

# Heterogeneous Firms, Globalization and the Distance Puzzle

Mario Larch\*

Pehr-Johan Norbäck†

Steffen Sirries‡

Dieter M. Urban§

May 21, 2012

## Abstract

Despite the strong pace of globalization, the distance effect on trade is persistent or even growing over time (Disdier and Head, 2008). To solve this *distance puzzle*, we use the recently developed gravity equation estimator from Helpman, Melitz and Rubinstein (2008), HMR henceforth. Using industry-level data in 28 industries from 1978 to 2003, we find that the distance coefficient increases over time when OLS is used, while the non-linear estimation of HMR leads to a decline in the distance coefficient over time. The distance puzzle thus arises from a growing bias of OLS-estimates. The latter is explained by globalization more significantly reducing the downward bias from omitting zero trade flows than it reduces the upward bias from omitting the number of heterogeneous exporting firms. Furthermore, we show that including zero-trade flows cannot solve the distance puzzle. The HMR estimates are strongly correlated with the time pattern in freight costs reported by Hummels (2007).

*JEL-Classification:* F13, F23

*Keywords:* Distance puzzle, gravity estimation, zero trade flows, firm heterogeneity

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\*University of Bayreuth, ifo Institute for Economic Research, CESifo and GEP at the University of Nottingham, Universitätsstraße 30, 95447 Bayreuth, Germany. E-mail: mario.larch@uni-bayreuth.de.

†Research Institute of Industrial Economics (IFN), P.O. Box 55665, SE-102 15 Stockholm, Sweden. E-mail: pehr-johan.norback@ifn.se. Home page: [www.ifn.se/pjn](http://www.ifn.se/pjn).

‡University of Bayreuth and Dept. of Business and Economics, RWTH Aachen University, 95447 Bayreuth, Germany. E-mail: steffen.sirries@uni-bayreuth.de.

§Dieter sadly passed away on 7th March, 2011. We will miss his friendship, kindness and brilliance.

# 1 Introduction

*“From the telegraph to the Internet, every new communications technology has promised to shrink the distance between people, to increase access to information, and to bring us ever closer to the dream of a perfectly efficient, frictionless global market.” (Thomas Friedman, 2005, p. 204)*

The many facets of globalization like the increased trade in final goods, intermediate inputs and services, or the increased international mobility of capital and labor, are perceived to bring countries closer together, shrinking the impediments of distance. However, gravity estimations regressing bilateral trade on distance, inter alia, tell us the opposite. Disdier and Head (2008) undertake a meta analysis of the magnitude of the distance coefficient based on 103 empirical studies and find that (i) the mean effect of the distance coefficient is about  $|-0.9|$  across studies, and (ii) the negative impact of distance on trade rose around the middle of the century and has remained persistently high since then.<sup>1</sup>

A stable or *rising* distance coefficient over time is puzzling because the distance coefficient has the structural interpretation of the elasticity of bilateral trade with respect to distance (e.g. Anderson and van Wincoop, 2003). Transport technology is known to be biased in favor of long distances (see Hummels, 2007), which should lead to a decrease of the distance effect. Hence, the elasticity of bilateral trade with respect to distance should fall with increasing globalization.

In this paper, we use the recently developed gravity equation estimator from Helpman, Melitz and Rubinstein (2008), henceforth HMR, which controls for sample selection and exporter heterogeneity, to solve this *distance puzzle*.

We apply the HMR estimator on world trade in 28 different manufacturing industries over the time period from 1978 until 2003, estimating a gravity equation for each industry and year separately.<sup>2</sup> We find that the HMR-estimator of the distance coefficient (in absolute value) is decreasing on average over time as expected. These estimated coefficients are also strongly correlated with the time pattern in freight costs reported by Hummels (2007) and Brun, Carrère, Guillaumont and de Melo (2005), which in turn depend on fluctuations of oil prices. In addition, we apply a gamma pseudo-maximum-likelihood (GPML) estimator, which was recently suggested by Santos Silva and Tenreyro (2006, 2008), albeit augmented by the correction factors of HMR, which also gives a very simi-

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<sup>1</sup>This paper also provides a good collection of references for the “distance puzzle”. Hence, we here dispense with a discussion of all relevant papers and with providing all references. Rather, we selectively discuss only papers which are directly related to our paper in their methodology.

<sup>2</sup>Berthelon and Freund (2008) document the distance puzzle on bilateral industry data rather than on bilateral country data.

lar time pattern of the estimated distance coefficients, augmenting the confidence in our estimates.

Having shown that the HMR estimator does produce distance coefficients which decrease over time, we then compare the outcome with OLS. We first confirm the finding of HMR that OLS produces larger distance coefficients (in absolute value). More importantly, we show that these distance coefficients increase over time. Hence, the distance puzzle arises due to the fact that *the bias of OLS increases over time*.

To explain the increasing bias of OLS, we formally derive how the bias of the OLS distance coefficient evolves over time if the true data generating process is the HMR model and the elasticity of trade with respect to distance<sup>3</sup> decreases during globalization through, for instance, improved transport and communication technologies.

We note that if the HMR model is the true model, OLS estimates suffer from two sources of bias. First, there is a *sample selection bias* because bilateral trade is measured as a logarithm and zero values of bilateral trade turn into missing values. As small or distant countries are more likely to have small trade flows, measurement errors in export flows will more likely lead to zero trade flows for those countries. This leads to a positive correlation of the error term with distance, causing a downward bias in the distance coefficient, i.e. the value of the distance coefficient is too small in absolute terms. Hence, accounting for zero trade flows is not able to explain the distance puzzle.

Second, there is an *omitted variable bias* from ignoring that firms are heterogeneous in productivity. If an index of the size and the number of exporting firms in an industry is not included as a control in the gravity estimation, then it appears in the regression error, causing a negative correlation between error and distance, because there are less exporters to more distant destinations. Hence, the distance coefficient is upward biased through omitting a control on firm productivity, i.e. the value of the distance coefficient is too large in absolute terms.

As these two biases work in opposite directions, the overall change of the bias from OLS estimates is ambiguous. We first reproduce previous findings that the OLS estimates are upward biased, i.e. the distance coefficient is too large in absolute value. Hence, the downward bias from sample selection due to omitting zero trade flows is outweighed by the upward bias due to ignoring that firms are heterogeneous.

We then show how the two biases evolve over time in the course of globalization measured as a fall in the elasticity of trade with respect to distance. We first show

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<sup>3</sup>We follow this interpretation of the distance coefficient throughout the paper. Assuming decreasing distance costs would lead to a *flatter world* without relative differences of trade volumes across trading partners w.r.t to distance. However, Buch et al. (2004) argue that the distance puzzle is not that puzzling when the effect of distance is interpreted in absolute terms. Under the assumption of linear dependency of trade costs with respect to distance, they show that a potential decline in the impact of distance would be caught by the constant term in the gravity equation. But still we should – but do not – observe a decline in the relative impact of distance on bilateral trade, which is exactly measured by the elasticity we look at.

that the downward bias through sample selection must decrease over time. Intuitively, as trade costs decrease, ever less country pairs have zero trade flows and eventually all countries trade with each other. But then the sample selection bias disappears, i.e. the distance coefficient rises. We then show that the upward bias from omitting the number of exporting firms also becomes smaller over time when the elasticity of trade with respect to distance falls. Intuitively, at a lower trade elasticity, most firms will export, reducing the upward bias, i.e. the distance coefficient decreases. Since both biases decrease in the course of globalization (measured as a fall of distance with respect to trade) globalization has an ambiguous effect on the bias of OLS in general.

Our estimates show that the bias of OLS increases over time. Hence, it must be the case that the downward bias from sample selection decreases faster than the upward bias from not controlling for the number and size of exporting firms. Thus, the HMR model implies that the distance puzzle arises by firm heterogeneity having become relatively more important over time. This is nicely in line with empirical evidence provided by Poschke (2011), that, as countries develop, the distribution of firm sizes becomes more dispersed.

For future work, we also suggest a linearization of the HMR estimator, which is comparable to the non-parametric approach of Helpman, Melitz and Rubinstein (2008). This approach is easy to implement with standard econometric programs because it is estimable via OLS. We show that such a simplified estimator performs just as well as the original nonlinear least squares version.

We also show that a Heckman estimator, while deviating from the HMR estimates, also produces a smaller distance coefficient and an increasing difference to the OLS estimates over time. This arises since the correction factor for sample selection of the Heckman estimator and the correction factor of HMR are both functions of the same underlying score variable, although the Heckman correction factor is monotonic in this score while the HMR correction factor follows a U-shape functional form. If the data points happen to be concentrated along one leg of the U-form, then the two correction factors are highly correlated and yield very similar results. We show this to be the case in our data, but it may not be true in general. However, even though the distance coefficient does fall using the Heckman and the HMR procedures, the interpretation why it falls is very different. The Heckman correction would lead to the conclusion that taking into account zero trade flows solves the distance puzzle,<sup>4</sup> while in the HMR procedure it is the omission of firm heterogeneity which is key. We then show that only the latter is consistent with theory: adding zero trade flows should exacerbate the distance puzzle.

Alternative attempts to solve the distance puzzle stem from Felbermayr and Kohler

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<sup>4</sup>Felbermayr and Kohler (2006), for example, suggested that accounting for zero trade flows is able to solve the distance puzzle.

(2006), using Tobit estimates to take zero trade flows into account.<sup>5</sup> Other studies explain why the substitution elasticity may have been rising over time (Glaeser and Kohlhase, 2004, Krautheim, 2011, Lawless and Whelan, 2007, Berthelon and Freund, 2008), possibly overcompensating the fall in trade costs, which both determine the distance coefficient in theory. Duranton and Storper (2008) provide an alternative model to rationalize rising overall trade costs besides falling transport costs. They assume vertically linked industries in which the quality of inputs is not contractible and where providing a given level of quality to suppliers becomes more costly with distance. Their main finding is that lower transport costs imply that higher quality inputs are traded in equilibrium, and the effect of this higher quality is that there is an increase in trade costs. None of them discuss the role of the omitted variable problem of firm heterogeneity in creating an increasing bias over time. Finally, using bilateral country data for the year 1986, HMR find that their estimated distance coefficient represents a drop of roughly one third as compared to OLS. However, HMR do not examine the evolution of the distance coefficient over time.

The remainder of the paper is organized as follows. Section 2 derives the gravity equation controlling for zero trade flows and firm-level heterogeneity following HMR in subsection 2.1, whereas we calculate the biases of OLS estimates in subsection 2.2. Section 3 presents our estimation equation in subsection 3.1, describes the data in subsection 3.2, and gives the results in subsection 3.3. The last section concludes the paper.

## 2 Theory

### 2.1 Deriving the gravity equation from Helpman, Melitz and Rubinstein (2008)

The HMR model is a multi-country monopolistic competition model with heterogeneous firms and identical consumers with CES “love-of-variety” utility functions à la Dixit and Stiglitz (1977). Since we have bilateral industry trade data, we will add the assumption of multiple sectors in the world economy, each characterized by monopolistic competition.

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<sup>5</sup>There is ample evidence from microdata for particular countries that the extensive margin matters. Bernard, Jensen and Schott (2006) use firm-level data and the entry and exit of firms into and out of exporting (extensive margin) from the export volumes of exporting firms (intensive margin). They find that a reduction in trade costs may increase industry productivity through changes on the extensive margin. Hummels and Klenow (2005) use disaggregated product-level data to distinguish between the variety dimension (extensive margin) and the quality as well as the quantity dimension (intensive margins). One of their main results is that adverse terms-of-trade effects occur more frequently if growth takes place mainly at the extensive margin. Similarly, Baldwin and Harrigan (2011) use product-level data on bilateral U.S. exports demonstrating that a large part of potential export flows are zero, and showing that the incidence of these zero export flows is strongly correlated with distance and importing country size. Hillberry and Hummels (2008) analyze trade at the five-digit zip codes and decompose the extensive and intensive margins of shipments. Their main finding is that distance reduces aggregate trade values primarily by reducing the number of commodities shipped and the number of establishments shipping. However, the extensive margins are important over very short distances.

There are  $N_{ih}$  firms in a sector  $h$  of country  $i$ , each producing a differentiated variety  $l$ . For ease of notation, we will drop the subscript  $h$  for sector whenever obvious. With a substitution elasticity between any two varieties  $\varepsilon > 1$ , the demand  $x_{ij}(l)$  for a variety  $l$ , consumed in country  $i$  and produced in country  $j$  is

$$x_{ij}(l) = \frac{p_{ij}(l)^{-\varepsilon}}{P_i^{1-\varepsilon}} \mu_i Y_i, \quad (2.1)$$

where  $p_{ij}(l)$  is the associated price,  $P_i = \left[ \int_{\mathcal{B}_i} p_{ij}(l)^{1-\varepsilon} dl \right]^{\frac{1}{1-\varepsilon}}$  is the price index on the set of  $\mathcal{B}_i$  symmetric domestic and imported differentiated goods consumed in country  $i$ ,  $Y_i$  is the income in country  $i$  and  $\mu_i$  is the (constant) share of income spent on a sector under consideration by consumers of country  $i$ .

A firm  $l$  in country  $j$  produces one unit of output at the cost  $c_j a$ , where  $c_j$  is the minimum cost of a bundle of inputs which is country- and sector-specific, and where  $a(l)$  is a firm-specific input coefficient implying that firm  $l$ 's productivity is given by  $1/a(l)$ . As in Melitz (2003), firms can be identified by their productivity, allowing us to exchange the index  $l$  by  $a$ . Shipping goods across borders involves iceberg trade costs, which implies that  $\tau_{ij} > 1$  units of output need to be shipped from country  $j$  to country  $i \neq j$  in order for one unit to arrive. Delivering to home country customers involves no trade costs, i.e.  $\tau_{ii} = 1$ . Exporting across borders is also associated with country- and sector-specific fixed export costs  $f_{ij} c_j$ , i.e.  $f_{ii} = 0$  and  $f_{ij} > 0$  for  $j \neq i$ .

The operating profit from producing a variety  $a$  in country  $j$  and selling it to country  $i$  is then  $\pi_{ij}(a) = [p_{ij}(a) - \tau_{ij} a c_j] x_{ij}(a) - f_{ij} c_j$ . From (2.1), this implies that a firm with productivity  $1/a$  producing in country  $j$  for exports to country  $i$  will charge the price:

$$p_{ij}(a) = \frac{1}{\alpha} \tau_{ij} a c_j, \quad (2.2)$$

where  $1/\alpha = \varepsilon/(\varepsilon - 1)$  is the standard mark-up. It also follows that domestic consumers are priced at  $p_{jj}(a) = 1/\alpha a c_j$ .

The assumption of the absence of fixed costs in home sales operations and fixed set-up costs incurred in exporting operations implies that only a fraction of country  $j$ 's  $N_j$  firms will export to country  $i$ . To characterize exporters, define the reduced-form operating profit for country  $j$  exporters as  $\pi_{ij}(a) = \pi_{ij}(p_{ij}(a))$ , or:

$$\pi_{ij}(a) = (1/a)^{\varepsilon-1} (1 - \alpha) \left( \frac{\tau_{ij} c_j}{\alpha P_i} \right)^{1-\varepsilon} \mu_i Y_i - f_{ij} c_j. \quad (2.3)$$

Let firm-productivity  $1/a$  be characterized from the cumulative distribution  $G(a)$  with density  $g(a)$  over the finite support  $a \in [a_L, a_H]$ , where  $a_L$  is the firm-specific input coefficient of the most productive firm and  $a_H$  that of the least productive firm, respectively.

We need the lower bound because we want to generate zero trade flows and the upper bound because we will assume a Pareto distribution.<sup>6</sup>

The cut-off productivity for being an exporter to country  $i$  based in country  $j$ ,  $1/a_{ij}$ , is then determined from the zero-profit condition,  $\pi_{ij}(a_{ij}) = 0$ , or:

$$a_{ij} = \left[ (1 - \alpha) \frac{\mu_i Y_i}{f_{ij} c_j} \right]^{\frac{1}{\varepsilon - 1}} \frac{\alpha P_i}{\tau_{ij} c_j}. \quad (2.4)$$

In Figure 1(iii), we show the operating profits for a country  $j$  firm as a function of the firm-specific input-coefficient  $a$  in exporting  $\pi_{ij}(a)$  and home sales  $\pi_{jj}(a)$ . The operating profits decrease in  $a$  and, hence, increase in productivity  $1/a$ , as shown in Figure 1(ii). Thus, firms in country  $j$  can only recover export fixed costs and export to country  $i$  if their productivity exceeds the cut-off productivity and firms with a productivity lower than the cut-off productivity will only sell on the domestic market.

