There Goes Gravity: How eBay Reduces Trade Costs*

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Abstract

We compare the impact of distance, a standard proxy for trade costs, on eBay and offline international trade flows. We consider the same set of 62 countries and the same basket of goods for both types of transactions. We find the effect of distance to be on average 65 percent smaller on the eBay online platform than offline. Using interaction variables, we show this difference is explained by a reduction of information and trust frictions enabled through online technology. We estimate the welfare gains from a reduction in offline frictions to the level prevailing online at 29 percent on average.

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1 Introduction

In the 1990s advances in transportation and communication technologies led many commentators to believe that geographic distance between countries would soon no longer encumber international transactions (e.g. Cairncross 1997). Despite some anecdotal evidence in support of the "death of distance" hypothesis (e.g. Friedman 2005), a large number of academic papers suggests that distance is "thriving", not "dying". Disdier and Head (2008), using a meta-analysis based on 1,000 gravity equations, found that the estimated coefficient on distance has been slightly on the rise since 1950. Chaney (2011) argues that the need for direct interactions between trading partners, resulting from information frictions first highlighted by Rauch (1999), explains why distance still matters for international trade today. Similarly, Allen (2011) suggests information frictions account for 93 percent of the distance effect. This would suggest that advances in technology in recent decades have failed to reduce information frictions. Is this the death knell for the "death of distance" hypothesis?

In this paper we breathe new life into the "death of distance" hypothesis. We argue that the right place to look is in online markets which, as opposed to "offline" markets, make full use of technologies that can reduce information frictions. Indeed, as argued by Hortaçsu et al. (2009) and Goldmanis et al. (2010), the main benefit of the internet as a trade facilitator is to reduce search costs, and it is reasonable to think of online marketplaces as "frictionless" in this regard. Exporters no longer need to make multiple phone calls, send faxes, write emails, attend trade fairs and networking events. And while importers still incur some search costs, these are typically brought down to a simple internet search. In any event, online search costs are not necessarily correlated with how remote markets are.

The heart of our paper is a dataset on cross-border transactions conducted over eBay, the world's largest online marketplace. This dataset allows us to examine the effect of distance on international online trade. Our approach is similar to that of Hortaçsu et al. (2009) who, using a sample of within-US eBay transactions, showed that the coefficient on distance on trade was much smaller online than offline. However, as noted by the authors, several caveats make their comparison with offline trade imperfect. One is that the products traded on eBay are mainly household durables, and thus comparison with total offline trade is problematic. Another is that the demographic characteristics of the eBay users may be online-specific and not representative of the offline world. A further shortcoming is that international search costs may be very different from those within the US. Hence their sample may not be fully appropriate to study the "death of distance" in international trade.[1] Our dataset allows us to overcome these criticisms and compare the distance effect on eBay and offline trade considering the same set of countries and goods. It covers all eBay transactions, disaggregated into 40 product categories, between 62 countries (representative of 92% of total world trade) during 2004-2007. To create the best-possible comparison groups, we match eBay product categories to product descriptions from the 6-digit level HS classification to build comparable basket of goods. We also drop from our eBay data all transactions that were concluded via auctions (60 percent of eBay traded value), as well as those sold by consumers, so that our eBay data reflect offline practises. Prima-facie evidence (Figure 1) indicates that the relationship between trade flows and distance is indeed more flat-sloped on eBay (left panel) than offline.

To identify as precisely as possible the effect of distance we use a gravity framework (Anderson and van Wincoop 2004), controlling for other standard gravity trade costs such as the absence of a common language, a common legal system, a border, a colonial history, or a free-trade agreement. We find the distance effect to be 65 percent smaller online than offline. This difference in distance coefficients is statistically significant at the 99 percent level, robust to using OLS or Poisson pseudo-maximum likelihood estimations as well as to various aggregations of goods online and offline, including using disaggregated data. We also run our gravity model by product category and show that distance matters less online for all products.

This supports the prediction of Chaney (2011), namely that in a world where search costs are greatly reduced, the role of distance in explaining trade flows is smaller. However, even though the importance of distance is 65 percent smaller on eBay, it still matters significantly. According to the literature, distance may capture different types of frictions, namely (i) shipping costs (e.g. Feyrer 2009), (ii) information frictions (e.g. Chaney 2011), or (iii) trust

[1] Hortaçsu et al. (2009) do provide international evidence using MercadoLibre, another online market, though it only covers 12 Latin American countries.

frictions.[2] In order to appreciate what is driving the distance-reducing effect brought about by eBay, we need to isolate these frictions.

We start by controlling for bilateral shipping costs, which are included in our eBay dataset. Somewhat surprisingly, we find that adding shipping costs barely affects the distance coefficient. As seen in Figure 4, this is because shipping costs are uncorrelated with distance. Furthermore, ad-valorem shipping costs seem higher online than offline, probably as there are less bulk-shipping scale economies for online shipments. It is thus highly unlikely that a reduction in shipping costs is driving the online death of distance.

To explore the trust and information channels we interact the distance coefficient with indicators of corruption and information frictions at the country level. We find that the distance-effect reduction is largest for exporting countries with high levels of corruption and which are relatively unknown to consumers, as measured by Google search results. This suggests that online markets reduce the distance effect by providing both both trust and information.[3] We obtain the same result when we interact distance with indices of information intensity at the product level, namely Broda and Weinstein's (2006) trade elasticities as well as indices we build using the WIPO Global Brand Database and eBay's trademark-infringement alert system. We also test whether the distance effect is reduced by the eBay seller-rating mechanism, which increases importer trust in exporters. As predicted, we find that distance matters significantly less for sellers with higher ratings. This confirms that distance captures trust and information frictions which are reduced by technology.

