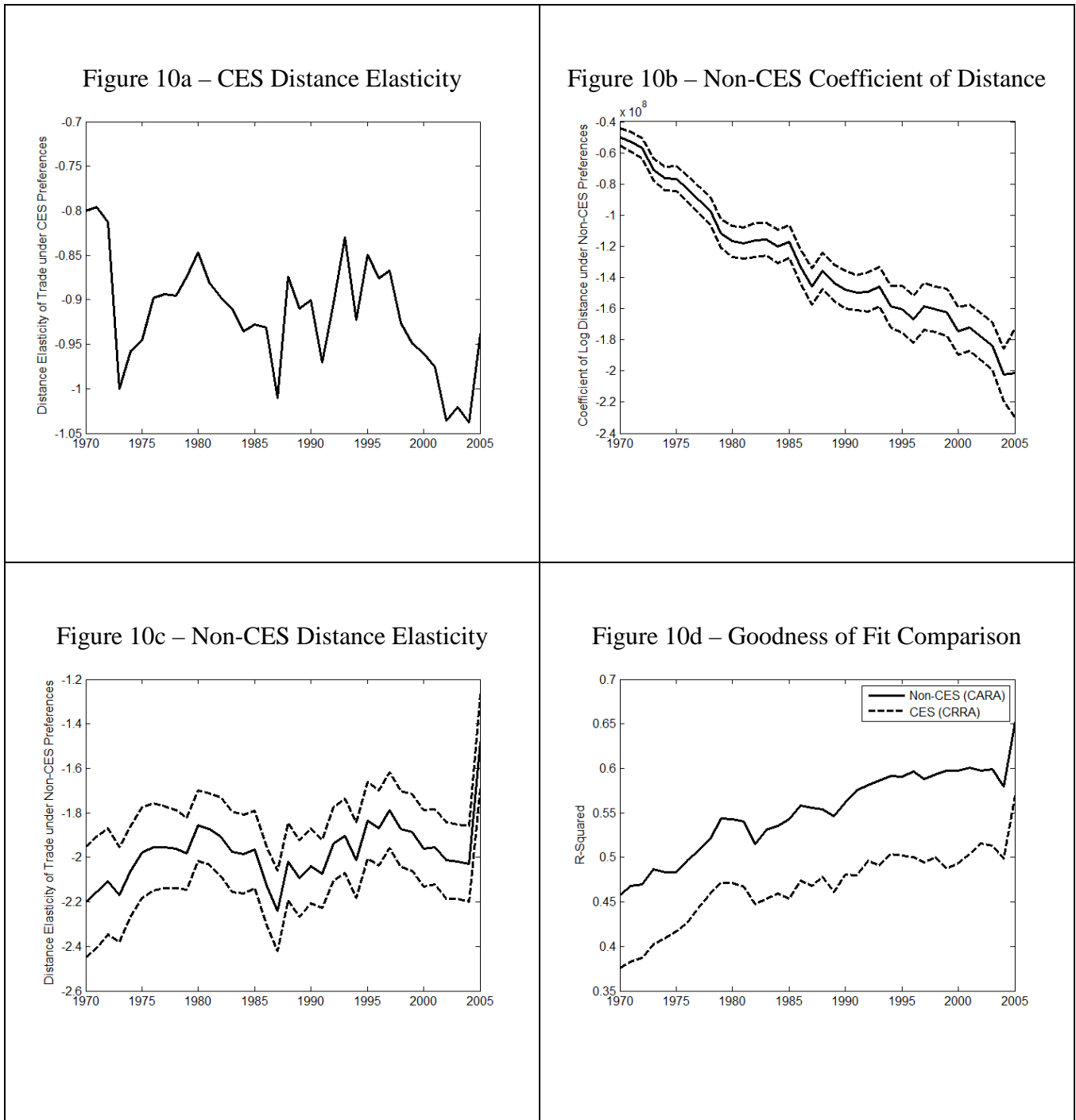
Notes: R-squared values correspond to the explained sum of squared over the total sum of squares for the *level* of trade.