Trade between countries  $i$  and  $j$  can now be characterized as follows: From (2.1) and (2.2), the export revenue for a country  $j$  firm is  $p_{ij}(l)x_{ij}(l) = (1/a)^{\varepsilon - 1} \left( \frac{\tau_{ij} c_j}{\alpha P_i} \right)^{1 - \varepsilon} \mu_i Y_i$ . As shown in Figure 1(i), the number of firms endowed with a productivity  $1/a$  is  $N_j g(a)$ . Hence, the aggregate imports of county  $i$  from country  $j$ ,  $M_{ij}$ , are:

$$M_{ij} = \int_{a_L}^{a_{ij}} (1/a)^{\varepsilon - 1} \left( \frac{\tau_{ij} c_j}{\alpha P_i} \right)^{1 - \varepsilon} \mu_i Y_i N_j g(a) da. \quad (2.5)$$

Define  $V_{ij}$  as a term indicating the share of exporting firms ( $g(a)$ ) weighted by a measure of firm size ( $a^{1 - \varepsilon}$ ):

$$V_{ij} = \begin{cases} \int_{a_L}^{a_{ij}} a^{1 - \varepsilon} g(a) da & \text{for } 1/a_L \geq 1/a_{ij}, \\ 0, & \text{otherwise.} \end{cases} \quad (2.6)$$

Combining (2.5) and (2.6), imports from country  $j$  to country  $i$  can be written:

$$M_{ij} = \left( \frac{c_j \tau_{ij}}{\alpha P_i} \right)^{1 - \varepsilon} \mu_i Y_i N_j V_{ij}. \quad (2.7)$$

To obtain an estimation equation from (2.7), HMR proceed in several steps. First, they specify trade costs as follows:

$$\tau_{ij}^{\varepsilon - 1} = D_{ij}^{\gamma}, \quad (2.8)$$

where  $D_{ij}$  is the distance between source and destination country and  $\gamma$  is the elasticity of bilateral trade with respect to distance, which may vary across industries.

Second, they assume a truncated Pareto distribution  $G(a) = (a^k - a_L^k)/(a_H^k - a_L^k)$ , where  $k > (\varepsilon - 1)$  is the shape parameter and show that  $V_{ij}$  in (2.6) takes the form

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<sup>6</sup>For an infinitely productive firm ( $a = 0$ ), the operating profits would always be large enough for finite positive fixed costs ( $f_{ij} c_j$ ) to ensure exports to every country.

$V_{ij} = \psi W_{ij}$ , where:

$$W_{ij} = \max \left\{ \left( \frac{a_{ij}}{a_L} \right)^{k-\varepsilon+1} - 1, 0 \right\}, \quad (2.9)$$

and  $\psi = (k a_L^{k-\varepsilon+1}) / ((k - \varepsilon + 1)(a_H^k - a_L^k))$  is a constant. Note that trade is observed whenever  $W_{ij} > 0$ , that is, if  $a_{ij} > a_L$ , implying that the cut-off productivity is smaller than the productivity of the most efficient firm in the industry,  $1/a_{ij} < 1/a_L$ . From Figure 1(i), note that the number of exporting firms  $\int_{a_L}^{a_{ij}} N_j g(a) da$  is increasing in  $a_{ij}$ . Importantly, from (2.9), it then follows that the number of country  $j$  exporters is increasing in  $W_{ij}$ , since  $W_{ij}$  is increasing in  $a_{ij}$ .<sup>7</sup> Note also that a reduction of  $\gamma$  thus increases the number of exporting firms since it lowers the threshold productivity level  $1/a_{ij}$ .

Third, they add a multiplicative error  $\exp(u_{ij})$  on the right-hand side of equation (2.7).  $u_{ij}$  is assumed to be log normally distributed such that  $u_{ij} \sim N(0, \sigma_u^2)$ .

Inserting (2.8) and (2.9) into (2.7) and adding  $\exp(u_{ij})$ , taking logs and denoting logged variables with lower-case letters, HMR obtain the gravity estimation equation in logs:

$$m_{ij} = \beta_0 + \lambda_j + \chi_i - \gamma d_{ij} + \omega_{ij} + u_{ij}, \quad (2.10)$$

where  $\beta_0 = (\varepsilon - 1) \ln(\alpha) + \ln(\psi)$ , importer country-fixed effects  $\chi_i$  contain  $\chi_i = (\varepsilon - 1)p_i + \ln \mu_i + y_i$ , and exporter country-fixed effects  $\lambda_j$  contain  $\lambda_j = (1 - \varepsilon) \ln c_j + n_j$  and the number of exporters is captured by

$$\omega_{ij} = \ln \left[ \left( \frac{a_{ij}}{a_L} \right)^{k-\varepsilon+1} - 1 \right]. \quad (2.11)$$

Note that the term  $\omega_{ij}$  is the only one anew in the gravity equation as compared to Anderson and van Wincoop (2003).

The estimation of (2.10) is hampered by two problems. First, it is only estimated on data with positive trade flows, since the dependent variable, the log of trade volume  $m_{ij}$ , is not defined for zero import values,  $M_{ij} = 0$ . Second, there is an omitted variable problem through  $\omega_{ij}$ , which captures the degree of firm heterogeneity in country  $j$ , an information typically not available for gravity estimations on a world trade dataset.<sup>8</sup>

HMR note that both problems are related to the extensive margin of trade. Rear-

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<sup>7</sup>As illustrated in Figure 1, note that positive trade  $M_{ij} > 0$  requires  $a_{ij} > a_L$ . But then  $W_{ij} = \max \left\{ \left( \frac{a_{ij}}{a_L} \right)^{k-\varepsilon+1} - 1, 0 \right\} = \left( \frac{a_{ij}}{a_L} \right)^{k-\varepsilon+1} - 1$ . Thus, we have  $\omega_{ij} \equiv \ln W_{ij} = \ln \left[ \left( \frac{a_{ij}}{a_L} \right)^{k-\varepsilon+1} - 1 \right]$ .

<sup>8</sup>Flam and Nordström (2008) have recently included a proxy variable for  $\omega_{ij}$ , which is available for Swedish exports. However, they did not estimate the distance coefficient over time, which is the focus of this paper.



ranging (2.4), they then define an auxiliary variable  $Z_{ij}$ :

$$\begin{aligned} \left(\frac{a_{ij}}{a_L}\right)^{\varepsilon-1} &= \frac{(1-\alpha)\left(\frac{\tau_{ij}c_j a_L}{\alpha P_i}\right)^{1-\varepsilon} \mu_i Y_i}{c_j f_{ij}} \\ &\equiv Z_{ij}. \end{aligned} \quad (2.12)$$

As illustrated in Figures 1(i) and 1(iii), changes in  $Z_{ij}$  will indicate both, i.e. changes in the number of exporting firms through the cut-off  $a_{ij}$  as well as zero trade links. Noting that changes in  $Z_{ij}$  are exclusively driven by changes in  $a_{ij}$ , Figure 1(iii) shows that there will be no exports if  $a_{ij} < a_L$ , which is equivalent to the condition  $Z_{ij} < 1$ . In contrast, the trade flows will be non-zero when  $a_{ij} > a_L$ , which implies  $Z_{ij} > 1$ .

Now, we can express the omitted variable  $\omega_{ij}$  by inserting equation (2.12) into (2.11)

$$\omega_{ij} = \ln [\exp[\delta z_{ij}] - 1], \quad (2.13)$$

where  $\delta = (k - \varepsilon + 1) / (\varepsilon - 1)$  and  $z_{ij} = \ln Z_{ij}$ . The estimation strategy of HMR is to obtain an estimate of the expected value of the omitted variable  $\omega_{ij}$  by estimating an expected value of the auxiliary variable  $z_{ij}$ .

To obtain another estimation equation, another error term is introduced by decomposing the fixed trade costs  $f_{ij}$  as follows:

$$f_{ij} = \exp [(\phi_{EX,j} + \phi_{IM,i} + \kappa\phi_{ij} - \nu_{ij})], \quad (2.14)$$

where  $\nu_{ij} \sim N(0, \sigma_\nu^2)$  and  $\phi_{EX,j}$  is a measure of the fixed export cost common across all export destinations,  $\phi_{IM,i}$  is a fixed trade barrier imposed by the importing country on all exporters, and  $\phi_{ij}$  is an observed measure of any additional country-pair specific fixed trade costs.<sup>9</sup>

Taking logs of  $Z_{ij}$  in (2.12) and using (2.8) and (2.14), HMR obtain an equation for a latent variable  $z_{ij} \equiv \ln Z_{ij}$ :

$$\begin{aligned} z_{ij} &= \gamma_0 + \xi_j + \zeta_i - \gamma d_{ij} - \kappa\phi_{ij} + \eta_{ij} \\ &= E[z_{ij} | d_{ij}, \xi_j, \zeta_i, \phi_{ij}] + \eta_{ij}, \end{aligned} \quad (2.15)$$

where  $\eta_{ij} = u_{ij} + \nu_{ij}$ ,  $\zeta_i = (\varepsilon - 1)p_i + y_i + \ln \mu_i - \phi_{IM,i}$  is an importer fixed effect,  $\xi_j = -\varepsilon \ln c_j - \phi_{EX,j}$  is an exporter fixed effect and  $\sigma_\eta^2$  is the variance of  $\eta_{ij}$ . While the latent variable  $z_{ij}$  cannot be observed, one can observe if trade takes place. Thus, an indicator variable  $T_{ij} = \mathcal{I}_{[z_{ij} > 0]}$  can be defined from which the selection equation for the

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<sup>9</sup> $\phi_{ij}$  takes the role of an instrument in the empirical implementation and is assumed to be statistically independent of  $\nu_{ij}$  as well as  $u_{ij}$ .

probability of strictly positive exports is obtained:

$$\begin{aligned}
\Pr(T_{ij} = 1 | d_{ij}, \xi_j^*, \zeta_i^*, \phi_{ij}) &= \Pr(z_{ij}^* > 0 | d_{ij}, \xi_j^*, \zeta_i^*, \phi_{ij}) \\
&= \Pr(\gamma_0^* + \xi_j^* + \zeta_i^* - \gamma^* d_{ij} - \kappa^* \phi_{ij} > -\eta_{ij}^* | d_{ij}, \xi_j^*, \zeta_i^*, \phi_{ij}) \\
&= \Phi(\gamma_0^* + \xi_j^* + \zeta_i^* - \gamma^* d_{ij} - \kappa^* \phi_{ij}) \\
&= E[z_{ij}^* | d_{ij}, \xi_j^*, \zeta_i^*, \phi_{ij}],
\end{aligned} \tag{2.16}$$

where  $\Phi(\cdot)$  is the cumulative distribution function of the unit normal distribution and every starred coefficient represents the original coefficient divided by  $\sigma_\eta$ .<sup>10</sup>

One can now in a first stage estimate (2.16) by a probit estimation. Inverting the predicted probability from (2.16) yields an estimate of the underlying latent variable  $\hat{z}_{ij}^*$ .

Defining  $\delta = \sigma_\eta \frac{k-\varepsilon+1}{\varepsilon-1} > 0$ , HMR use  $\hat{\omega}_{ij}^* \equiv \ln\{\exp[\delta(\hat{z}_{ij}^* + \hat{\eta}_{ij}^*)] - 1\}$  as an estimate for  $E[\omega_{ij} | \cdot, z_{ij}^* > 0]$ ,<sup>11</sup> where  $\hat{\eta}_{ij}^* = \phi(\hat{z}_{ij}^*)/\Phi(\hat{z}_{ij}^*)$  is the inverse Mills ratio from the first-stage probit estimation, which itself is well-known to be a consistent estimate of  $E[u_{ij} | \cdot, z_{ij}^* > 0]$ .<sup>12</sup> Inserting these terms into (2.10), HMR show that estimation of the gravity model requires estimating the following specification:

$$m_{ij} = \beta_0 + \lambda_j + \chi_i - \gamma d_{ij} + \ln\{\exp[\delta(\hat{z}_{ij}^* + \hat{\eta}_{ij}^*)] - 1\} + \beta_{u\eta} \hat{\eta}_{ij}^* + e_{ij}, \tag{2.17}$$

where  $\beta_{u\eta} \equiv \text{corr}(u_{ij}, \eta_{ij})(\sigma_u/\sigma_\eta) = \text{corr}(u_{ij}, u_{ij} + \nu_{ij})(\sigma_u/\sigma_\eta) > 0$ . The term  $\ln\{\exp[\delta(\hat{z}_{ij}^* + \hat{\eta}_{ij}^*)] - 1\}$  corrects for the omitted variable  $\omega_{ij}$  in the presence of sample selection<sup>13</sup> and  $\beta_{u\eta} \hat{\eta}_{ij}^*$  is the well-known correction of the error term  $u_{ij}$  in the presence of sample selection. As a result,  $e_{ij}$  is an i.i.d. error term satisfying  $E[e_{ij} | \cdot, T_{ij} = 1] = 0$ . Therefore, one can estimate (2.17) using NLS and obtain an estimate of the distance coefficient  $\gamma$ , having the structural interpretation of the elasticity of bilateral trade with respect to distance for all country-pairs in the population, i.e. for positive and zero trade flows.

## 2.2 HMR and the distance puzzle

In this section, we use the HMR model to examine the distance puzzle. We will assume the HMR model to be the data generating process and examine to what extent the OLS estimation of (2.10) is biased and in what direction this bias goes. Then, we examine

<sup>10</sup>As in every discrete choice model, the scale can be arbitrarily chosen, i.e. the model must be properly normalized. We normalize by dividing through  $\sigma_\eta$ , following HMR. This leads the error term  $\eta_{ij}^* = \eta_{ij}/\sigma_\eta$  to be distributed unit normal.

<sup>11</sup>Santos Silva and Tenreyro (2008) note that this is not a consistent estimate because of Jensen's inequality. However, Santos Silva and Tenreyro (2008) also note that it might be a reasonably accurate approximation in many practical situations. In order to check the robustness with respect to this critique, we compare our results when applying different approaches.

<sup>12</sup>This term is also known as Heckman's lambda (see Heckman, 1979).

<sup>13</sup>In the absence of a sample selection bias but in the presence of the omitted variable bias, the correction term would simplify to  $\ln\{\exp(\delta \hat{z}_{ij}^*) - 1\}$ , since  $\text{plim} \hat{\eta}_{ij}^* = E[u_{ij} | \cdot, z_{ij}^* > 0] = 0$  in this case.

how the bias of OLS is affected by globalization.

### 2.2.1 The Bias of OLS

Let us start by examining the properties of an OLS estimate of the distance coefficient,  $\hat{\gamma}^{OLS}$ , from estimating gravity equation (2.10) without a sample selection correction and when not controlling for the omitted variable bias due to firm heterogeneity by  $\omega_{ij}$ . To gain some intuition on these two biases and their direction, we first look at them in turn before considering them simultaneously. We begin by first discussing the sample selection bias and then continue with the omitted variable bias.

**Selection bias** We first show that the selection bias leads to an underestimation of the elasticity of bilateral trade with respect to distance. Consider Figure 2, which contains distance  $d_{ij}$  on the horizontal axis and imports  $m_{ij}$  on the vertical axis. We depict by circles imports to country  $i$  from countries  $j = 1, 2, 3, 4, 5$ , holding the control variables constant over countries  $j$  for the purpose of graphical illustration. From the selection equation for the probability of strictly positive exports (2.16), we note that  $\frac{\partial \Pr(T_{ij}=1|\cdot)}{\partial d_{ij}} = -\gamma^* \phi(\cdot) < 0$ , where  $\phi(\cdot)$  is the normal density function. Thus, missing observations are more likely the larger is the distance. In addition, the smaller is the error term  $u_{ij}$ , the more likely is trade to be predicted to be zero. For this reason, we draw potential imports between countries  $i$  and  $j = 4$  and  $j = 5$  such that the distance is large and the error terms  $u_{i4}$  and  $u_{i5}$  negative, causing these two observations to drop out of the sample, which we indicate by hollow circles. Since the negative  $u_{i4}$  and  $u_{i5}$  are not only contained in the selection equation (2.16) but also in the gravity equation (2.10), the imports that drop out do not only occur at a large distance but also at unusually low values of imports.<sup>14</sup> The non-missing imports at large distances, indicated by filled circles, are those with positive values of  $u_{ij}$ , i.e.  $E[u_{ij}|d_{ij}, T_{ij} = 1] > 0$  if the distance  $d_{ij}$  is large. Since the unconditional expected value of  $u_{ij}$  is zero by construction of the OLS estimator,<sup>15</sup> i.e.  $E[u_{ij}|T_{ij} = 1] = 0$ , the conditional expected value of  $u_{ij}$  is negative,  $E[u_{ij}|d_{ij}, T_{ij} = 1] < 0$ , if the distance  $d_{ij}$  is small. But then the error term in the outcome equation  $u_{ij}$  and distance  $d_{ij}$  are positively correlated. The conditional expected value of the error term feeds back into the estimated regression line, since

$$E[m_{ij}|d_{ij}, T_{ij} = 1] = E[m_{ij}|d_{ij}] + E[u_{ij}|d_{ij}, T_{ij} = 1], \quad (2.18)$$

<sup>14</sup>Note that we have drawn negative values of  $m_{ij}$ . Naturally, negative values of  $m_{ij}$  can never exist, but are generated by the gravity equation (2.10), since shocks are, by assumption, normally distributed on a range from  $-\infty$  to  $+\infty$ . However, whenever  $m_{ij}$  is negative, it is not observed.