As highlighted earlier, different demographics could also be driving the different distance effects. To control for these differences, all our specifications include importer and exporter fixed effects that are specific to online and offline flows. Yet it could be argued that country characteristics that drive the selection of eBay traders are correlated with the distance effect. For example, in highly unequal societies only a few privileged buyers may have access to the internet. This type of buyers may be more 'international', i.e. may have a preference for purchases from remote countries, and hence this selection may explain why distance

[2] An alternative explanation are taste differences. Blum and Goldfarb (2006) showed that gravity holds in the case of website visits and argued this was because distance proxies for taste similarity.

[3] We also find that the distance differential is highest for country pairs that do not share a language, i.e. when information and trust frictions are high.

matters less online. A selection of 'international' exporters on eBay could also be driving the difference. In countries with low barriers to export and high internet penetration exporters should be most similar online and offline. Using interaction terms, we show that even in the extreme scenario in which all countries would be as equal as Sweden and as easy to export from as Hong Kong, eBay would still significantly reduce the distance effect.

We conclude with an estimate of the gains from trade brought about by internet technologies. We use the formula proposed by Arkolakis, Costinot and Rodríguez-Clare (2012) to calculate the welfare gains that would result from a drop in offline search costs to the online level, as captured by the difference in distance effects. We find that in the average country, real income would increase by 29 percent.

The reminder of the paper is organized as follows. In section 2 we provide some descriptive statistics regarding international trade flows on eBay. Section 3 presents our empirical strategy and section 4 the results. Section 5 presents the trade gains from world flattening. Section 6 concludes.

2 International trade on eBay: Descriptive statistics

Our data covers all eBay trade flows between 62 developing and developed countries over the period 2004-2009. These 62 countries, identified in Figure 2 , represent around 92 percent of global offline trade in 2008. Total cross-border flows on eBay were on average USD 6 billion per year over that period, representing a small fraction (0.06 percent) of world trade. The correlation between the logs of bilateral offline and eBay trade is 0.71, suggesting trade patterns are geographically similar online and offline. Since we want to compare online and offline trade flows as precisely as possible, we focus on the period 2004-2007 to abstract from unusual experiences during the Great Trade Collapse of 2008-2009 (Baldwin 2009).[4] We then average trade flows over this four-year period. To improve the matching between online and offline flows we only look at eBay exports by businesses, and we ignore of all imports

[4]The Great Trade Collapse may have come with goods shifting, trade finance problems, or new protectionist pressures that may have affected online and offline trade differently.

purchased via auctions, which are prevalent on eBay but quite uncommon offline.[5]

Our dataset also allows us to focus on the same goods traded online and offline. It covers all eBay transactions disaggregated into 40 product categories that we match with product codes at the 6-digit level of the HS classification using information on sub-categories from the eBay website (see our matching table (9)). Since it is impossible to match some eBay categories to HS codes, we dropped those goods from our eBay aggregate. This allows us to have an offline basket with the same goods, similarly distributed across categories, as our eBay trade flow (Figure 3). It is also important to note that the selected HS categories all fall into the "final good" category of the WTO's Trade Policy Review classification, and are all classified as "consumer goods" in the BEC classification. All HS 6-digit lines also fall in the differentiated goods category in Rauch's (1999) classification.

The matching of goods is crucial as it allows us to control for differences in trade costs due to the composition of trade.[6] For example, tickets to sport-events traded online are likely to be very sensitive to distance whereas exports of rare earths, which are produced in a few countries but consumed all over the world, are not likely to be very sensitive to distance. If tickets tend to be traded online and rare earths offline, differences in the impact of distance will be explained by the different goods,and not by information and communication technology.

To verify whether our product matching is correct, we estimate the elasticity of substitution associated with our baskets of goods online and offline. This step is important as different elasticity of substitutions could also be behind the difference in distance effects (see Archanskaia and Daudin 2012). Indeed the coefficient in front of each trade-cost variable in the gravity equation is a combination of the trade elasticity (i.e. the elasticity of trade with respect to trade costs) which depends on the elasticity of substitution, and the elasticity of total trade costs with respect to each trade cost variable. Thus, a smaller coefficient on distance for online flows could simply signal that the bundle of online products has a

[5]The share of sales by consumers is 66 percent and the share of sales through auctions is 65 percent. Once we exclude both, we are left with 15 percent of total eBay's cross border flows.As we show in our robustness checks, results hold when including all flows.

[6]See Berthelon and Freund (2008) or Carrère et al. (2009) for a discussion of the impact of the composition of trade on the role of distance.

lower elasticity of substitution than the offline bundle. To estimate these elasticities of substitution we assume that trade costs online and offline are Gamma distributed with shape parameter k^f, where f is the type of flow, but an identical scale parameter. Then using existing estimates of the elasticity of substitution for aggregate trade flows, we can back up consistent estimates of the elasticity of substitution online and offline using the fact that the variance of a gamma distributed variable is proportional to the mean by a factor equal to the scale parameter. For a detailed description of the methodology to estimate the online and offline elasticities of substitution, see section 5.1.

Our results suggest that for an estimate of the aggregate elasticity of substitution of 5 (see Eaton and Kortum 2012), the online elasticity of substitution equals 4.5, whereas the offline elasticity of substitution equals 5.6. The online estimate is within the [3.6 ; 5.9] range estimated by Einav et al. (2012) using intra-US trade flows and identified with differences in sales tax across states.[7] The offline estimate is quite close to the Broda and Weinstein (2006) median estimate of 5.9 in our bundle of HS-6 digit goods. Moreover, while the online and offline elasticities of substitution are statistically different from zero at the 5 percent level, they are not statistically different from each other. This comforts us in our matching of online and offline products, and suggests that statistical differences in the estimated coefficients of the gravity equation will be due to the contribution of these variables to trade costs, rather than to differences in the elasticity of substitution.

Our eBay data also includes data on average bilateral ad-valorem shipping costs. While we do not have an equivalent for bilateral offline flows, in the case of US imports we do have data on freight and insurance costs from USITC. When plotting these costs against distance (see Figure 4) we find that for both online and offline flows, shipping costs are uncorrelated with distance, even though shipping costs seem to be much higher online.[8] This suggests that the introduction of observable shipping costs in the gravity equation, which are often omitted due to lack of data, is not going to explain the importance of distance in the gravity equation. But this is a testable hypothesis at least in the online sample.