Figure 9 – Further Robustness: Results Based on a Balanced Set of Countries



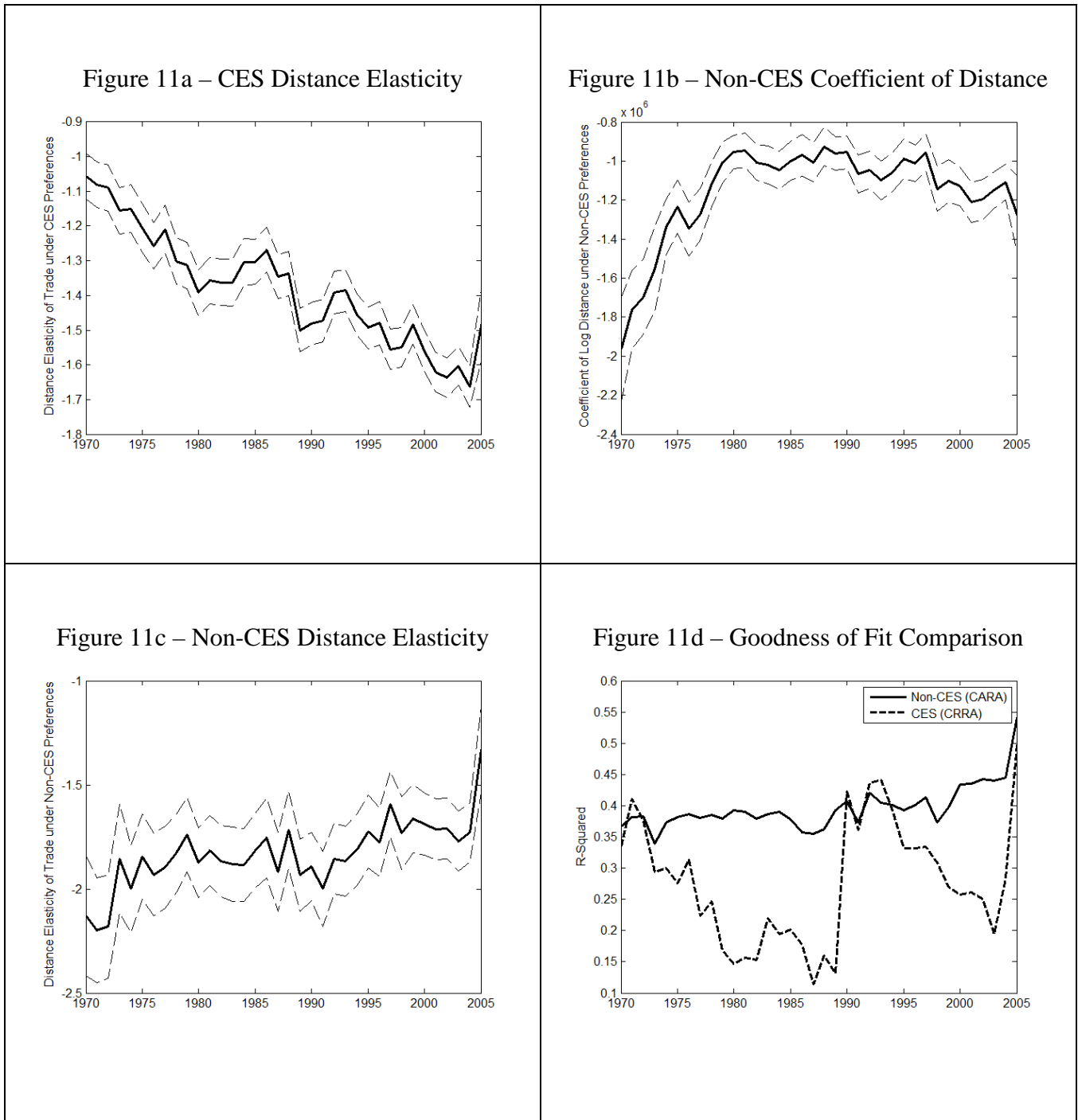
Notes: The dashed lines represent the 90% confidence interval. R-squared values correspond to the explained sum of squared over the total sum of squares for the *level* of trade.