<sup>15</sup>The estimated regression constant will always ensure that the unconditional expected value of the error term is zero in an OLS regression, whereas the conditional expected value of the error term is only zero for a correctly specified model, i.e. a model without endogeneity problems.

for all observations with  $T_{ij} = 1$ ,<sup>16</sup> where  $E[m_{ij}|d_{ij}, T_{ij} = 1]$  is fitted by an OLS regression on the remaining three strictly positive import data from  $j = 1, 2, 3$  and  $E[m_{ij}|d_{ij}]$  is fitted by an OLS regression on the entire population including  $j = 4$  and  $j = 5$  which, in turn, is asymptotically equivalent to an OLS regression with a sample selection correction denoted by *Heckman* in Figure 2. Hence, the positive slope of  $E[u_{ij}|d_{ij}, T_{ij} = 1]$  in  $d_{ij}$  results in a flatter declining slope of an OLS regression without sample selection,  $E[m_{ij}|d_{ij}, T_{ij} = 1]$ , than one with sample selection,  $E[m_{ij}|d_{ij}]$ . This implies that the distance coefficient estimated with OLS ignoring zero trade flows will be too small in absolute values. Accounting for zero trade flows will aggravate the distance puzzle, as the estimates of the distance coefficient based on *Heckman* will be larger in absolute values. *To sum up: the selection bias due to omitting zero trade flows is not able to explain the distance puzzle.*

**Omitted variable bias** We next show that the omitted variable bias leads to an overestimation of the elasticity of bilateral trade with respect to distance. We first need to understand how the omitted variable  $\omega_{ij}$  is correlated with distance  $d_{ij}$ . This can easily be seen by inserting (2.15) into (2.13) and taking the expected value conditional on distance  $d_{ij}$  and the other control variables  $z_0 \equiv \gamma_0 + \zeta_i + \xi_j - \kappa\phi_{ij}$  to obtain

$$E[\omega_{ij} | d_{ij}, z_0] = \int f_{\omega_{ij}}(\omega_{ij}) \ln[\exp[\delta(z_0 - \gamma d_{ij} + \eta_{ij})] - 1] d\omega_{ij} \equiv \Omega(z_0, d_{ij}), \quad (2.19)$$

where  $f_{\omega_{ij}}(\omega_{ij})$  is the marginal distribution function of  $\omega_{ij}$ , and we take  $\omega_{ij}$  to be conditionally independent of  $d_{ij}$  and  $z_0$ , i.e. we investigate the omitted variable bias after having properly controlled for the selection bias (such as by the Heckman correction factor) or, equivalently, considering the case where no trade flows are missing.<sup>17</sup> This has the purpose of comparing the Heckman estimator, which controls the selection bias but suffers from the omitted variable bias with the HMR estimator which controls for both biases. Controlling conceptually for the selection bias while analyzing the omitted variable bias implies that  $e^{\delta(z_0 - \gamma d_{ij} + \eta_{ij})} > 1$  to ensure that there are no missing observations causing selection bias. Moreover,  $\Omega(z_0, d_{ij})$  is the non-linear conditional expectation function, the shape of which is easy to analyze. Taking the derivative of (2.19) with respect to

<sup>16</sup>See, e.g., equation (16.34) in Cameron and Trivedi (2005, p. 549).

<sup>17</sup>To see how this equation is obtained, note that by definition of a conditional expected value  $E[\omega_{ij} | d_{ij}, z_0] = \int \hat{f}(\omega_{ij} | d_{ij}, z_0) \omega_{ij} d\omega_{ij}$ , where  $\hat{f}(\omega_{ij} | d_{ij}, z_0)$  is the conditional distribution of  $\omega_{ij}$ . According to Greene (2012), (B-51), this can be written as  $E[\omega_{ij} | d_{ij}, z_0] = \int f(\omega_{ij} | d_{ij}, z_0) \omega_{ij} d\omega_{ij}$  with  $f(\omega_{ij} | d_{ij}, z_0)$  being the conditional distribution of  $\omega_{ij}$ . If we then assume that  $\omega_{ij}$  is conditionally independent of  $d_{ij}$  and  $z_0$ , we obtain from (B-60)  $f(\omega_{ij} | d_{ij}, z_0) = f_{\omega_{ij}}(\omega_{ij})$ , where  $f_{\omega_{ij}}(\omega_{ij})$  is the marginal probability density (see B-45). Inserting this relation above, we obtain:  $E[\omega_{ij} | d_{ij}, z_0] = \int f_{\omega_{ij}}(\omega_{ij}) \omega_{ij} d\omega_{ij}$ . Inserting (2.15) and (2.13) into this relation yields (2.19).

distance  $d_{ij}$ , we obtain

$$\frac{\partial E[\omega_{ij} | d_{ij}, z_0]}{\partial d_{ij}} = -\gamma\delta \int f_{\omega_{ij}}(\omega_{ij}) \frac{e^{\delta(z_0 - \gamma d_{ij} + \omega_{ij})}}{e^{\delta(z_0 - \gamma d_{ij} + \eta_{ij})} - 1} d\omega_{ij} < 0. \quad (2.20)$$

Hence, there is a negative correlation between  $\omega_{ij}$  and  $d_{ij}$ , because the share of exporting firms becomes smaller the larger is distance. If  $\omega_{ij}$  is known (and other controls are kept constant), a linear OLS regression of import values  $m_{ij}$  on distance  $d_{ij}$  controlling for  $\omega_{ij}$  is like a regression of  $(m_{ij} - \omega_{ij})$  on distance  $d_{ij}$ . This follows from the fact that the regression coefficient of  $d_{ij}$  explains the remaining variation of the corresponding variable that is not at the same time common variation with another control variable (Frisch-Waugh theorem) and  $\omega_{ij}$  enters the regression equation (2.10) with coefficient one. An OLS estimator fitting the regression line  $E[m_{ij} - \omega_{ij} | d_{ij}]$  then has the same slope in  $d_{ij}$  as one fitting  $E[m_{ij} | d_{ij}, \omega_{ij}]$  or, indeed, one using a consistent correction factor that controls for  $\omega_{ij}$ , i.e. the *HMR* estimator (while at the same time controlling for the sample selection effect).

To obtain  $(m_{ij} - \omega_{ij})$  in Figure 2, which is indicated by crosses, we can read off the difference between  $m_{ij}$  and  $\omega_{ij}$ , an example of which is given for  $\omega_{i1}$ . As can be seen, the crosses indicating  $(m_{ij} - \omega_{ij})$  are systematically located below the circles indicating  $m_{ij}$  at low distances and above at large distances.<sup>18</sup> Hence, a fit of the crosses by the solid *HMR* line  $E[m_{ij} - \omega_{ij} | d_{ij}]$  rather than the circles by the Heckman line  $E[m_{ij} | d_{ij}]$  is flatter, implying an upward bias of the distance coefficient. Hence, the OLS estimator omitting  $\omega_{ij}$  overestimates the elasticity of bilateral trade with respect to distance. This implies that the distance coefficient estimated with OLS ignoring the omitted variable bias will be too large in absolute values. Accounting for the omitted variable bias is therefore potentially able to solve the distance puzzle, as the estimates of the distance coefficient based on *HMR* will be smaller in absolute values. *To sum up: the omitted variable bias due to neglecting the heterogeneity of firms can potentially explain the distance puzzle.*

**Interacting the two biases** Distance has three influences on imports. There is a direct one on positive trade flows through the intensive margin (and which is the only one present in homogeneous firm models), and an indirect one on positive trade flows through the extensive margin at the firm-level, i.e. the share of exporting firms  $\omega_{ij}$ . A third margin is given by the extensive margin of positive overall trade flows. If omitting a proper control for the extensive margin  $\omega_{ij}$ , and for the selection of countries into positive

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<sup>18</sup>Note that the *HMR* regression line fits all crosses for  $j = 1, 2, 3, 4, 5$ , because it does not only correct for the omitted variable bias, but also for sample selection simultaneously. If only the omitted variable bias was controlled for but not the sample selection bias, such a regression line would only fit the crosses corresponding to  $j = 1, 2, 3$ .

trade flows, the distance coefficient captures all three margins.<sup>19</sup>

Overall, it is then indeterminate whether the OLS line  $E[m_{ij}|d_{ij}, T_{ij} = 1]$  is flatter or steeper than the HMR line  $E[m_{ij} - \omega_{ij}|d_{ij}]$ . In anticipation of our empirical results, we have drawn it such that the OLS line is steeper than the HMR line, which implies that the omitted variable bias dominates the sample selection bias in levels. We depict this as *Bias OLS* in Figure 2.

Let us now consider both biases simultaneously, formally taking into account the interaction of the two biases. For this purpose, we need to draw on an approximation of (2.13),

$$\omega_{ij} \approx \delta z_{ij}, \quad (2.21)$$

where  $\delta = \partial\omega_{ij}/\partial z_{ij}$  evaluated at the mean of  $z_{ij}$ .

We then have the following proposition:

**Proposition 1.** *When assuming that the HMR model is the data generating process, then the OLS estimate of  $\gamma$  in (2.10) may be (asymptotically) up- or downward biased, depending on whether the omitted variable bias from the share of exporting firms or the sample selection bias due to the omission of zero trade flows dominates, respectively.*

We derive the simultaneous bias term in the Appendix, which is given by the following simple expression:

$$\text{Bias}(\hat{\gamma}^{OLS}) = \gamma\delta - \Xi[\delta + \beta_{u\eta}] \bar{\eta}_{ij}^* \begin{matrix} \geq \\ \leq \end{matrix} 0, \quad (2.22)$$

where  $\Xi = \sum_i \sum_j d_{ij} / \sum_i \sum_j (d_{ij})^2$ .

Thus, as shown in Figure 2, the term  $\delta\gamma > 0$  in (2.22) represents an upward bias in OLS (and Heckman) from not controlling for the number of exporting firms, and the last two terms measure a downward bias from sample selection in OLS, when omitting zero trade flows, as  $\beta_{u\eta}$ ,  $\bar{\eta}_{ij}^*$  and  $\Xi$  are positive.

### 2.2.2 Globalization

How would the bias of OLS evolve over time when globalization reduces the responsiveness of bilateral trade flows with respect to distance because of new and better communication and transport technologies? Make the following assumption:

**Assumption** Increased globalization implies that  $\frac{\partial\gamma}{\partial t} < 0$ .

We then have the following proposition:

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<sup>19</sup>Chaney (2008) and Krauthaim (2011) theoretically derive the effects on the elasticity of bilateral trade flows with respect to distance disentangling the intensive and extensive margin.

**Proposition 2.** *When assuming that the HMR model is the data generating process, both the downward bias from sample selection due to zero trade flows and the upward bias from omitting the number of exporting firms decrease in the pace of globalization.*

The change in the bias of the distance coefficient  $\frac{\partial \text{Bias}(\hat{\gamma}^{OLS})}{\partial t}$  can once more be understood intuitively, looking at the two biases separately. Beginning with the change of the sample selection bias over time, we first notice that the bias depends on how the slope of  $E[u_{ij}|d_{ij}]$  changes when  $\gamma$  changes over time. To understand this, we need to first look at how the selection process is influenced by a reduction in  $\gamma$ . An observation is missing whenever  $z_{ij}^* < 0$  according to (2.16). Obviously, a reduction in  $\gamma$  decreases  $z_{ij}^*$  ( $\partial z_{ij}^*/\partial \gamma = -d_{ij} < 0$ ), where some missing trade links turn positive. Eventually, all missing trade links have turned into positive ones at sufficiently low  $\gamma$ . Hence, the true line fitting the data after globalization becomes flatter.

Turning to the change of the omitted variable bias over time, we once more need to understand how the slope of the conditional expectation function  $E[\omega_{ij}|d_{ij}]$  changes with a reduction of  $\gamma$ . For this purpose, it is sufficient to look at how  $\omega_{ij}$  changes for each observation when  $\gamma$  falls. From (2.15) and (2.13), we immediately obtain

$$\frac{\partial \omega_{ij}}{\partial \gamma} = -d_{ij} \delta \frac{e^{\delta z_{ij}}}{e^{\delta z_{ij}} - 1} < 0, \quad (2.23)$$

for all  $\omega_{ij}$  that are nonmissing. Hence, the share of exporting firms of a country  $j$  exporting to country  $i$  is increasing for each country pair when  $\gamma$  falls. More importantly, this share increases less for further distant trading partners:

$$\frac{\partial^2 \omega_{ij}}{\partial \gamma \partial d_{ij}} = -\delta \frac{e^{\delta z_{ij}}}{e^{\delta z_{ij}} - 1} - d_{ij} \gamma \delta^2 \frac{e^{\delta z_{ij}}}{(e^{\delta z_{ij}} - 1)^2} < 0, \quad (2.24)$$

for all  $\omega_{ij}$  that are nonmissing.

Since  $E_a[\omega_{ij}|d_{ij}]$  is flatter after globalization than  $E_b[\omega_{ij}|d_{ij}]$  is before globalization, the upward bias in the distance coefficient from omitting the variable  $\omega_{ij}$  also becomes smaller.

Considering changes in both biases simultaneously, we cannot tell whether the difference in slopes between the HMR-line and the OLS-line will increase or decrease over time, because the downward bias from sample selection decreases and the upward bias from the omitted variable  $\omega_{ij}$  also decreases. Since we cannot tell how the bias of OLS will behave under globalization, the OLS estimate of the distance coefficient may also increase or decrease over time.

**The HMR estimator and the distance puzzle** Let us now show how the HMR estimator can be used to explain the distance puzzle. That is, let us now show how

the HMR estimator can be used to explain the finding in the literature that the OLS estimates of the elasticity of bilateral trade with respect to distance do not fall over time.

Suppose that the omitted variable bias dominates in levels at the beginning of the data period such that there is an overall upward bias in the distance coefficient (see the estimates of Helpman, Melitz and Rubinstein (2008)), i.e. the OLS estimated schedule is steeper than the true line (HMR) just as in Figure 2. A decrease in the upward bias through the omitted variable  $\omega_{ij}$  makes the OLS estimate flatter and a decrease in the downward bias through less sample selection makes the OLS schedule steeper. Now, if the downward bias from sample selection due to the omission of zero trade flows decreases faster than the upward bias from omitting the share of exporting firms, then, overall, the estimated OLS schedule will become steeper.

Note also that the sample selection bias alone cannot solve the distance puzzle, contrary to what is stated in Felbermayr and Kohler (2006). As the sample selection bias leads to a downward bias, the importance of distance will be underestimated. Hence, the level cannot be correctly captured accounting for sample selection alone. However, to capture the change of the bias for the distance coefficient, we need a larger decrease in the zero-trade flows bias as compared to the omitted variable bias due to firm heterogeneity. A first glance at the data and anecdotal evidence cope with these facts. Whereas there has been a dramatic decrease in zero-trade flows over the last two decades, firm sizes and productivities are still heavily dispersed (Poschke (2011)) and the share of exporting firms remains small.

### 3 Econometric analysis

#### 3.1 Base-line estimation equation and alternative estimators

Our baseline estimation equation is the HMR gravity equation (2.17). Since our main interest rests on the coefficient of the distance variable  $\gamma$  and how it evolves over time, we will estimate this equation separately by year and industry. We use the following augmented specification:

$$m_{ij} = \beta_0 - \gamma d_{ij} + \alpha_1 \text{BORDER}_{ij} + \alpha_2 \text{RTA}_{ij} + \alpha_3 \text{REXCH}_{ij} + a_4 \text{GDPPCDIF}_{ij} \quad (3.1) \\ + \lambda_j + \chi_i + \ln \left\{ \exp \left[ \delta \left( \hat{z}_{ij}^* + \hat{\eta}_{ij}^* \right) - 1 \right] \right\} + \beta_{un} \hat{\eta}_{ij}^* + e_{ij},$$

where we explain the additional variables below. Once more, note that  $\ln \left\{ \exp \left[ \delta \left( \hat{z}_{ij}^* + \hat{\eta}_{ij}^* \right) - 1 \right] \right\}$  captures the omitted variable bias due to firm-level heterogeneity in the presence of sample selection, whereas  $\hat{\eta}_{ij}^*$  captures the sample selection bias of the error term from estimating (3.1) for non-zero trade. To estimate these correction terms, we add a first-



stage equation in order to estimate (2.16), where:

$$z_{ij}^* = \varphi_0^* + \varphi_1^* \text{BORDER}_{ij} + \varphi_2^* \text{RTA}_{ij} + \varphi_3^* \text{REXCH}_{ij} + \varphi_4^* \text{GDPPCDIF}_{ij} + \varphi_5^* \text{COMM\_REL}_{ij} + \varphi_6^* \text{COMM\_LANG}_{ij} + \xi_j^* + \zeta_i^* - \gamma^* d_{ij} + \eta_{ij}. \quad (3.2)$$

### 3.1.1 Other estimators

We have shown that the distance puzzle can be studied by systematically comparing the estimates from HMR with corresponding estimates obtained with OLS. The OLS estimator estimates equation (3.1), omitting the correction terms for firm-level heterogeneity and sample selection, i.e. excluding  $\ln \{ \exp [\delta (\hat{z}_{ij}^* + \hat{\eta}_{ij}^*) - 1] \}$  and  $\hat{\eta}_{ij}^*$ . By comparing the HMR and OLS estimators, we can evaluate how the bias of OLS evolves over time as predicted by Propositions 1 and 2. We will also compare our estimates with HMR with a number of other estimators.

**Heckman** The usual Heckman estimator estimates equation (3.1) omitting the correction terms for firm-level heterogeneity but including that for sample selection, i.e. excluding  $\ln \{ \exp [\delta (\hat{z}_{ij}^* + \hat{\eta}_{ij}^*) - 1] \}$  but including  $\hat{\eta}_{ij}^*$ .