[7] They are significantly lower than the estimates of De los Santos et al. (forthcoming) but these correspond to price elasticites of particular book varieties, and therefore we would expect them to be higher than our aggregated bundle of goods.

[8] Using data on all country pairs online gives a similar picture.

Offline trade data and trade cost variables come from the usual sources and are described in the Data Appendix.

3 The empirical model

To examine the impact of trade costs online and offline, our starting point is the gravity model. It suggests that bilateral trade between two countries is proportional to their economic mass and the multilateral resistance indices of the importer and the exporter,[9] and inversely proportional to trade costs between the two countries, often proxied by the geographic distance between them (see Anderson and Van Wincoop (2003) for an elegant derivation):

$$(1) \quad m_{ij} = \frac{y_i y_j}{y_w} \left(\frac{t_{ij}}{P_i \Pi_j} \right)^{\epsilon}$$

where m_{ij} are imports of country i from country j, y_i is total income in importing country i, y_j is total income in exporting country j, y_w is total world income, t_{ij} are trade costs between country i and country j, ϵ is the trade cost elasticity of bilateral imports,[10] and P_i and Π_j are the multilateral resistance terms in the importing (inward) and exporting (outward) country, respectively.[11]

We follow the literature and model bilateral trade costs (t_{ij}) as a function of geographic distance and other trade cost variables:

$$(2) \quad t_{ij} = D_{ij}^{\alpha_D} e^{NB_{ij}\alpha_{NB}} e^{NC_{ij}\alpha_{NC}} e^{NCL_{ij}\alpha_{NCL}} e^{NCLS_{ij}\alpha_{NCLS}} e^{NFTA_{ij}\alpha_{NFTA}}$$

where all αs are parameters, D_{ij} is the geographic distance between countries i and j, NB_{ij}

[9] The multilateral resistance terms are weighted averages of price indices in the importer's and exporter's trading partners.

[10] Given by 1 - σ in Anderson and Van Wincoop (2003) where σ is the elasticity of substitution between different import sources in the importing country.

[11] The expressions for the inward and outward multilateral resistance terms are $P_i = \left[\sum_j (t_{ij}/\Pi_j)^{\epsilon} \frac{y_j}{y_w} \right]^{1/\epsilon}$ and $\Pi_j = \left[\sum_i (t_{ij}/P_i)^{\epsilon} \frac{y_i}{y_w} \right]^{1/\epsilon}$.

is a dummy variable taking the value 1 when countries i and j do not share a border, NC_{ij} is a dummy variable taking the value 1 when countries i and j did not share a colonial link, NCL_{ij} is a dummy variable taking the value 1 when countries i and j do not share a common language, $NCLS_{ij}$ is a dummy variable taking the value 1 when countries i and j do not share a common legal system, and $NFTA_{ij}$ is a dummy variable taking the value 1 when countries i and j are not part of the same Free Trade Agreement.[12]

We then substitute (2) into (1) and take logs on both sides to obtain:[13]

$$
\begin{aligned}
\ln(m_{ij}) = \quad & \ln(y_i) + \ln(y_j) - \ln(y_w) + \beta_D \ln(D_{ij}) + \beta_{NB} NB_{ij} + \\
& \beta_{NC} NC_{ij} + \beta_{NCL} NCL_{ij} + \beta_{NCLS} NCLS_{ij} + \beta_{NFTA} NFTA_{ij} + \\
& -\epsilon \ln(P_i) - \epsilon \ln(\Pi_i)
\end{aligned}
\tag{3}
$$

where all βs are parameters to be estimated and $\beta_k = \epsilon \alpha_k$, where k is the subscript indicating the different trade cost variables. Because we are interested in understanding the variation of different βs offline and online, and because P_i and Π_i are not observable (and difficult to estimate) we proceed as in much of the empirical literature and control for the multilateral resistance terms (and y_i and y_j) including importer i and exporter j fixed effects.

A stochastic fixed-effect version of equation (3) is our baseline specification to understand the importance of different trade costs offline and online. We estimate it separately for online and offline flows, but also append the offline and online data so that we can test whether coefficients are statistically different online and offline by introducing an eBay dummy that we interact with each of the trade cost variables. If the interaction term is statistically significant then the offline and online coefficients are statistically different. In both cases we allow for importer and exporter fixed effects to be different online and offline. This captures differences in prices for online and offline products, and can also correct for a selection of buyers and sellers into online and offline platforms that could bias our estimate as argued

[12]Note that we measure the absence of common language, common legal system, colonial links or trade agreements, rather than their presence as in most of the literature. This has no consequences for the estimates, but it allows to interpret these variables as trade costs (like distance) rather than as trade-enhancing variables.

[13]Since some of our left-hand side variables were zeros (21 percent on eBay, less than 1 percent offline), we added a dollar the the import value before taking the logs.

by Goolsbee (2000). We use a least-square dummy-variable estimator (LSDV), but also a Poisson estimator to control for heteroscedasticity (see Santos-Silva and Tenreyro 2006). To make sure results are not subject to aggregation bias, we also run the same specifications as in equation (3) but at the product level and using exporter-product and importer-product fixed effects, which also vary for online and offline flows.

To uncover what drives the difference in distance coefficients online and offline we use interaction terms between distance and country or product characteristics that capture information asymmetries and trust problems. The idea is that if results are partly driven by technologies that reduce information asymmetries and trust problems, the differences in the distance coefficients online and offline should be larger for countries and products affected by information asymmetries.

4 Results

Table 1 provides the results of the estimation of (3) using distance as the only trade costs in columns (1) and (5). The elasticity of distance is 61 percent smaller online than offline. In columns (2) and (6) of Table 1 we provide the estimates of (3) including the other usual trade costs variables. When we introduce these additional trade costs, the coefficient on distance declines both online and offline. Still it remains around 65 percent smaller online, suggesting a flatter world on the eBay platform.