Figure 10 – Further Robustness: Results including Zero-Trade Observations



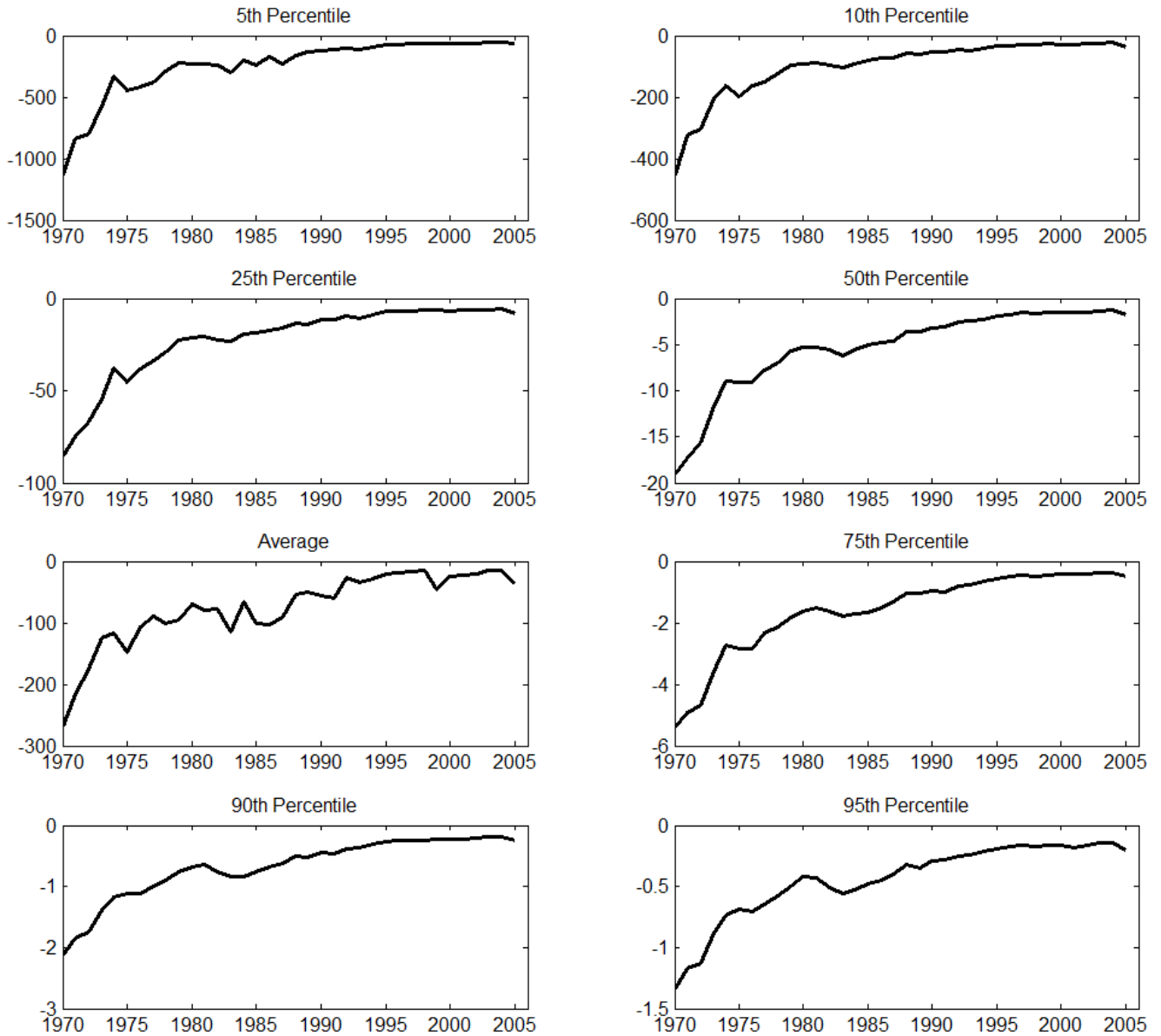
Notes: The dashed lines represent the 90% confidence interval. R-squared values correspond to the explained sum of squared over the total sum of squares for the *level* of trade.