**Linear approximation of HMR** As  $\delta$  enters the estimation equation non-linearly, we first estimate equation (3.1) via non-linear least squares, as proposed by HMR. However, as discussed in Santos Silva and Tenreyro (2008), this correction term is biased if their theoretical model is the data generating process. However, for a wide range of  $\hat{z}_{ij}^* + \hat{\eta}_{ij}^*$ , the term  $\ln \{ \exp [\delta (\hat{z}_{ij}^* + \hat{\eta}_{ij}^*) - 1] \}$  may be well approximated by  $\bar{\delta} (\hat{z}_{ij}^* + \hat{\eta}_{ij}^*)$  for some appropriate parameter  $\bar{\delta}$ , which can be estimated by OLS (see our discussion in section 2.1). Hence, we also estimate the model via OLS and include  $\varpi_{ij} = \bar{\delta} (\hat{z}_{ij}^* + \hat{\eta}_{ij}^*)$  instead of  $\ln \{ \exp [\delta (\hat{z}_{ij}^* + \hat{\eta}_{ij}^*) - 1] \}$ .<sup>20</sup>

**Pseudo Maximum Likelihood** In a final comparison, we will estimate (3.1) directly, that is we have a multiplicative model, given by:

$$\exp(m_{ij}) = g\left(\beta_0 - \gamma d_{ij} + \alpha_1 \text{BORDER}_{ij} + \alpha_2 \text{RTA}_{ij} + \alpha_3 \text{REXCH}_{ij} + \alpha_4 \text{GDPPCDIF}_{ij} + \lambda_j + \chi_i + \delta \varpi_{ij} + \beta_{un} \hat{\eta}_{ij}^* + u_{ij}\right), \quad (3.3)$$

where  $g(\cdot)$  is some distribution function belonging to the family of generalized linear models.<sup>21</sup> As discussed in Santos Silva and Tenreyro (2006), the Poisson distribution is a

<sup>20</sup>HMR use a polynomial of degree 3 in the score variable in one of their robustness checks. We will point out that even a linear approximation works well in practice.

<sup>21</sup>Generalized linear models (GLMs) are based on a distribution function of the linearized exponential family which includes, for instance, the Gaussian, Poisson, negative binomial, or Gamma distributions.

prime candidate, leading to the Poisson pseudo-maximum-likelihood (*PPML*) estimator. However, if the variance is a function of higher powers of the mean, a more efficient estimator may be obtained by downweighting observations with a larger conditional mean. An example for such an estimator is the Gamma pseudo-maximum-likelihood (*GPML*).

## 3.2 Data

### 3.2.1 Dependent variable

The dependent variable  $m_{ij}$  in (3.1) is the natural logarithm of bilateral imports of country  $i$  from country  $j$  in a given industry  $l$  at a given year  $t$ , measured in million US\$ converted by the Penn World Tables 2.0 purchasing power parity exchange rate (PPP) and deflated by the U.S. consumer price index. Data on imports are taken from Nicita and Olarreaga (2001), who have compiled an industry dataset corresponding to the 3-digit ISIC, revision 2, level and contains 28 manufacturing industries for up to 100 countries during 1976-2004. Because there is a large number of missing values in the early years and we were lacking a control variable in the last year, we have restricted the sample to 1978-2003. The dataset is available for downloading from the World Bank ([www.worldbank.org/trade](http://www.worldbank.org/trade)). In turn, this dataset draws its bilateral industry import data from COMTRADE of the UN which is based on the Standard International Trade Classification (SITC) and then transformed into ISIC. Production data are taken from UNIDO (International Yearbook of Industrial Statistics).

### 3.2.2 Explanatory variables

The trade dataset is merged into a balanced geography dataset covering 170 countries. These geography variables appear in (3.1)-(3.3) as follows:  $d_{ij}$  is the log of the distance in kilometers between capitals of countries  $i$  and  $j$ .  $\lambda_j$  and  $\chi_i$  are a full set of exporter and importer dummy variables, respectively, which control for, among others, the multilateral resistance terms pointed out by Anderson and van Wincoop (2003). Additional variables used are  $BORDER_{ij}$  which is a dummy variable indicating a common border between  $i$  and  $j$ ,  $RTA_{ij}$  indicates whether there is a common trade agreement between exporter  $i$  and importer  $j$  (EU, MERCOSUR, NAFTA, ASEAN, CARICOM, PATCRA, ANZD, CACM, SPARTECA, CEFTA, USIS), the real exchange rate  $REXCH_{ij}$  is measured as the ratio of exporter to importer purchasing power parity from the Penn World Tables 2.0 with a value larger than 1 indicating a real overvaluation of the exporter relative to the importer currency based on the prices of the Penn World Table 2.0 consumption baskets. To control for differences in trade structure, we also include a rough measure of difference in development stage,  $GDPPCDIF_{ij}$ , which measures the log difference in per capita real GDP per worker of the exporter from that of the importer country according

to the Penn World Tables 2.0.

### 3.2.3 Instruments

To estimate the probability of exporting, we use the same control variables as in (3.1) in addition to two excluded selection variables following HMR. The first excluded variable is a measure of to what extent the importer and the exporter share a common religion in the population according to data from the Christian Research Association for the year 2003. In particular, the measure takes the sum over the set of all existing religions summing up a population's share of the importer country confessing a religion multiplied with the same share of the exporter country. This measure is bounded between 0 and 1, with large numbers indicating a large degree of overlap in the religious structure of importer and exporter country. The second excluded variable is an indicator variable that indicates whether the importer and the exporter share a common language.

## 3.3 Results

To explore the distance puzzle, we thus estimate (3.1) by industry and year. With data for 28 industries over 26 years, 1978-2003 and with five specifications, this amounts to estimating  $28 \times 26 = 728$  first-stage regressions and  $28 \times 26 \times 5 = 3640$  second-stage regressions. For expositional reasons, we therefore show our results graphically.

### 3.3.1 HMR versus OLS

The top panel of Figure 3 depicts distance coefficients estimated with OLS and the non-linear method from HMR. For each year, the mean distance coefficient is calculated over all 28 industries, which is then plotted over the full time period 1978-2003. To indicate the time pattern for each estimator, we have added a quadratic trend with an associated 95 percent confidence interval. In the lower panel, we also add the linear approximation of HMR which is again compared to OLS. Several interesting features are present in Figure 3.

Note that the trend of the distance coefficient, when estimated by OLS,  $\hat{\gamma}^{OLS}$ , is slightly *increasing* over time. This confirms the puzzling result in previous studies that the negative impact of distance on trade seems to increase and not decrease over time, which would be expected from the globalization process. Turning to the HMR distance coefficient,  $\hat{\gamma}^{HMR}$ , we note that  $\hat{\gamma}^{HMR}$  is indeed decreasing over time. Examining the bias of OLS,  $\hat{\gamma}^{OLS} - \hat{\gamma}^{HMR}$ , we note that this is positive. From Proposition 1, this is consistent with the upward bias from omitting the number of exporters dominating the selection bias from omitting zero trade flows. In addition, the bias grows over time. From theory, this suggests that globalization and reduced trade costs seem to decrease the downward bias from selection more than they reduce the upward bias from the number of exporters

see Proposition 2. Hence, the omitted variable bias seems to dominate the selection bias, and becomes relatively more important than the selection bias over time.

In Figure 3(ii), we compare OLS with the linear approximation of HMR. We note that the results are qualitatively the same as in Figure 3(i): the HMR distance coefficient is decreasing over time, whereas the OLS coefficient increases with the associated bias of OLS increasing. Figure 3(iii) compares OLS with the PML estimator using a gamma function as suggested by Santos Silva and Tenreyro (2006, 2008). Comparing Figures 3(i), 3(ii) and 3(iii) we note that the linear approximation of HMR gives very similar results to the non-linear version of HMR and the PML estimate. That the linear approximation of the HMR works satisfactorily is useful information for a future application of the linear approximation of the HMR methodology, given the cumbersome estimation of the non-linear version of HMR.

### 3.3.2 HMR versus Heckman

Finally, we make a comparison with results obtained with the usual Heckman procedure. Once more, the results are qualitatively similar, as can be seen in Figure 4(i). Since the Heckman estimator is standard in most econometric packages, would this estimator do just as well as the HMR estimator? To understand the difference, we next compare the two correction factors of Heckman and HMR. Both are functions of  $\hat{z}_{ij}^*$ . While the Heckman correction factor  $\beta\phi(\hat{z}_{ij}^*)/\Phi(\hat{z}_{ij}^*)$  is well-known to be monotonically decreasing in  $\hat{z}_{ij}^*$ , the HMR correction factors are in sum non-monotonic in  $\hat{z}_{ij}^*$  as it consists of two correction factors working in opposite directions, see Proposition 1 and its proof.

Hence, Heckman and HMR estimates will only give similar results if the observations happen to be distributed such that the values of  $\hat{z}_{ij}^*$  are so concentrated that they are in the vicinity of each other and therefore happen to form a monotonic relation in  $\hat{z}_{ij}^*$ . To see that this is often the case in our data, explaining why Heckman estimators often give similar results to the HMR estimator, we have plotted an average over all industries and years of the functions of the Heckman and HMR correction factors on  $\hat{z}_{ij}^*$  in Figure 4(ii). We can see that, in general, the HMR correction factor is U-shaped but most observations are on one leg of the U. Then, the Heckman estimator can even pick up the bias from the omitted variable. While this works fairly well in our data, there is no guarantee that it works in general. Additionally, even though the Heckman estimator works in our data, we should bear in mind that the interpretation why it falls is very different. The Heckman correction would lead to the conclusion that taking into account zero trade flows solves the distance puzzle, while in the HMR procedure it is the omission of firm heterogeneity which is key. We then show that only the latter is consistent with theory: adding zero trade flows should exacerbate the distance puzzle.

### 3.3.3 Industries

Figure 5 shows changes over time in the level of distance coefficient for each of the 28 industries from HMR and OLS. Most industries show a similar pattern, where the distance coefficient with OLS is increasing over time and the HMR distance coefficient is decreasing over time, producing an increasing bias of the OLS estimates.<sup>22</sup> In particular, these patterns are present in industries that are characterized by intra-industry trade (e.g. “Footwear“ or “Manufacture of machinery”), whereas the patterns seem weaker in industries where the pattern of trade is to a larger extent explained by comparative advantage (e.g. “Tobacco manufactures” or “Wood and cork products”). This is also what should be expected since trade in the HMR model generates intra-industry trade.

Descriptive evidence on these results provides Table 1 where the ISIC classification is linked to the industry classification with respect to product differentiation according to Rauch (1999) and the information whether we do find an increase in the bias of OLS or do not. Rauch classifies industries at the SITC 4-digit level to be differentiated or not. However, we first subsume these SITC 4-digit classification to our ISIC classification which actually aggregates the SITC 4-digit industries at a higher level, i.e. the ISIC codes consist of more than one SITC 4-digit code. We then calculate the share of differentiated SITC 4-digit industries according to Rauch (1999) within our ISIC 28 industries (*Differentiated share*).

In Table 1 we do find a correlation between the dummy *Increase in bias* and *Differentiated share* of 0.27.<sup>23</sup> The mean *Differentiated share* within the 20 industries where we do find an increasing bias is 0.75 which is much higher than 0.52 within the 8 industries where we do not find an increase in the bias. If we would draw an arbitrary cut-off for differentiated versus homogeneous industries at a *Differentiated share* of 0.5 we see that 15 out of 20 cases are differentiated according to the Rauch classification. Since the size of the SITC 4-digit industries is not accounted for when subsuming them into the ISIC classification we now concentrate on ISIC codes where we calculated a clear-cut *Differentiated share* of either 0 or 1. Within these 15 observations we do find 11 matches, either between no increase in the bias and a clear-cut *Differentiated share* of 0 or between increase in the bias and a clear-cut *Differentiated share* of 1.

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<sup>22</sup>Actually, the bias can be identified visually from Figure 5. Therefore we added again quadratic fits and 95% confidence intervals over time to our estimates. We mostly observe an increase in the difference between the quadratic fit of the OLS estimates and the quadratic fit of the HMR estimates over time, at least for the second half of our data period. Note that this difference is always significant since an overlap of the confidence intervals between the two fits is not indicated at any figure and never converges to the end of our data period.

<sup>23</sup>However, left with 28 industries/observations, regression results lack in their precision, but can serve as additional descriptives: Point estimates of regressions (probit, logit or linear probability) of the dummy which indicates a bias increase on *Differentiated share* give results in our favor (positive) but are not significant at the usual levels.

### 3.3.4 Globalization and transport costs

Finally, we provide evidence that the HMR-data-generating process fits the data well and that (3.1) might consistently estimate the distance coefficient. Figure 6 shows our results from relating the estimated distance coefficient  $\hat{\gamma}^{HMR}$  to actual trade costs. Firstly, Figure 6(i) shows that the estimated distance coefficients are strongly positively correlated with shipping costs in data recently published by Hummels (2007). Secondly, Figure 6(ii) shows that the  $\hat{\gamma}^{HMR}$  is also positively correlated with oil prices, which should be an important determinant of transport costs. Additionally, we note that the OLS estimate of the distance coefficient is negatively correlated with these data on transport costs. Once more, this non-intuitive correlation can be explained because OLS neither controls for the omitted variable of the number of exporters nor for the omission of zero trade flows.

## 4 Conclusions

Globalization has advanced rapidly during the last two decades. In contrast, the influence of distance in empirical estimates of bilateral trade flows has remained high and has not declined. In this paper, we use the model by Helpman, Melitz and Rubinstein (2008), emphasizing zero trade flows and firm heterogeneity, to resolve this “distance puzzle”.

Using industry level data in 28 industries from 1978 to 2003, the non-linear estimation of HMR leads to declining distance coefficients over time. These coefficients also reflect the variation in “true trade costs” as the estimated HMR distance coefficients are also strongly correlated with the variation in freight costs and oil prices. When estimating the effect of distance on trade with OLS, we do not only find a larger distance coefficient but also that it increases over time. Thus, the distance puzzle arises from a growing bias of OLS-estimates.

We show how the growing bias of OLS-estimates can be explained from the two sources of bias generated from applying OLS to a gravity estimation when the HMR model is the data-generating process. The upward bias of the OLS estimates implies that the omitted variable bias (from the number of heterogeneous exporting firms) must dominate the sample selection bias (due to the omission of zero trade flows). When relating globalization to a fall of the true distance coefficient, both the downward bias from sample selection from omitting zero trade flows and the upward bias from omitting the number and size of exporting firms will decrease from globalization (in absolute value). Since we find that the bias of OLS increases over time, the distance puzzle must arise because globalization had a weaker impact on the omitted variable bias from the number of heterogeneous exporters.

On a final note, the gravity equation is perhaps the most widely used tool in empirical

work using aggregate international trade data. While firm-level data is becoming more frequent, applying gravity equations on aggregate trade data will also remain common in the future when various policy issues are investigated. In this paper, we have shown how taking sample selection and exporter firm heterogeneity into account is crucial for understanding the effect of distance on international trade when aggregate trade data is used. Then, we have shown the usefulness of a linear approximation of the HMR estimator. As this estimator is much simpler to apply than the non-linear estimator of HMR, we suggest that the linear approximation could be fruitfully used in many other research questions.

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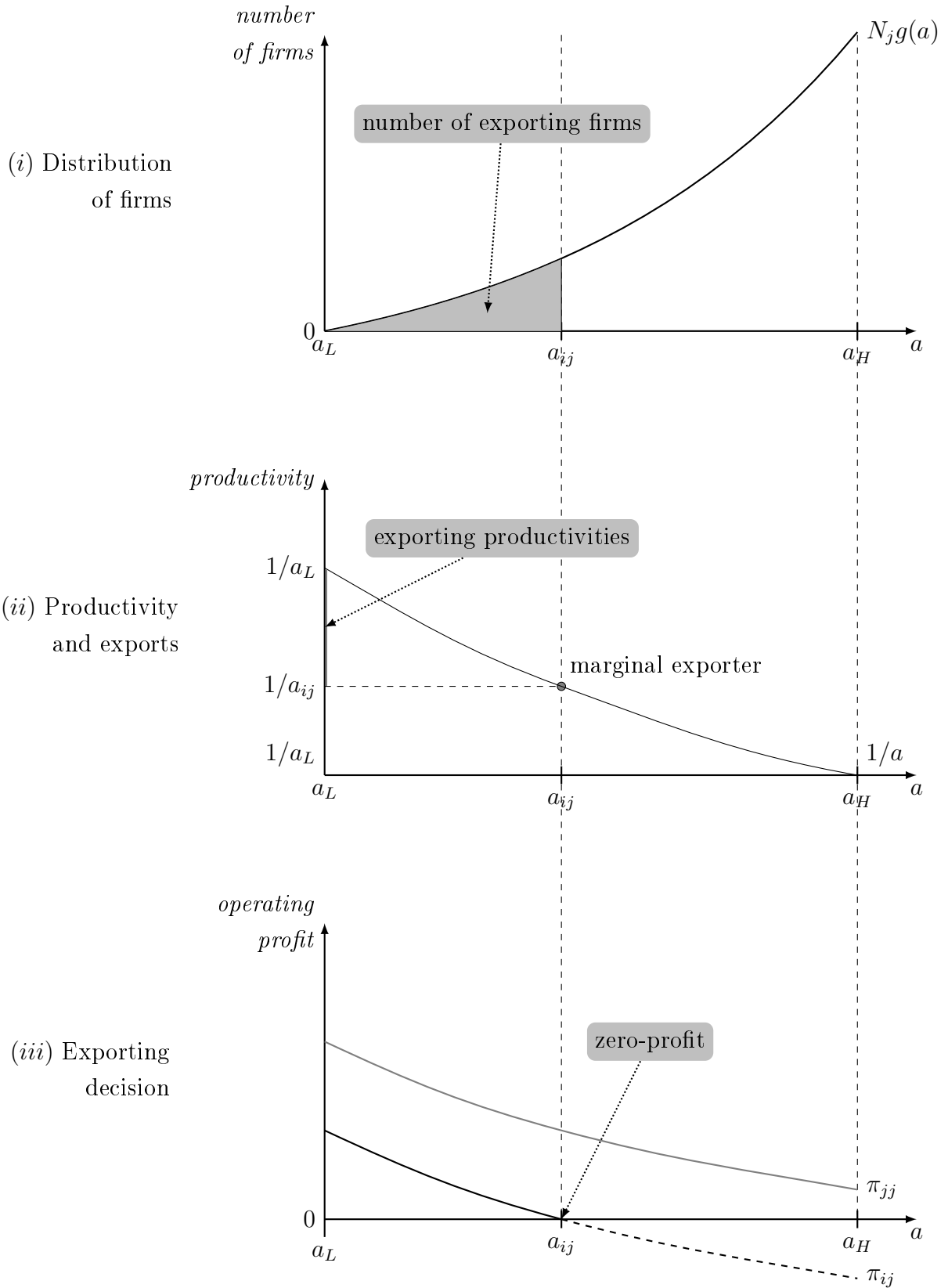


Figure 1: The HMR Model, where (i) illustrates the number of exporting firms of a Pareto distribution  $N_j g(a)$  productivity higher than marginal exporter's productivity  $1/a_{ij}$ , which is illustrated in (ii), while (iii) shows the zero-profit condition for export sales  $\pi_{ij}$  and the home sales  $\pi_{jj}$  function over the firm-specific input coefficient.