Some interesting patterns emerge regarding the other trade-cost variables. Common legal systems, trade agreements, colonial links and borders seem to matter much more offline. On the other hand the absence of a common language seem to matter more online than offline. We test for the statistical significance of these differences by appending the online and offline datasets and estimating the gravity equation including interactions of each trade costs with an eBay dummy which takes a value of one if the flow on the left-hand side is the eBay flow and zero if it is the offline flow. As argued above we also include importer-eBay and exporter-eBay fixed effects that control for any country-level differences between importers and exporters online and offline. As seen in Table 2, we find that the difference in the effect of distance is statistically significant. What's more, we find that the absence of colonial links and common legal systems also matter significantly less online, though only at the 90 percent level. Hence technology may also reduce the distortions caused by historical legacies. We find no significant difference in the effect of free-trade agreements, borders, or languages.

Columns (3) and (7) of Table 1 add shipping costs to the set of explaining variables. Since these are not available for offline data, they are not usually included in gravity equations. But since our eBay data includes shipping costs, we include this bilateral ad-valorem average as a control both online and offline where it may also be a valid proxy for shipping costs. Surprisingly, we find no significant effect for shipping costs,[14] and our results are unaffected by this inclusion, which can be explained by the fact that shipping costs are not necessarily correlated with distance.[15]

Columns (4) and (8) provide the results using the Poisson pseudo-maximum likelihood estimator which was suggested for gravity models by Santos Silva and Tenreyro (2006) to control for heteroscedasticity. Again we find that distance matters more offline. The estimated distance elasticity is around 55 percent smaller online.

To check that our result is not driven by a composition effect within the online and offline bundles, we estimate gravity equations for each eBay category using the specification of column (2) of Table 1 . The estimated coefficients, using both LSDV and Poisson pseudo maximum likelihood estimators, are summarized in Figure 5 which shows that distance always has a bigger effect offline. It is on average 2.5 times bigger. Pooling the product regressions together and estimating an average effect using importer-category and exporter-category fixed effects yields distance coefficients of -0.287 online and -1.167 offline (columns 1-2 of Table 5).

In Table 3 we include the results of various robustness checks. As an important part of eBay trade is in used goods (25 percent) or occurs through auctions (65 percent) we replicate Table 1 disaggregating imports into used vs. new goods (this is done on a 2008 cross section

[14] This could be explained by endogeneity problems, as larger trade flows create incentives for investment in transport infrastructure along those routes, or measurement error problems.

[15] This result also suggests that the death of distance online is not due to a reduction in shipping costs. Adding other controls such as bilateral average tariffs or trade-restrictiveness indices does not affect the results (not shown).

because it is the only year for which we have the used versus new good information) and auctions vs. direct sales. We also report results when looking at all trade flows reported on comtrade, i.e. not just the eBay image, as well as all eBay trade flows and not only those that match offline products. Results are consistent across aggregations suggesting that across all types of eBay flows distance matters less. Interestingly, the distance coefficient is smaller for new than for used goods, and for goods sold through auctions than for goods sold through set-price transactions. Thus when information is more difficult to obtain regarding the quality of the goods or the price at which it will be sold (i.e. in the case of used goods and auction transactions) distance seems to matter more, suggesting that the reason the distance coefficient declines for eBay may be because it helps reducing information asymmetries regarding product or seller characteristics.[16]

The final two columns of Table 3 verify whether eBay seller reputation matters for the impact of distance on trade flows. Online platforms adopt mechanisms to overcome the incentives for opportunistic behavior in global markets where buyers and sellers do not necessarily meet repeatedly. The eBay PowerSeller status is one of these mechanisms.[17] It certifies that the seller has received 98% positive feedback, has been active for more than 90 days, has completed at least 100 transactions or transactions worth at least $3000 during the past year, and complies with eBay policies.[18] Seller reputation is in principle much more important than buyer reputation on eBay as transactions are usually of the "cash-in-advance" type where the buyer pays first and waits for the seller to send the goods.[19] The last two columns of Table 2 look at whether the impact of distance on trade flows is different for PowerSellers and non-PowerSellers. If the distance coefficient partly captures the costs of trust in exporters, and if the PowerSeller mechanism were to be effective, then we would expect a smaller distance coefficient for transactions undertaken by PowerSellers.

[16]We also run the same specification for sales by non-business exporters (e.g. consumers) and perhaps surprisingly found a similar distance elasticity as for B2C flows of around -0.5.

[17]Another important mechanism is the disclosure of information through photos and text. Lewis (2011) shows that they strongly influence auction prices on eBay motors as they help define the terms of the contract between sellers and buyers who cannot directly observed the goods they are buying.

[18]See eBay's website for more details here:
http://pages.ebay.com/sellerinformation/sellingresources/powerseller.html.

[19]See Cabral and Hortaçsu (2010) for a recent analysis of the consequences of seller reputation on eBay.

As predicted, we find that distance affects non-PowerSellers significantly more. We test for the statistical significance of the difference on the distance coefficient of PowerSellers by appending the PowerSeller and non-PowerSeller data and interacting each of the trade cost variables with a dummy indicating whether the flow involves PowerSeller or not. The only statistically-different coefficient at the 5 percent level is the distance one as shown in Table 4.

To examine whether eBay reduces search costs associated with product information as suggested by Rauch (1999), we use three measures of information asymmetries at the product level. First, we use Broda and Weinstein's (2006) estimates of elasticity of substitution.[20] The median of their HS-6 digit estimates measures the need for information, or the level of product differentiation, within each category. Indeed as substitution among import sources is smaller there is a stronger need for product information. Next, we construct two measures of trademark intensity that also capture the presence of product information in each sector. Our first measure of trademark intensity uses data from the WIPO Global Brand Database which contains around 660,000 records relating to internationally protected trademarks. We base our trademark intensity measure on the number of registered brands per keyword search, where the keyword is the eBay category. For example, there are 605 registered brands that match the keyword 'music', and 284 that match 'electronics'. We suggest that the lower this number, the higher the need for information gathering and diligence by importers. If the search costs lowered by eBay are related to product information, we should find eBay to reduce the role of distance most in categories with low trademark intensity for which asymmetric information regarding product characteristics is stronger. Our second indicator of trademark intensity comes from our eBay data and measures the intensity of complaints by trademark owners to eBay about potentially-illegal transactions. We take the share of companies who complain per category as an indicator of trademark intensity. We then suggest that the more complaints there are, the more branded the product category should be. We then interact these product-information indices with distance in our gravity regressions. The results are summarized in Figure 6 (drawn from coefficients found in Table

[20]The use of Rauch's (1999) classification into homogenous and differentiated goods is not possible in our sample as all categories fall within the differentiated-good category.