Figure 11 – Further Robustness: Results Based on Country Specific Deflators



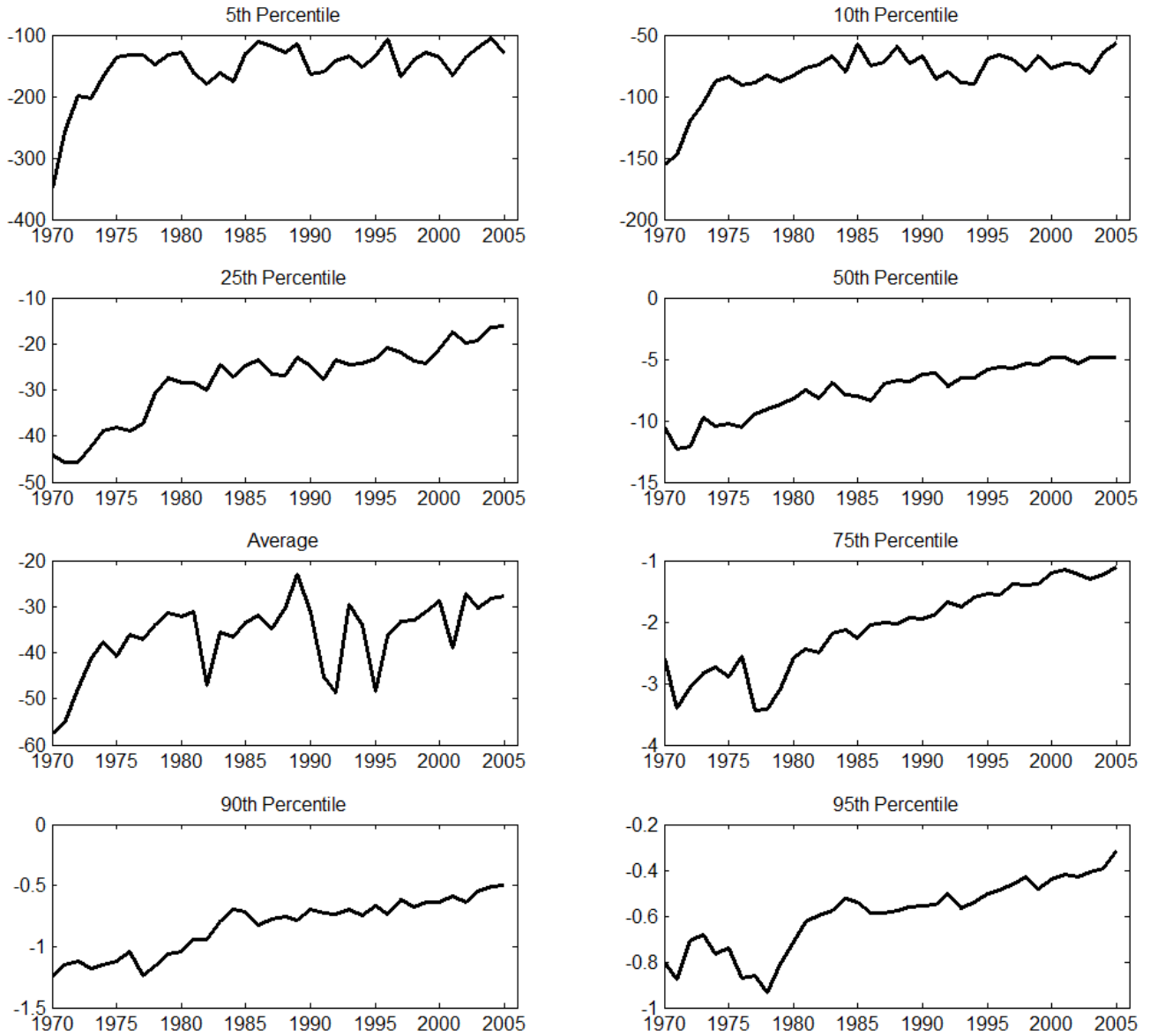
Notes: The dashed lines represent the 90% confidence interval. R-squared values correspond to the explained sum of squared over the total sum of squares for the *level* of trade.

Figure 12 – Further Robustness: Distribution of Non-CES Distance Elasticity Measures across Country Pairs with a Balanced Set of Countries



Notes: Percentiles and average represent the corresponding values within each year across all country pairs, where a balanced panel has been used, excluding zero-trade observations.

Figure 13 – Further Robustness: Distribution of Non-CES Distance Elasticity Measures across Country Pairs with a Balanced Set of Countries including Zero-Trade Observations



Notes: Percentiles and average represent the corresponding values within each year across all country pairs, where a balanced panel has been used, including zero-trade observations.