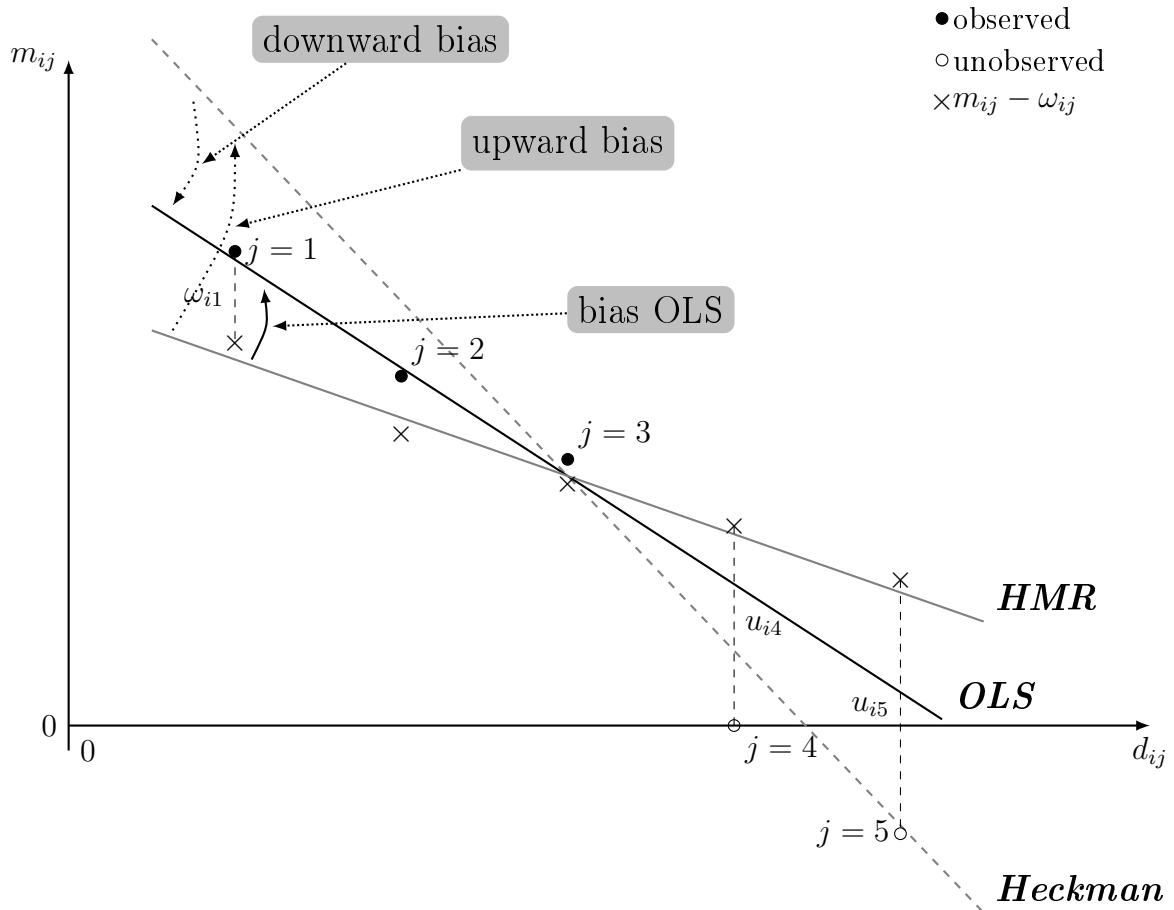


Figure 2: Illustrating the bias of OLS, where  $d_{ij}$  denotes distance between  $i$  and  $j$  and  $m_{ij}$  as imports from  $j$  to  $i$ . **HMR** is given by  $E[m_{ij} - \omega_{ij}|d_{ij}]$  with distance coefficient  $\gamma$ . **Heckman** is given by  $E[m_{ij}|d_{ij}]$  and **OLS** by  $E[m_{ij}|d_{ij}, T_{ij} = 1]$ . The *bias OLS* corresponds to  $Bias(\hat{\gamma}^{OLS}) = \gamma\delta - \Xi[\delta + \beta_{u\eta}]\bar{\eta}_{ij}^*$ , where  $(\gamma\delta)$  is denoted by *upward bias* and  $(-\Xi[\delta + \beta_{u\eta}]\bar{\eta}_{ij}^*)$  by *downward bias* in the figure.  $\omega_{ij}$  controls for the omitted variable due to firm heterogeneity.  $u_{i4}, u_{i5}$  are large negative errors causing observations  $j = 4$  and  $j = 5$  to drop out of the sample.

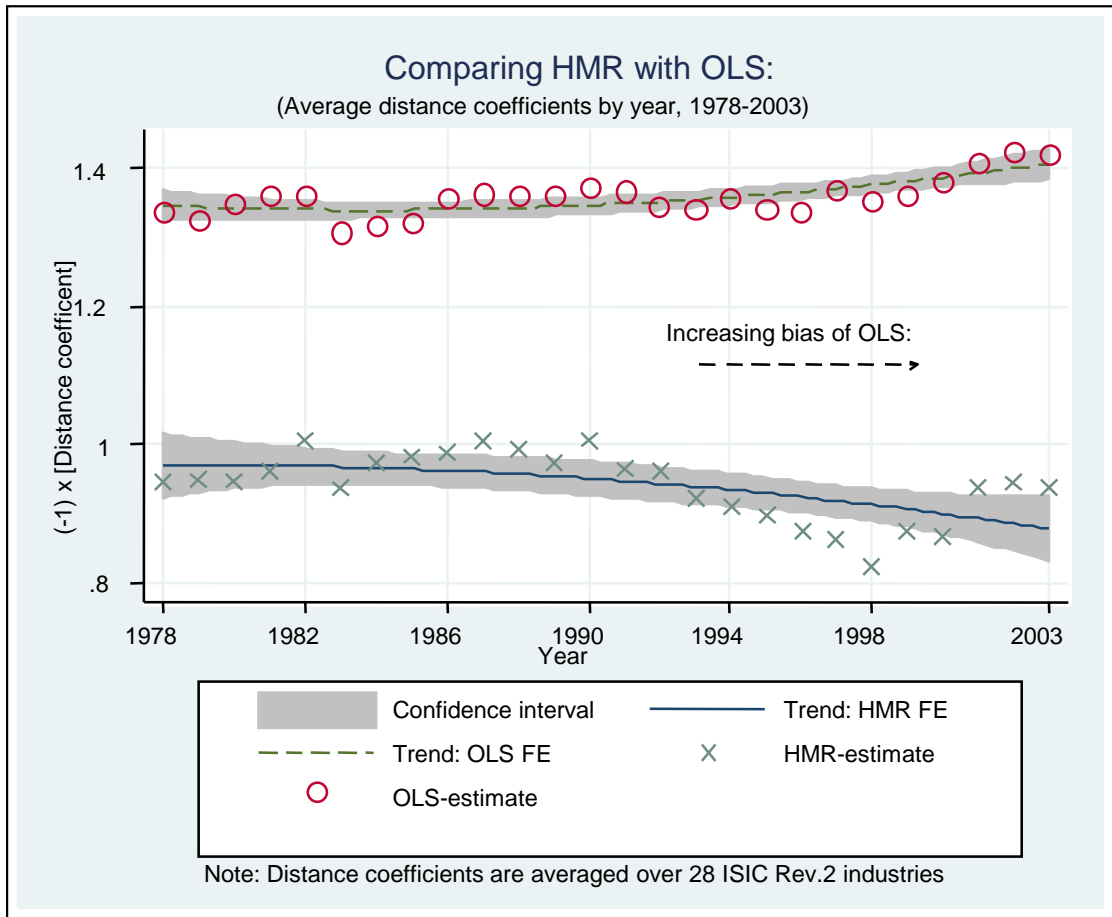


Figure 3 (i)

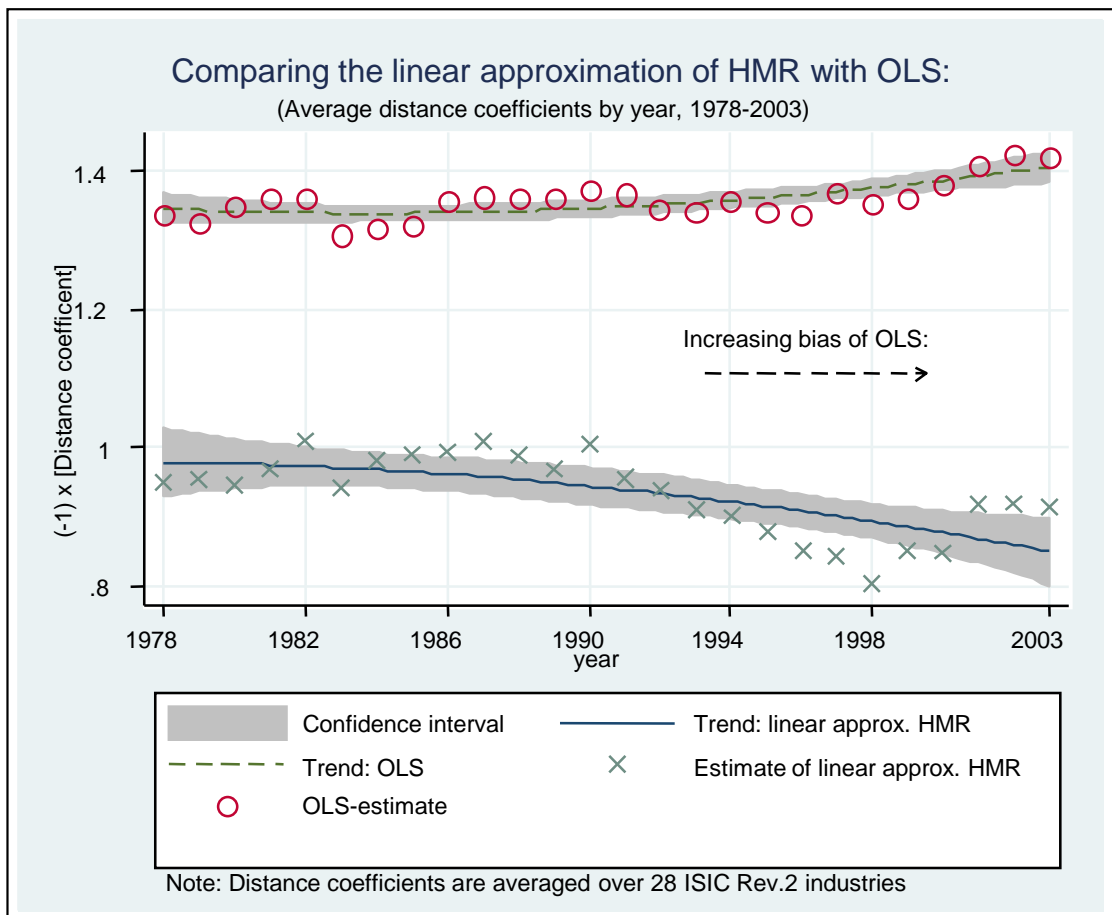


Figure 3 (ii)

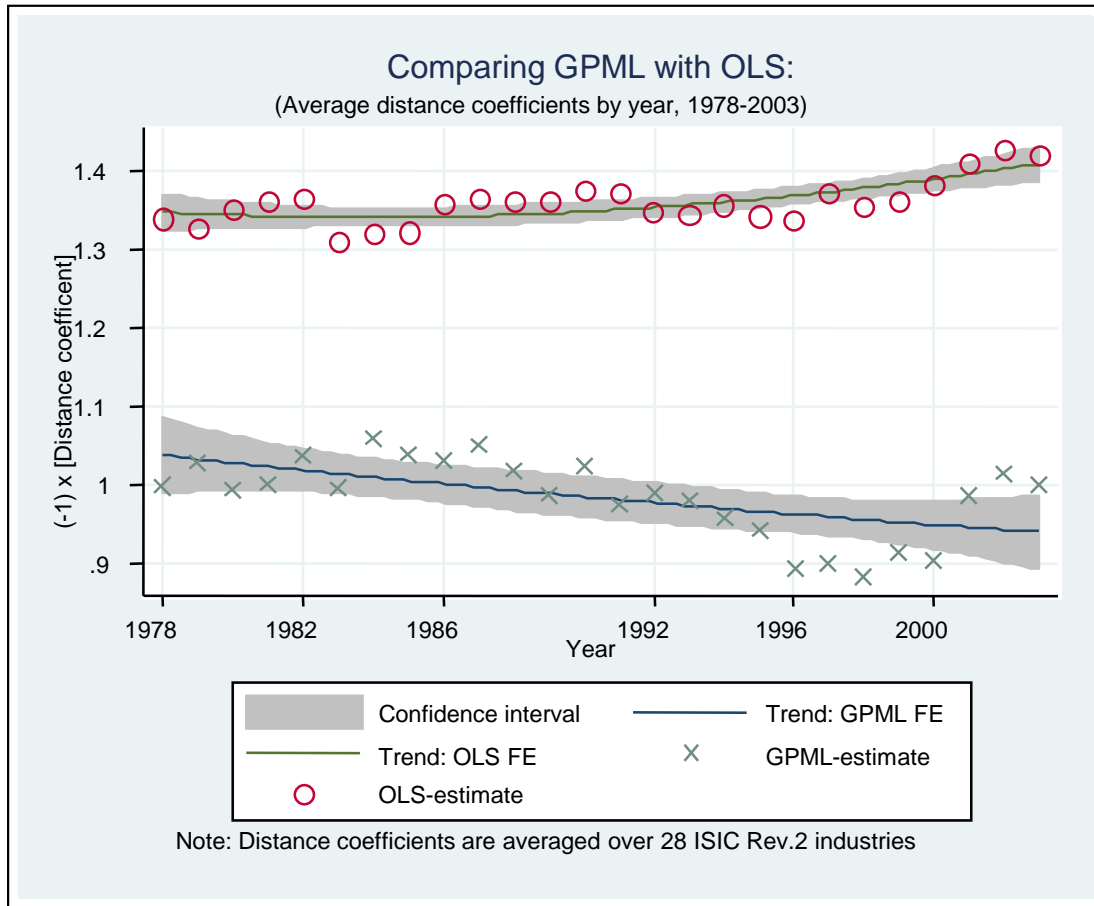


Figure 3 (iii)

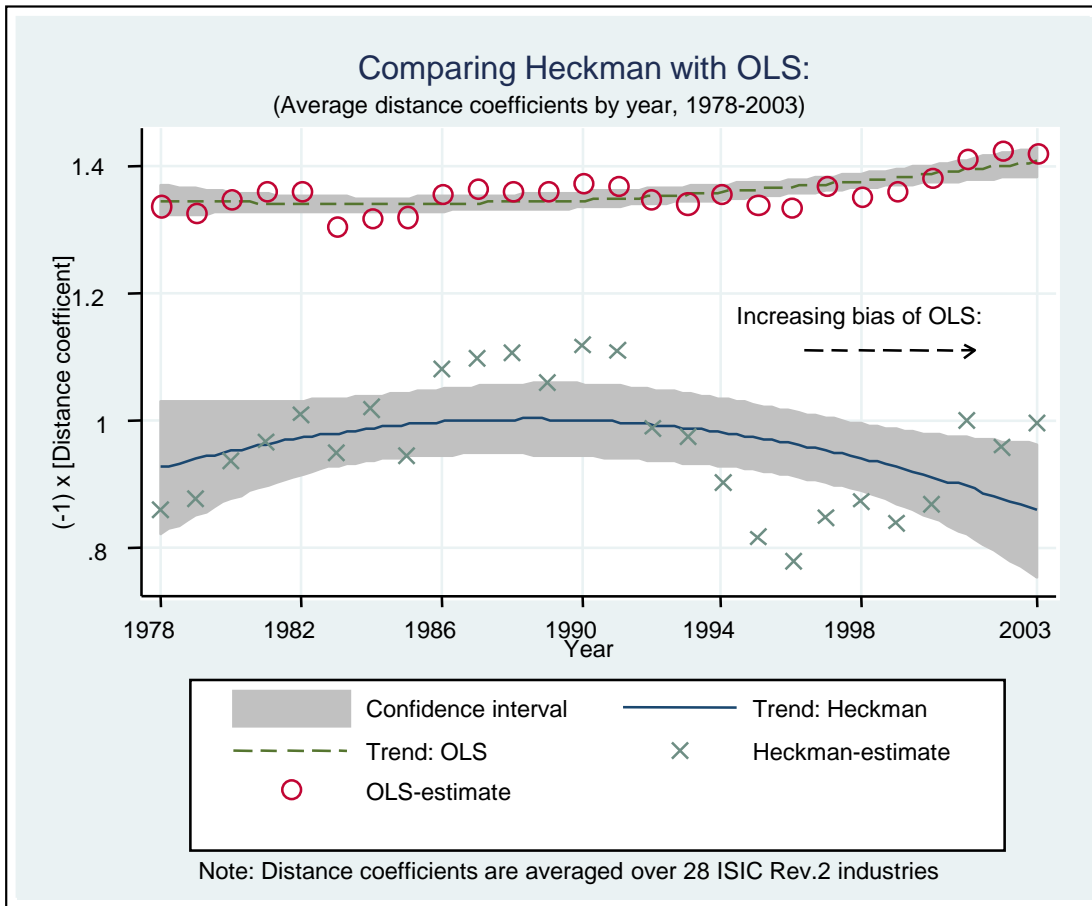


Figure 4 (i)