5). It shows that the distance-effect difference is much larger for products with low elasticities of substitution or low trademark-intensity. As suggested above, it seems eBay is particularly efficient at reducing the distance effect for products that require more information and trust, and hence may be reducing information asymmetries.

To further understand the mechanisms through which eBay reduces the impact of distance on bilateral trade flows, we interact distance with measures of exporter corruption and information-availability. Our corruption measure is from the World Governance Indicators. Our measure of country information-availability is the number of Google search results for the country name. The idea is that there is more available information about countries that have more Google results. The marginal effects of distance as a function of corruption and country popularity are reported in Figure 7 (drawn from Table 6). The higher the level of corruption in the importing or the exporting country, the larger the distance-effect difference between online and offline flows. Similarly, the lower the degree of country information, the larger the difference in distance coefficients. Furthermore, these differences in distance effects are largest when exporters, rather than importers, are corrupt or unpopular. This confirms that due to eBay's 'cash-in-advance' system, it is trust in the exporter that matters most.

Finally, as noted earlier, the difference in the effect of distance could be due to a selection of 'international' buyers rather than a 'technology' effect. While the appended model including importer-eBay and exporter-eBay fixed effects partly corrects for these selection effects, buyer and seller characteristics might also affect the impact of distance. For example, online buyers may tend to be richer and rich individuals may prefer purchasing goods from faraway countries. Ideally, we would like to observe individual characteristics of buyers online and offline, but we do not have access to that data. Thus, we check whether distance matters less online at different levels of income inequality and internet penetration in the importing country. The idea is that in highly unequal societies with low internet penetration only a few privileged 'international' buyers have access to internet and buy on eBay. In these countries buyers on eBay and offline are likely to be most different. As reported in Figure 8 (drawn from Table 7), we find the biggest differences in distance effects in unequal countries and in countries with low internet penetration, suggesting part of the difference may reflect a selection of 'international' buyers online. Still, we find that even for the most equal or most internet-penetrated countries, where the online and offline buyers are plausibly most similar, the distance effect is still statistically smaller online. This reinforces the idea that technology has a distance-reducing impact beyond importer selection. A similar selection of 'international' exporters could also be driving the difference. To check for this we interact distance with the number of days required to export from each country, as well as exporter internet penetration. The idea here is that in countries with low barriers to exports and high internet penetration, exporters should be most similar offline. If a selection of 'international' sellers on eBay explains the difference, the latter should be bigger in countries from which it is hard to export. This is indeed what we find (Figure 8 (drawn from Table 7). Still, the distance effect is statistically smaller in all countries. Hence, even in the extreme scenario in which eBay exporters would be as international as Hong Kong's and importers all a country as equal as Sweden, distance would still matter less online.

5 Welfare gains

We have seen that the distance-reducing effect of online markets is larger where most needed, i.e., in countries which are little known, with weak institutions, high levels of income inequality, inefficient ports, and low internet penetration. But how large are these effects in terms of welfare gains?

In order to estimate the welfare gains that would result from search costs being reduced to the level on online platforms, i.e. if distance mattered offline as little as online, we first need to calculate the change in intranational trade shares in each country using our gravity estimates. We can then compute the changes in real income following Arkolakis, Costinot and Rodríguez-Clare (2012). Indeed, according to their proposition 1, assuming that trade is balanced, that the ratio of profits to total income is constant, and that the import demand system is such that bilateral trade flows are given by a gravity specification consistent with the presence of a single production factor (labor), we can express the welfare change as:[21]

[21]Trade balance implies that imports cannot be larger than GDP which is inconsistent with what we observed in the data for some of the countries in our sample. We therefore drop these countries from the

$$(4) \quad \widehat{W}_i = \left[\frac{\widehat{m_{ii}}}{y_i}\right]^{1/\epsilon}$$

where, for any variable x, $\widehat{x} = x'/x$, and x' is the value of x after the shock. The change in intranational trade as a share of income is given by (see Proposition 2 in Arkolakis et al. 2012):

$$(5) \quad \frac{\widehat{m_{ii}}}{y_i} = \frac{1}{\sum_{j=1}^{n} \frac{m_{ij}}{y_i} \left(\widehat{w_j}\widehat{t_{ij}}\right)^{\epsilon}}$$

Hence, in order to calculate the change in welfare associated with a partial 'death of distance' offline, we need an estimation of the change in trade costs ($\widehat{t_{ij}}$), as well as an estimation of the change in wages ($\widehat{w_j}$) in all n countries. The former can be obtained using the estimates of the distance coefficient online and offline:

$$(6) \quad \widehat{t_{ij}} = e^{\frac{1}{\epsilon}\left(\beta_D^{\text{online}} - \beta_D^{\text{offline}}\right)\ln D_{ij}}$$

We use the β_D coefficients reported in columns (4) and (8) of Table 1 which have been consistently estimated using importer and exporter fixed effects specific to online and offline flows and a Poisson estimator to control for heteroscedasticity. We can then easily compute $\widehat{t_{ij}}$ using an estimate of ϵ for aggregate trade flows from the existing literature. Eaton and Kortum (2012) suggest that the current best estimate sets $\epsilon = -4$.

The estimation of $\widehat{w_j}$ requires solving the general equilibrium wages of all countries in our sample. Taking the change in wages in the United States as numéraire ($\widehat{w_{\text{USA}}} = 1$), the change in wages in all other countries are implicitly given by (see Arkolakis et al. 2012):

welfare calculations.

$$(7) \quad \widehat{w_j} = \sum_{i'=1}^{n} \frac{m_{i'j}\widehat{w_{i'}}\left(\widehat{w_j}\widehat{t_{i'j}}\right)^{\epsilon}}{y_j \sum_{j'=1}^{n} m_{i'j'}/y_i' \left(\widehat{w_{j'}}\widehat{t_{i'j'}}\right)^{\epsilon}}$$

We solve the n non-linear equations for the changes in wages ($\widehat{w_j}$) numerically using the Matlab solver. Substituting these and the estimates of the changes in trade costs in equation (6) into (5) and the result into (4) yields the changes in real income following a drop in the distance effect offline to the level prevailing online.

One important assumption we have been making is that the elasticity of substitution online is not different from that offline. Without this assumption, the percentage changes in trade costs cannot be approximated by the difference in β coefficients as $\beta_D = \epsilon\alpha_D$. Differences in ϵ would therefore be contaminating differences in β_D. We test this assumption below.

5.1 Estimates of the elasticity of substitution online and offline

Let us assume that offline trade costs $\ln(t_{ij})$ are generated by a Gamma distribution with scale parameter θ and shape parameter k:

$$(8) \quad \ln(t_{ij}) \sim \frac{1}{\theta^k \Gamma(k)} (\ln(t_{ij}))^{k-1} e^{\frac{-\ln(t_{ij})}{\theta}}$$

The empirical distribution of $-\epsilon\ln(t_{ij})$ can be consistently estimated using a log-linearized version of equation (1) estimated with importer and exporter fixed effects. Since $\ln(t_{ij}) \sim \Gamma(k, \theta) \leftrightarrow -\epsilon\ln(t_{ij}) \sim \Gamma(k, -\epsilon\theta)$, we can estimate k using the third moment of the empirical distribution of $-\epsilon\ln(t_{ij})$. Indeed, the skewness of the Gamma distribution is given by $2/\sqrt{k}$. It yields $k = 5.0$. Then to obtain an estimate of θ we use the closed-form solution for the mode of the Gamma distribution which is given by $(k-1)\theta$. Using the mode calculated from the empirical distribution of $-\epsilon\ln(t_{ij})$, we can then back up θ using our estimate of k and existing estimates in the literature for ϵ (equal to -4). Using the mode of the empirical distribution of $-\epsilon \ln(t_{ij})$ we have $\theta = \text{mode}/\left[(k-1)*(-\epsilon)\right] = 0.04$.

Assuming that the log of trade costs online and their offline image are also drawn from a Gamma distribution with the same scale parameter θ, we can estimate the online and offline elasticities of substitution, recalling that the variance-to-mean ratio of a Gamma distribution is given by its scale parameter. Thus, for online and offline flows $\theta\epsilon = \text{var}(-\epsilon \ln(t_{ij}))/\text{mean}(-\epsilon \ln(t_{ij}))$. For both online and offline flows we can solve for $\sigma = 1 - \epsilon$:

$$(9) \qquad \sigma = 1 + \frac{\text{Var}\left[-\epsilon \ln(t_{ij})\right]}{\text{mean}\left[-\epsilon \ln(t_{ij})\right]\theta}$$

This procedure yields an estimate of the elasticity of substitution for online flows equal to 4.5, and an estimate for the offline image flow equal to 5.6. The current best estimate of σ is around 5 (if $\epsilon = -4$), i.e., in between our online and matched offline estimates.

To check that our elasticities of substitution are statistically different from zero, but not statistically different from each other we construct bootstrapped standard errors taking into account the sampling error as well as the error associated with the offline aggregate elasticity-of-substitution estimates. For the latter, we assume that ϵ is normally distributed with mean -4 and a variance equal to 1. The bootstrapping yields a standard error equal to 0.9 for the estimate of $\sigma^{\text{online}} = 4.5$ and a standard error equal to 1.1 for an estimate of $\sigma^{\text{online}} = 5.6$. These elasticities are not statistically different from each other or from the estimated $\sigma = 5$ for aggregate offline flows.

Finally, we can perform an additional external test of our assumption that $\ln(t_{ij})$ is Gamma distributed with coefficient equal to θ. Indeed, with an estimate of $\epsilon = -4$, we can easily construct $\ln(t_{ij})$. Using a Kolmogorov-Smirnov test of equality-of-distributions we check whether $\ln(t_{ij}) \sim \Gamma(k = 5.00, \theta = 0.04)$.[22] The value of the Kolmogorov-Smirnov statistic (D) is close to zero and therefore we cannot reject at the 5 percent level the null hypothesis that $\ln(t_{ij})$ is Gamma distributed with shape parameter $k = 5.00$ and scale parameter $\theta = 0.04$.

[22]For a discussion of the Kolmogorov-Smirnov test see Chakravarti, Laha, and Roy (1967).

5.2 Results

We could estimate the welfare gains only for 56 of the 62 countries in our sample. The reason is that for some countries imports are larger than GDP which is inconsistent with the assumptions used to derive the welfare gains. Other countries were dropped because we didn't have the full square matrix of trade costs which is necessary for the simulation.[23]. The welfare-gains gains per country are given in Table 8.

The increase in real income associated with a reduction in the distance-effect for all trade flows is on average equal to 29 percent, ranging from over 80 percent for Brazil to -0.9 percent for Belgium, which currently gains from information frictions. Hence, our results suggest that potential gains from the reduction in information asymmetries brought about by online platforms are quite large. Unsurprisingly, as shown in Figure 9, the largest welfare gains would occur in remote countries.