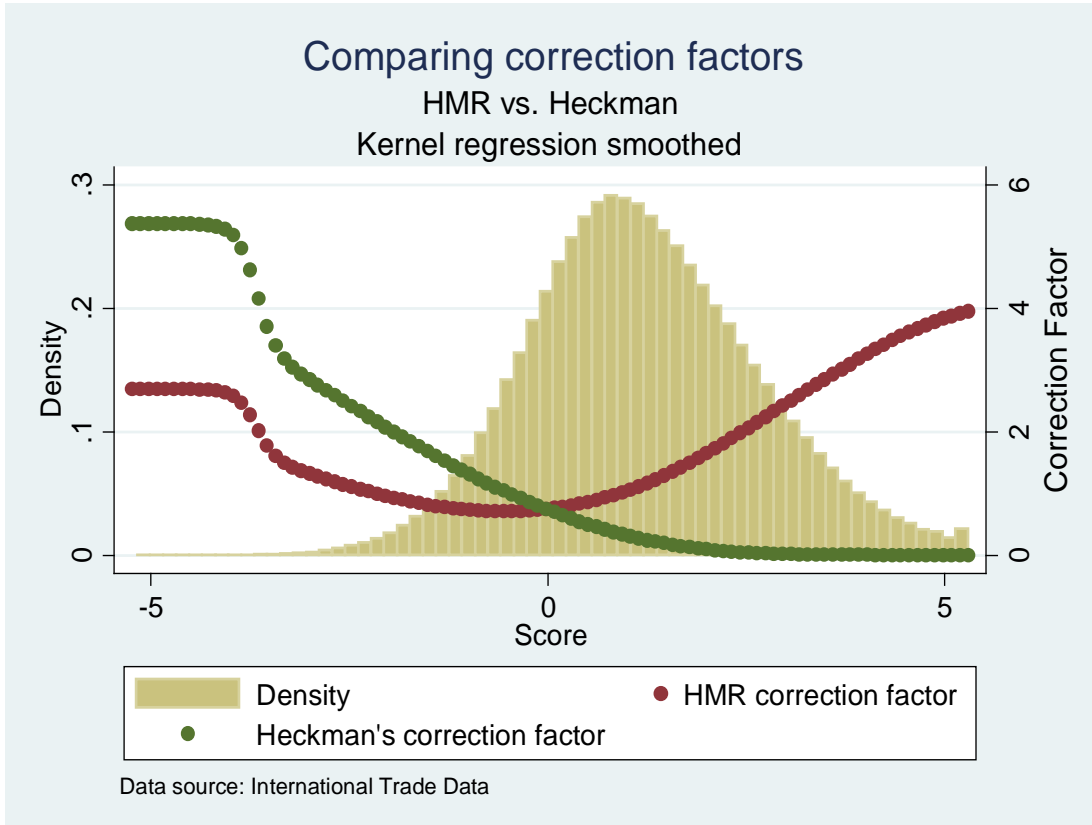


Figure 4 (ii)

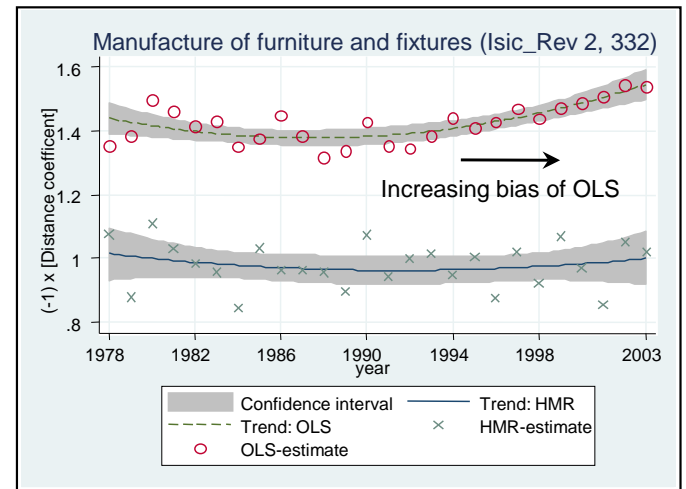
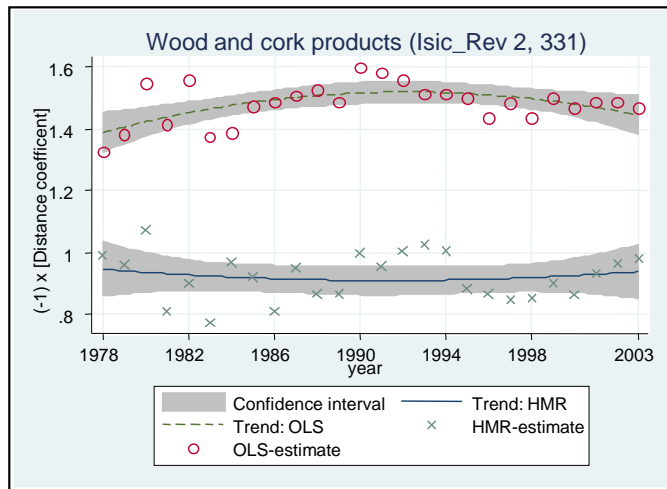
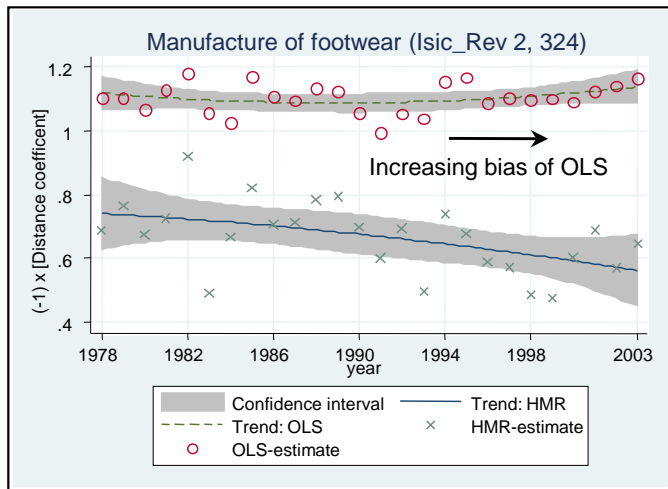
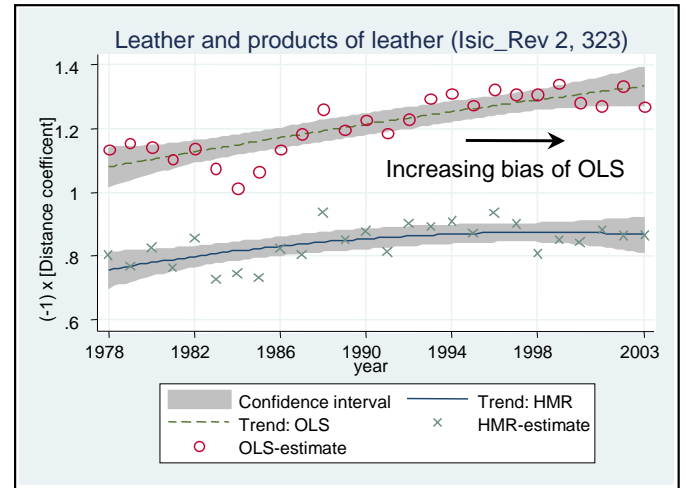
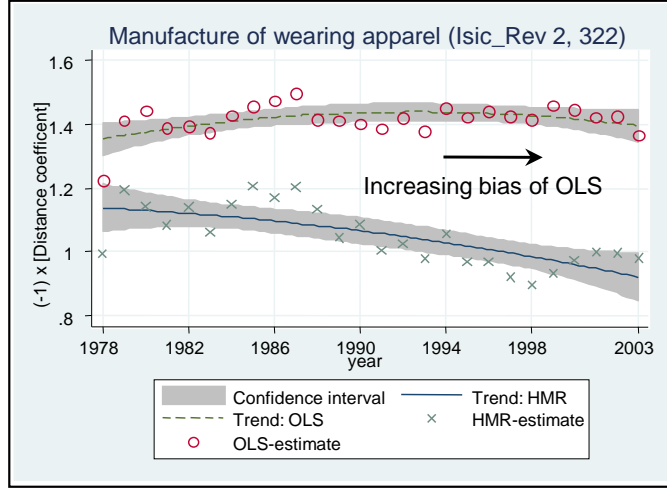
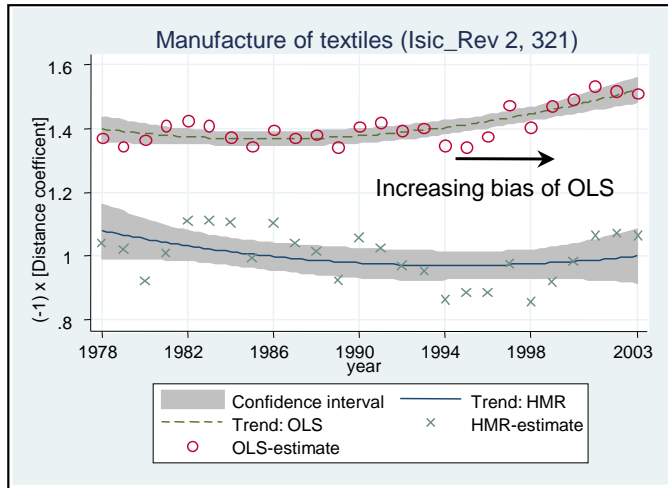
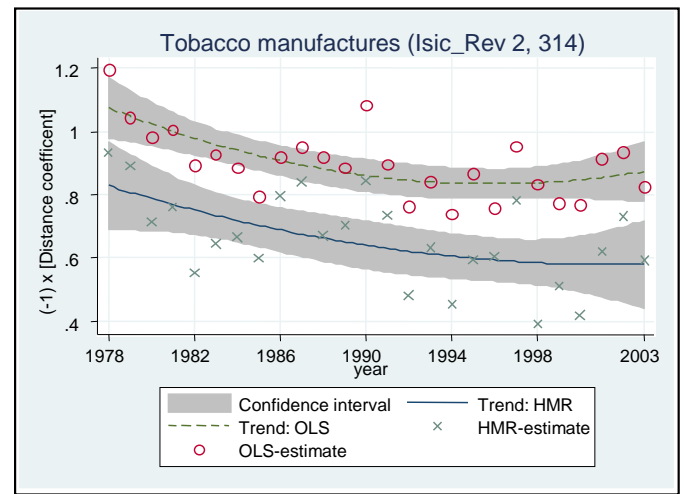
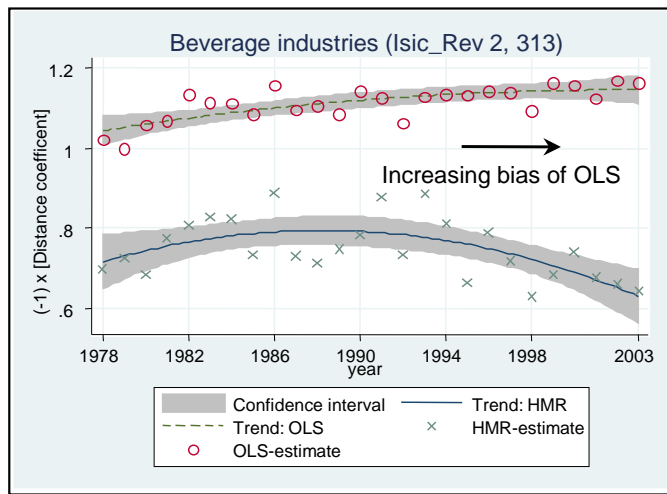
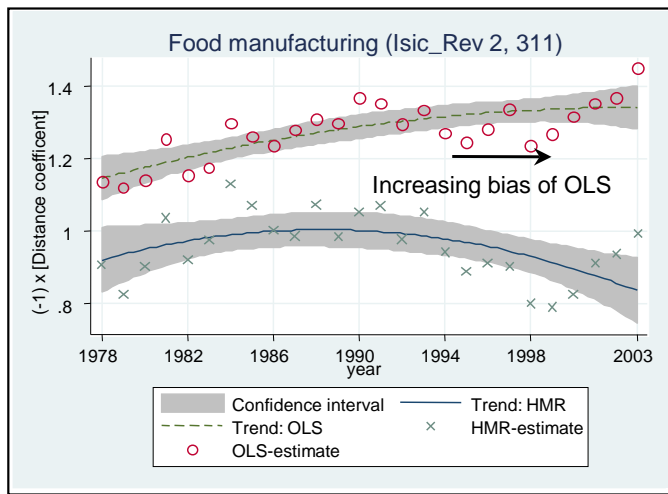


Figure 5a: Industry estimates for HMR and OLS, 1978-2003.