6 Concluding Remarks

Using a dataset on eBay cross-border transactions and comparable offline trade flows, we estimated a distance effect on trade flows about 65 percent smaller online than offline. Using various measures of information asymmetries at the product and country level, we argued this difference in distance effects was due to online technologies that reduce information and trust frictions associated with geographic distance. The largest distance reducing effects are observed where they are most needed, i.e., in countries which are little known, have corrupt governments, high levels of income inequality, little internet penetration and inefficient ports. This is promising in terms of the potential for technology to render trade more efficient and development friendly. Importantly, the welfare gains from the reduction in distance related trade costs are large. If information frictions offline were reduced to the level prevailing online, real income would increase by 29 percent on average.

[23]Omitted countries are ALB, ARM, HKG, SGP, SRB, and TWN

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Data Appendix

Below we discuss variable construction and data sources for all variables used in the empirical sections. The appendix Table provides descriptive statistics for each variable.

- Distance (D): Distance between two countries based on bilateral distances between the largest cities of those two countries, those inter-city distances being weighted by the share of the city in the overall country's population. Source: CEPII Distances database.

- Shipping cost (T): Ad-valorem shipping costs as a share of product price (logged). Source: eBay.

- No Border (NB): dummy variable indicating whether the two partners share a border. Takes the value 1 when the two partners do not share a border. Source: CEPII Distances database.

- No Colony (NC): dummy variable indicating whether the two countries have ever had a colonial link. It takes the value 1 when the two trading partners do not share a colonial link. Source: CEPII Distances database.

- No Common Language (NCL): dummy variable indicating whether the two countries share a common official language. It takes the value 1 when the two trading partners do not share a common language. Source: CEPII Distances database.

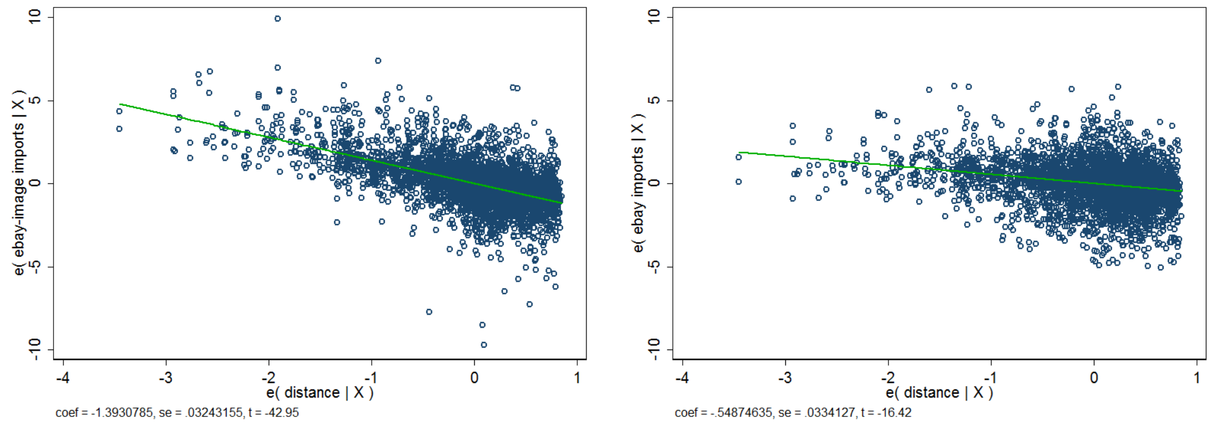
- No Common Legal System ($NCLS$): dummy variable indicating whether the two countries have the same legal origin. It takes the value 1 when the two partners do not share a legal origin. Source: CEPII Gravity database.

- No FTA ($NFTA$): dummy variable indicating whether the two countries have a free-trade agreement declared at the WTO. It takes the value 1 when the two partners do not have a free-trade agreement. Source: WTO.

- Corruption (C): Negative of control-of-corruption which captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests. Source: Kaufmann et al. (2010).

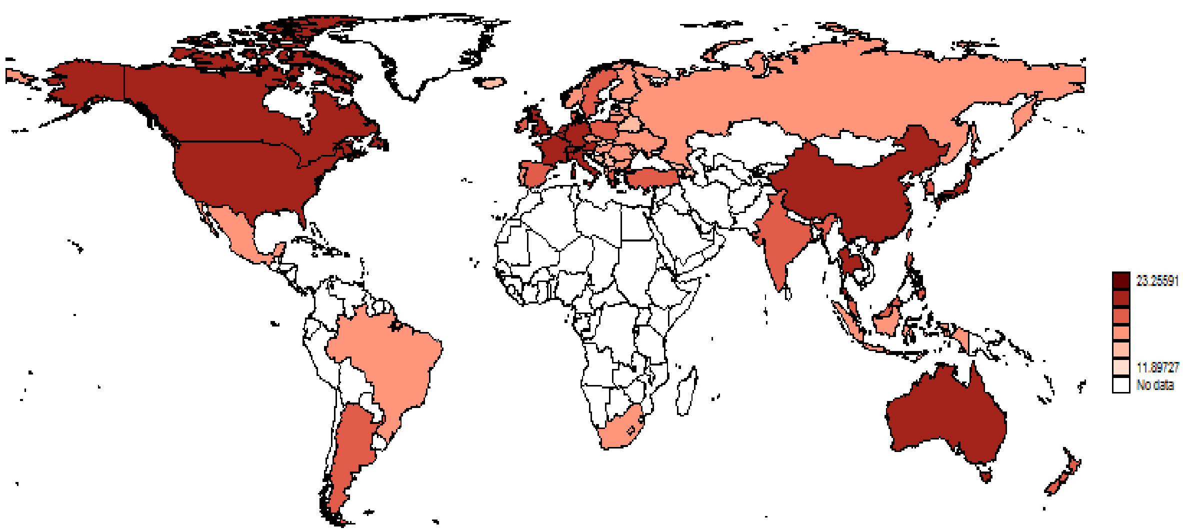
- Google coverage (G): Log of the number of results of a Google search for the country name in English . Source: Google.
- Trademark Intensity (VERO) ($VERO$): Share of companies who complain about parallel imports on eBay. Source: eBay.
- Trademark Intensity (WIPO) ($WIPO$): Log of the number of registered brands per keyword search, where the keyword is the eBay category. Source: WIPO Global Brands Database.
- Trade elasticity (sigma): Elasticity of substitution within HS-6 product categories. Source: Broda and Weinstein (2006).
- eBay imports: Total eBay imports in current US dollars. Source: eBay.
- eBay-image imports: Total bilateral imports in HS codes corresponding to eBay categories in current US dollars. Source: Comtrade
- Offline imports: Total bilateral imports in current US dollars. Source: Comtrade
- PowerSeller status (PS): Dummy indicating whether the exporters had a power seller status on eBay. Source: eBay.
- Internet penetration (@): Number of internet users over population. Source: World Bank World Development Indicators.
- Gini (Gini): Gini coefficient of income inequality. Source: World Bank World Development Indicators.
- Days to export: Number of days required to go through export procedures and port handling. Ocean transport time is not included. Source: Doing Business.