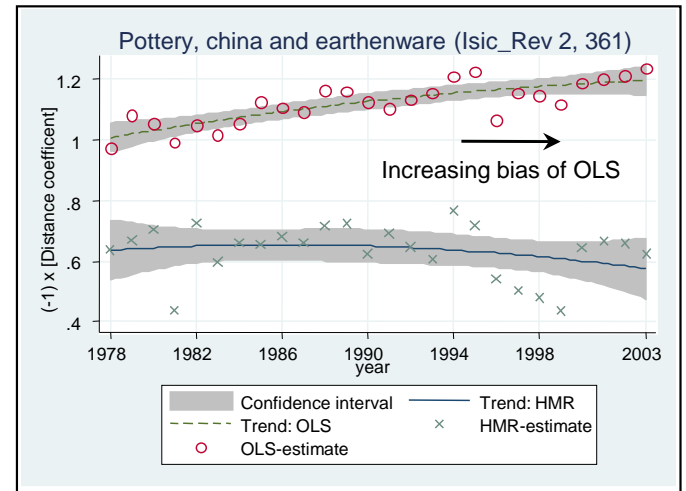
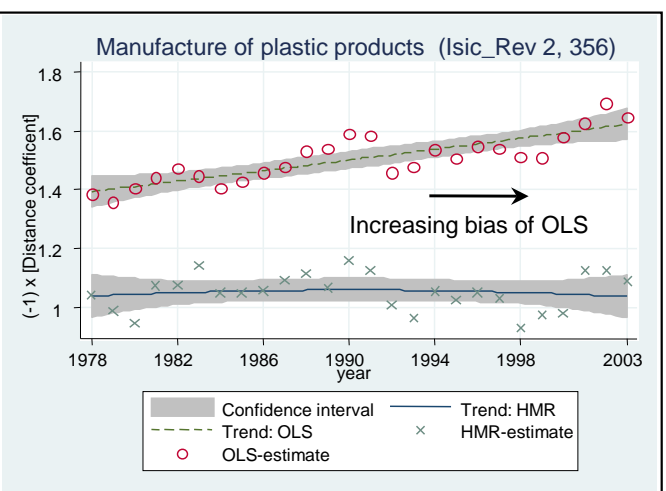
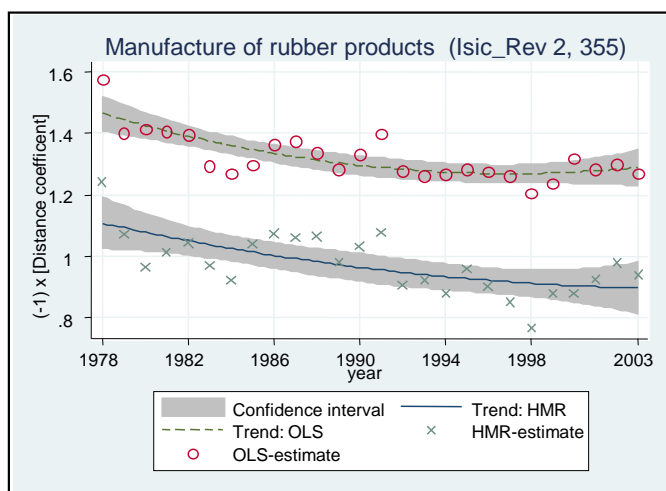
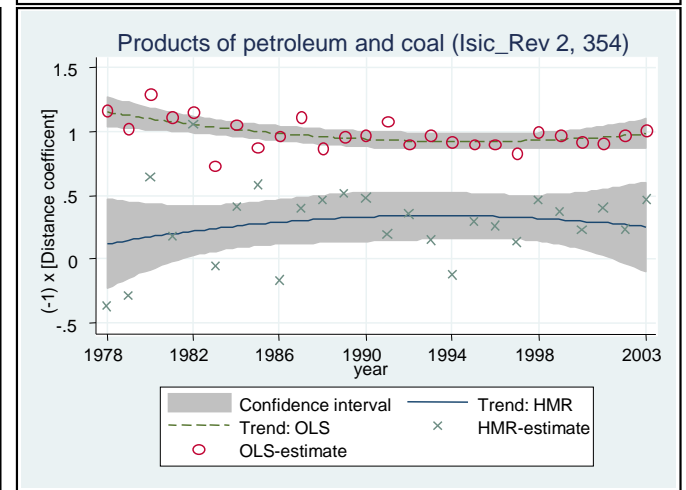
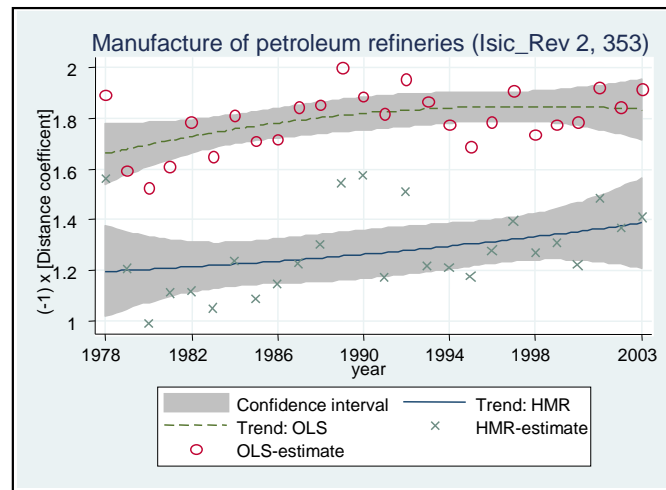
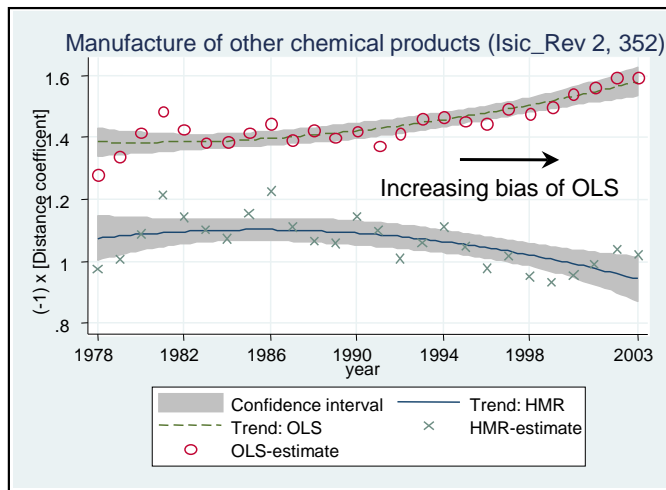
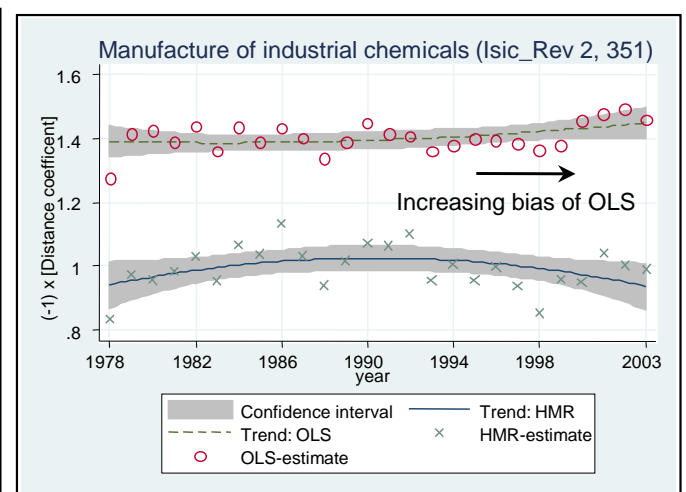
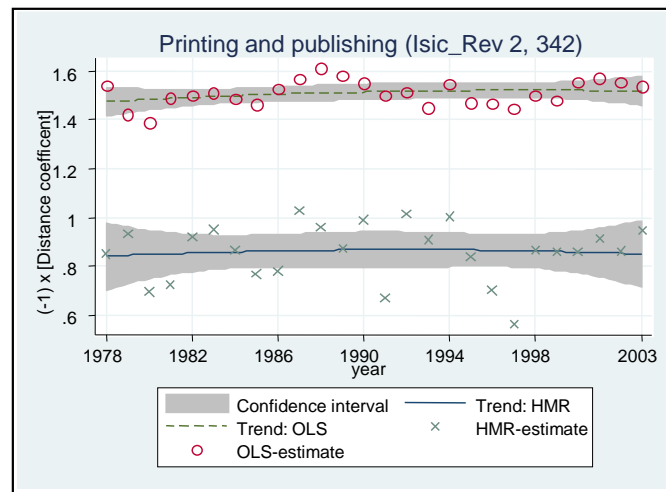
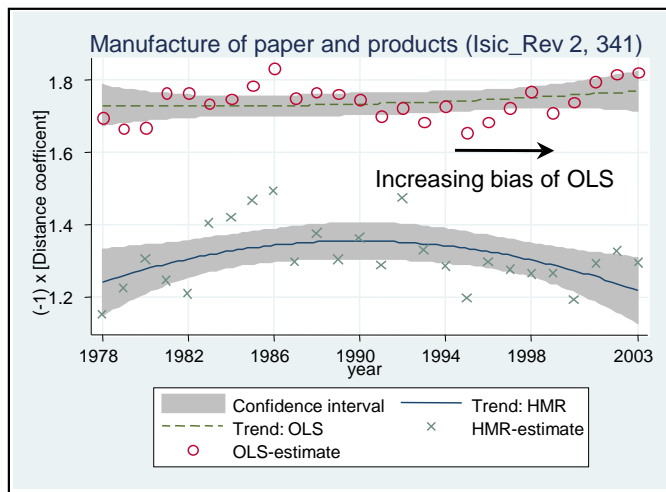


Figure 5b: Industry estimates for HMR and OLS, 1978-2003.

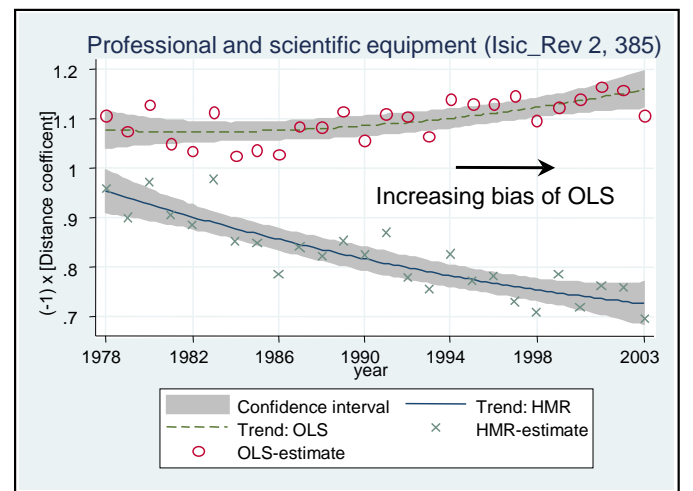
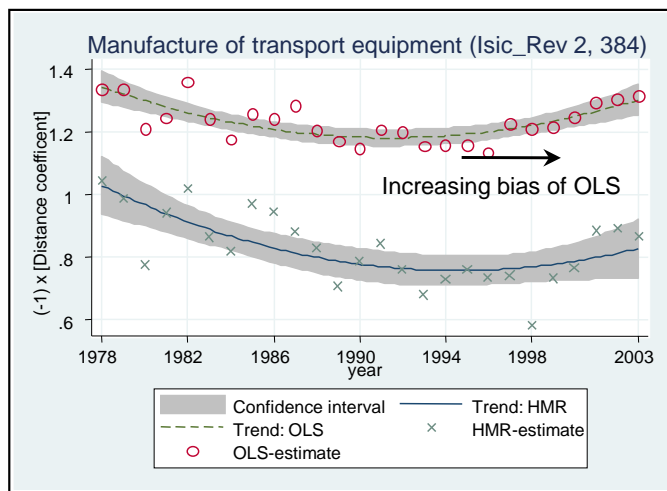
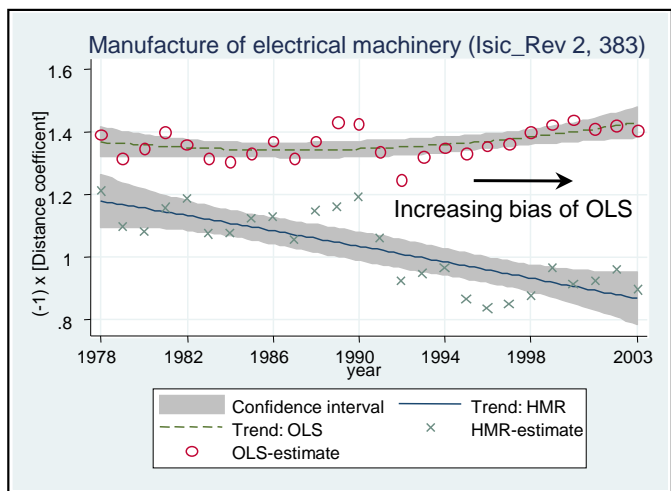
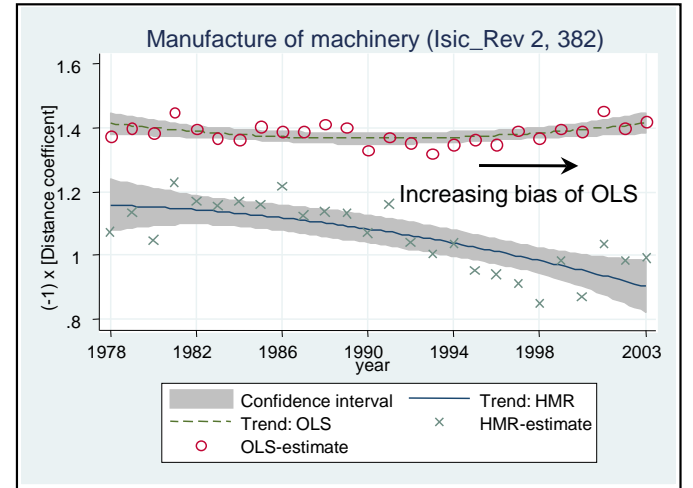
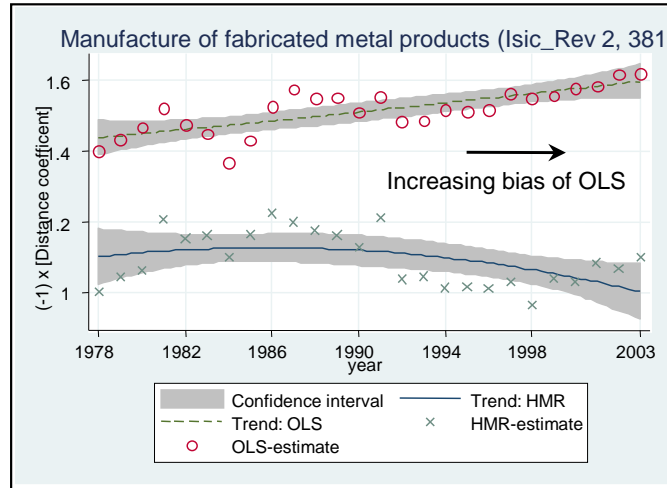
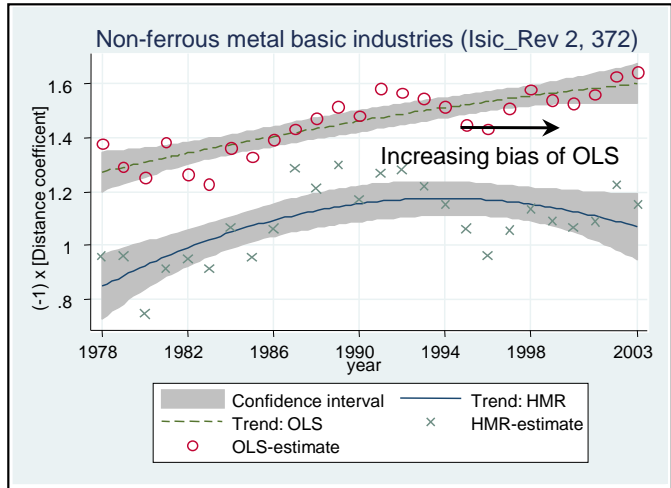
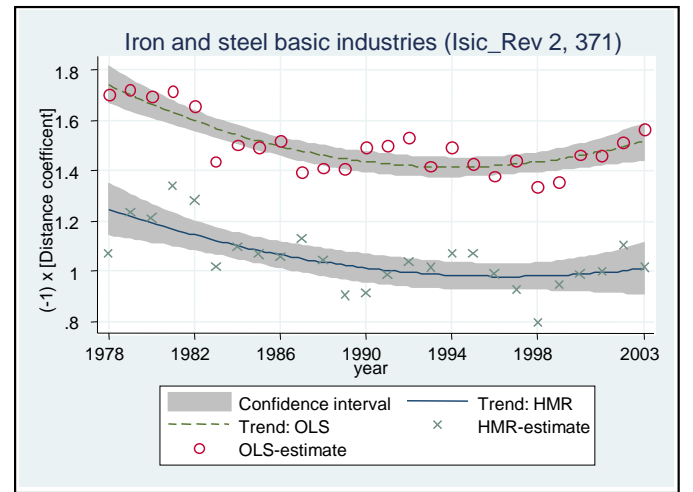
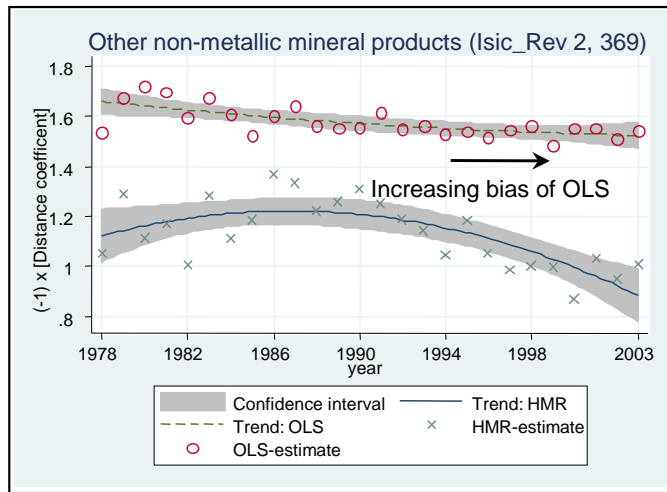
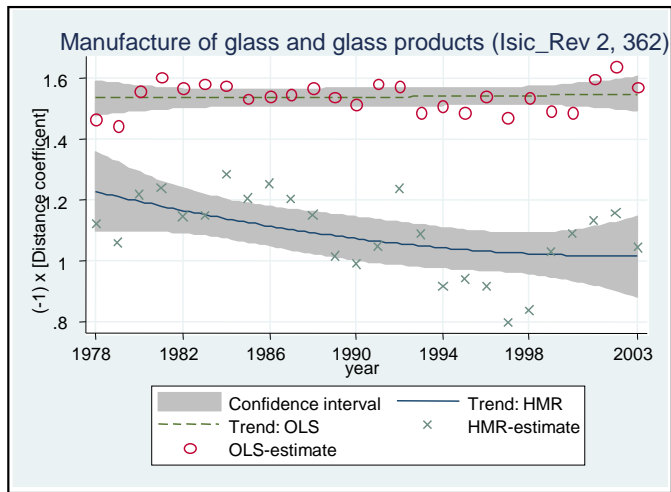


Figure 5c: Industry estimates for HMR and OLS, 1978-2003.

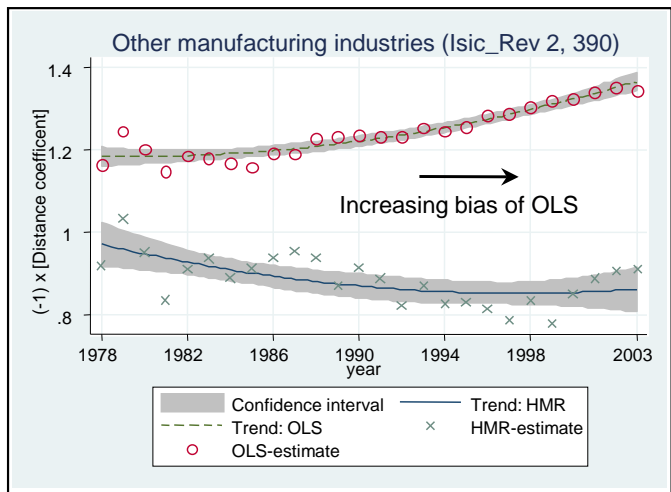


Figure 5d: Industry estimates for HMR and OLS, 1978-2003.

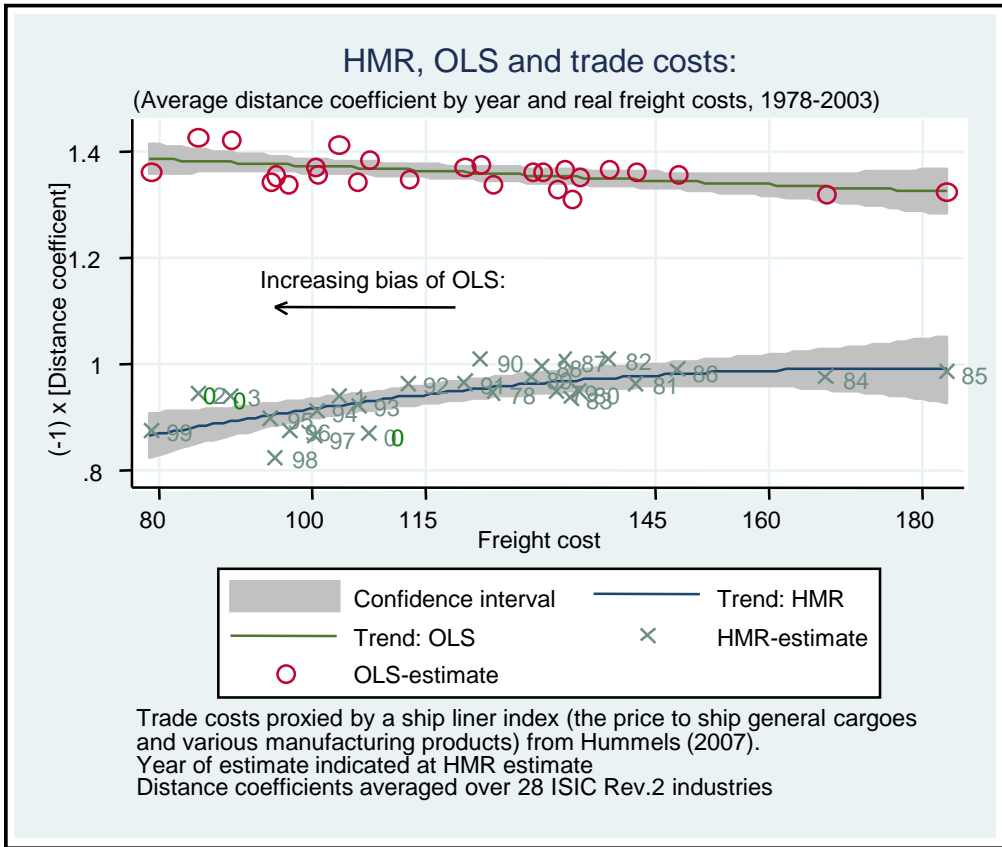


Figure 6 (i)

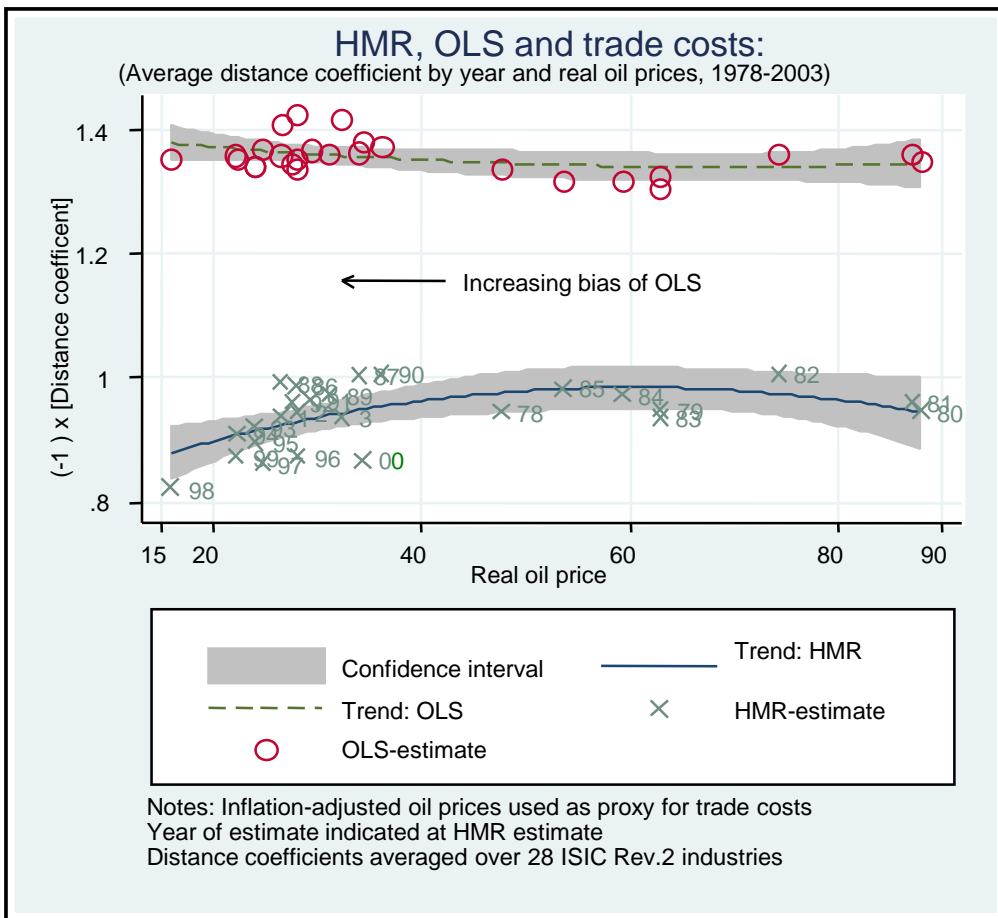


Figure 6 (ii)

ISIC Code	Industry	Increase in bias	Differentiated share
311	Food	yes	0.28
313	Beverage	yes	0.2
314	Tobacco	no	0
321	Textiles	yes	0.68
322	Wearing apparel	yes	0.96
323	Leather	yes	0.88
324	Footwear	yes	1
331	Wood and cork	no	0.7
332	Furniture	yes	1
341	Paper	yes	0.18
342	Printing	no	1
351	Industrial chemicals	yes	0.19
352	Chemical products	yes	0.92
353	Petroleum refineries	no	0.13
354	Products of petroleum and coal	no	0
355	Rubber products	no	1
356	Plastic products	yes	1
361	Pottery, china and earthenware	yes	1
362	Glass	no	1
369	Non-metallic mineral	yes	0.8
371	Iron and steel	no	0.33
372	Non-ferrous metal	yes	0
381	Fabricated metal	yes	1
382	Machinery	yes	1
383	Electrical machinery	yes	1
384	Transport equipment	yes	1
385	Scientific equipment	yes	1
390	Other manufacturing	yes	0.92

Table 1: 28 ISIC Rev. 2 manufacturing industries, where *yes* corresponds to a dummy which is equal to 1 if we do find an increase in the bias  $\hat{\gamma}^{OLS} - \hat{\gamma}^{HMR}$  from Figure 5. *Differentiated share* is the share of differentiated SITC 4-digit industries according to Rauch (1999) within the ISIC industry.

# A Appendix

## A.1 Proof of Proposition 1

**Proof:** Rewrite (2.10) as  $m_{ij} = \beta' \mathbf{X}_{ij} + \omega_{ij} + u_{ij}$  and  $z_{ij}^*$  in (2.16) as  $z_{ij}^* = \varphi^{*'} \mathbf{X}_{ij} + \eta_{ij}^*$  where  $\beta \equiv (\beta_0, \lambda_j, \chi_i, -\gamma)'$ , and  $\varphi^* = (\gamma_0^*, \xi_j^*, \zeta_i^*, -\gamma^*)', -\kappa^*$ . Let,  $\hat{\beta}^{OLS}$  denote the OLS estimator of  $\beta$  ignoring the sample selection and omitted variable corrections. We then obtain:

$$\mathbb{E} \left( \hat{\beta}^{OLS} \right) = \beta + [\mathbf{X}_{ij} \mathbf{X}_{ij}']^{-1} \mathbf{X}_{ij} \mathbb{E} [\omega_{ij} + u_{ij} | z_{ij}^* > 0], \quad (\text{A.1})$$

where we have exploited that the  $\mathbf{X}_{ij}$  variables contain only geography information and are therefore deterministic. To evaluate (A.1), examine the conditional expectations  $\mathbb{E} [\omega_{ij} | z_{ij}^* > 0]$  and  $\mathbb{E} [u_{ij} | z_{ij}^* > 0]$ . Using formula (16.36) on p. 549 in Cameron and Trivedi (2005), we first obtain:

$$\begin{aligned} \mathbb{E} [u_{ij} | z_{ij}^* > 0] &= \text{cov} (u_{ij}, \eta_{ij}^*) \mathbb{E} [\eta_{ij}^* | \eta_{ij}^* > \varphi^{*'} \mathbf{X}_{ij} - \kappa^* \phi_{ij}] \\ &= \text{corr} (u_{ij}, u_{ij} + \nu_{ij}) \frac{\sigma_u \phi (\varphi^{*'} \mathbf{X}_{ij} - \kappa^* \phi_{ij})}{\sigma_\eta \Phi (\varphi^{*'} \mathbf{X}_{ij} - \kappa^* \phi_{ij})} \\ &\equiv \beta_{u\eta} \bar{\eta}_{ij} > 0, \end{aligned} \quad (\text{A.2})$$

where  $\beta_{u\eta} = \text{corr} (u_{ij}, u_{ij} + \nu_{ij}) \sigma_u / \sigma_\eta$  and  $\bar{\eta}_{ij} = \frac{\phi (\varphi^{*'} \mathbf{X}_{ij} - \kappa^* \phi_{ij})}{\Phi (\varphi^{*'} \mathbf{X}_{ij} - \kappa^* \phi_{ij})}$ . Further, we have assumed that  $u_{ij}$  and  $\eta_{ij}^*$  are bivariate normally distributed. Note that this implies that  $u_{ij} = \text{cov} (u_{ij}, \eta_{ij}^*) \eta_{ij}^* / \sigma_\eta^2 + \varrho_{ij}$ , where  $\varrho_{ij}$  is independent of  $\eta_{ij}^*$  and has zero mean. Hence,  $\mathbb{E} [u_{ij} | \eta_{ij}^* > \varphi^{*'} \mathbf{X}_{ij} - \kappa^* \phi_{ij}] = \text{cov} (u_{ij}, \eta_{ij}^*) / \sigma_\eta^2 \mathbb{E} [\eta_{ij}^* | \eta_{ij}^* > \varphi^{*'} \mathbf{X}_{ij} - \kappa^* \phi_{ij}]$  and  $\text{cov} (u_{ij}, \eta_{ij}^*) = \text{corr} (u_{ij}, u_{ij} + \nu_{ij}) \sigma_u \sigma_\eta$ . To proceed, use a linear approximation of  $\omega_{ij} = \ln [(Z_{ij}^*)^\delta - 1]$  for  $z_{ij}^* > 0$ . We can then write  $\omega_{ij} = \ln [(Z_{ij}^*)^\delta - 1] = \ln [\exp (\delta z_{ij}^*) - 1] \approx \delta z_{ij}^* > 0$ , where  $\delta = \sigma_\eta \frac{k-\epsilon+1}{\epsilon-1}$  is defined as above.<sup>24</sup> We then obtain:

$$\begin{aligned} &\mathbb{E} [\omega_{ij} | z_{ij}^* > 0], \\ &= \mathbb{E} [\delta z_{ij}^* | z_{ij}^* > 0] = \delta \mathbb{E} [\{ \mathbb{E} [z_{ij}^* | \mathbf{X}_{ij}] + \eta_{ij}^* \} | z_{ij}^* > 0] \\ &= \delta \mathbb{E} [z_{ij}^* | \mathbf{X}_{ij}] + \delta \mathbb{E} [\eta_{ij}^* | z_{ij}^* > 0], \\ &= \delta \mathbb{E} [\gamma_0^* + \xi_j^* + \zeta_i^* - \gamma^* d_{ij} - \kappa^* \phi_{ij} | \mathbf{X}_{ij}] + \delta \mathbb{E} [\eta_{ij}^* | z_{ij}^* > 0], \\ &= \delta [\gamma_0^* + \xi_j^* + \zeta_i^* - \gamma^* d_{ij} - \kappa^* \phi_{ij} + \bar{\eta}_{ij}^*], \\ &= \delta \varphi^{*'} \mathbf{X}_{ij} + \delta \bar{\eta}_{ij}^*. \end{aligned} \quad (\text{A.3})$$

Noting that  $[\mathbf{X}'\mathbf{X}]^{-1} \mathbf{X}'\mathbf{X} \varphi^* \delta = \varphi^* \delta$ , we obtain:

$$\mathbb{E} \left( \hat{\beta}^{OLS} \right) = \beta + \varphi^* \delta + [\mathbf{X}_{ij} \mathbf{X}_{ij}']^{-1} \mathbf{X}_{ij} \delta \bar{\eta}_{ij}^* + [\mathbf{X}_{ij} \mathbf{X}_{ij}']^{-1} \mathbf{X}_{ij} \beta_{u\eta} \bar{\eta}_{ij}^* \geq 0. \quad (\text{A.4})$$

<sup>24</sup>It can be shown that this approximation works very well in the range of  $\omega_{ij}$  from  $[0.5, \infty]$  and estimated values of  $\delta$  around 1.

Since country dummies in  $\mathbf{X}_{ij}$  are not correlated by construction and distance is hardly correlated with country dummies the matrix  $\mathbf{X}'\mathbf{X}$  can be viewed as diagonal. But then:

$$E(-\hat{\gamma}^{OLS}) = -\gamma - \gamma\delta + \frac{\sum_i \sum_j d_{ij}}{\sum_i \sum_j (d_{ij})^2} [\delta + \beta_{un}] \bar{\eta}_{ij}^*, \quad (\text{A.5})$$

and hence

$$\text{Bias}(\hat{\gamma}^{OLS}) = \gamma\delta - \frac{\sum_i \sum_j d_{ij}}{\sum_i \sum_j (d_{ij})^2} [\delta + \beta_{un}] \bar{\eta}_{ij}^*.$$

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## A.2 Proof of Proposition 2

**Proof:** From (2.22), we have  $\text{Bias}(\hat{\gamma}^{OLS}) = \gamma\delta - \Xi [\delta + \beta_{un}] \bar{\eta}_{ij}^*$ . Thus, it follows that  $\frac{\partial \text{Bias}(\hat{\gamma}^{OLS})}{\partial t} = \delta \frac{\partial \gamma}{\partial t} - \Xi [\delta + \beta_{un}] \frac{\partial \bar{\eta}_{ij}^*}{\partial t}$ . The change of the omitted variable bias over time is simply given by:

$$\frac{\partial (\delta\gamma)}{\partial t} = \delta \frac{\partial \gamma}{\partial t} < 0.$$

The sign of the change in sample selection bias depends on the sign of

$$\begin{aligned} \frac{\partial \bar{\eta}_{ij}^*}{\partial t} &= \frac{\partial \left( \frac{\phi(z_{ij}^*)}{\Phi(z_{ij}^*)} \right)}{\partial t} \\ &= \frac{1}{\Phi(z_{ij}^*)^2} \left[ \left( \phi'(z_{ij}^*) \cdot \Phi(z_{ij}^*) - \phi(z_{ij}^*)^2 \right) \right] \frac{\partial z_{ij}^*}{\partial t} \\ &= \left[ \frac{-z_{ij}^* \phi(z_{ij}^*)}{\Phi(z_{ij}^*)} - \left( \frac{\phi(z_{ij}^*)}{\Phi(z_{ij}^*)} \right)^2 \right] \frac{\partial z_{ij}^*}{\partial t} \\ &= \left[ -z_{ij}^* \bar{\eta}_{ij}^* - (\bar{\eta}_{ij}^*)^2 \right] \frac{\partial z_{ij}^*}{\partial t} \\ &= -\bar{\eta}_{ij}^* [z_{ij}^* + \bar{\eta}_{ij}^*] \frac{\partial z_{ij}^*}{\partial t}. \end{aligned} \quad (\text{A.6})$$

Note that

$$\frac{\partial z_{ij}^*}{\partial t} = -d_{ij} \frac{\partial \gamma(t)}{\partial t} > 0.$$

The derivative of the mills ratio  $\frac{\partial \bar{\eta}_{ij}^*}{\partial z_{ij}^*} = -\bar{\eta}_{ij}^* [z_{ij}^* + \bar{\eta}_{ij}^*]$  is negative. This can be shown by noting that

$$E[\eta_{ij}^* | \eta_{ij}^* > -\varphi' \mathbf{X}] = \frac{\phi(\varphi' \mathbf{X})}{\Phi(\varphi' \mathbf{X})} = \frac{\phi(-\varphi' \mathbf{X})}{1 - \Phi(-\varphi' \mathbf{X})}, \quad (\text{A.7})$$

and using the result derived in Sampford (1953) and also given in Theorem 19.2 on page 876 in Greene (2012), that for  $\phi(x) / (1 - \Phi(x))$  the derivative with respect to  $x$  is given

by

$$\frac{\phi(x)}{1-\Phi(x)} \left[ \frac{\phi(x)}{1-\Phi(x)} - x \right], \quad (\text{A.8})$$

and bounded between zero and one. Using the equality given in equation (A.7), we may write this as:

$$\frac{\phi(\varphi'\mathbf{X})}{\Phi(\varphi'\mathbf{X})} \left[ \frac{\phi(\varphi'\mathbf{X})}{\Phi(\varphi'\mathbf{X})} + \varphi'\mathbf{X} \right] = \bar{\eta}_{ij} [z_{ij} + \bar{\eta}_{ij}]. \quad (\text{A.9})$$

Hence, this expression differs from our derivative of  $\bar{\eta}_{ij}^*$  only by the multiplication with  $-1$ . Hence, the derivative of  $\bar{\eta}_{ij}^*$  with respect to  $z_{ij}^*$  is bounded between  $-1$  and  $0$ . But then  $\frac{\partial \bar{\eta}_{ij}^*}{\partial t} = \partial [\phi(z_{ij}^*) / \Phi(z_{ij}^*)] / \partial t < 0$ . The change in the bias for OLS is therefore ambiguous, depending on whether the change in the sample selection bias or the change in the omitted variable bias is larger:

$$\frac{\partial \text{Bias}(\hat{\gamma}^{OLS})}{\partial t} = \delta \frac{\partial \gamma}{\partial t} - \Xi [\delta + \beta_{un}] \frac{\partial \bar{\eta}_{ij}^*}{\partial t} \begin{matrix} \geq \\ < \end{matrix} 0. \quad (\text{A.10})$$

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