Figure 1
The importance of distance with and without search costs



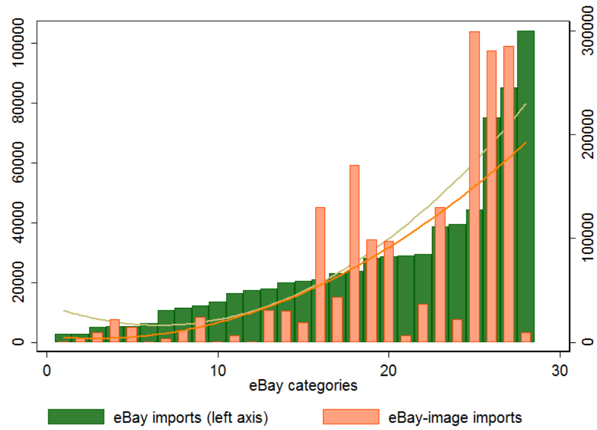
Note: Offline bilateral trade data is from UN Comtrade for 62 countries which represent more than 92 percent of world trade and is restricted to the set of goods which are traded on the eBay platform. eBay bilateral trade data is from eBay for the same set of countries. Distance is from CEPII and is measured as the bilateral distance between the capitals of the two trading partners weighted by the share of the capital's population in the total population of the country.

Figure 2
Country coverage



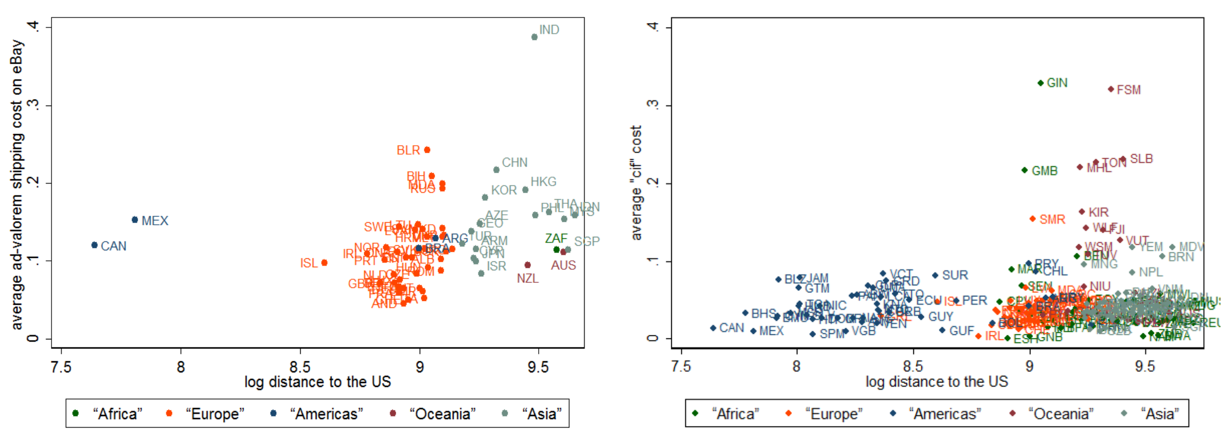
Note: The intensity of the red color signals the value of the log of eBay exports

Figure 3 Distribution across eBay categories



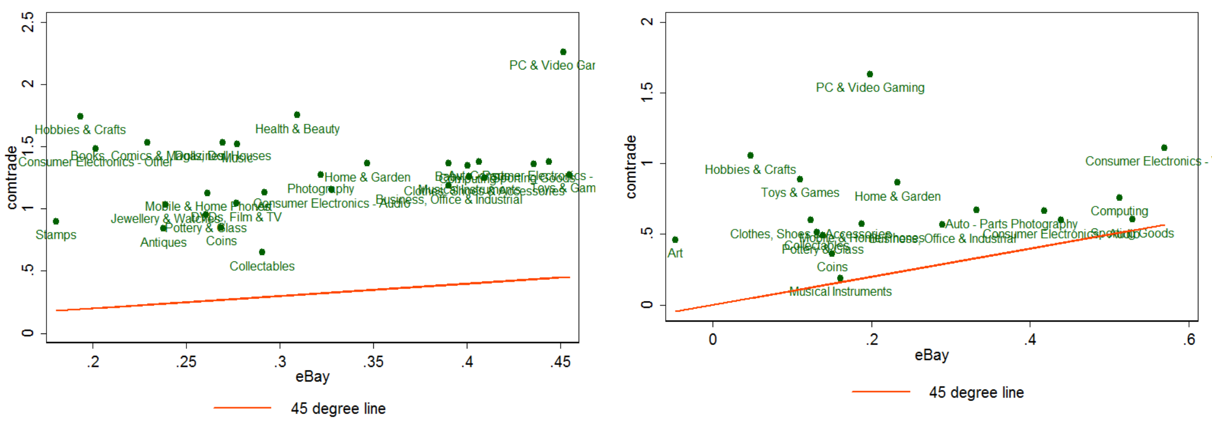
Note: The lines are quadratic fits.

Figure 4
Distance and shipping costs offline and online



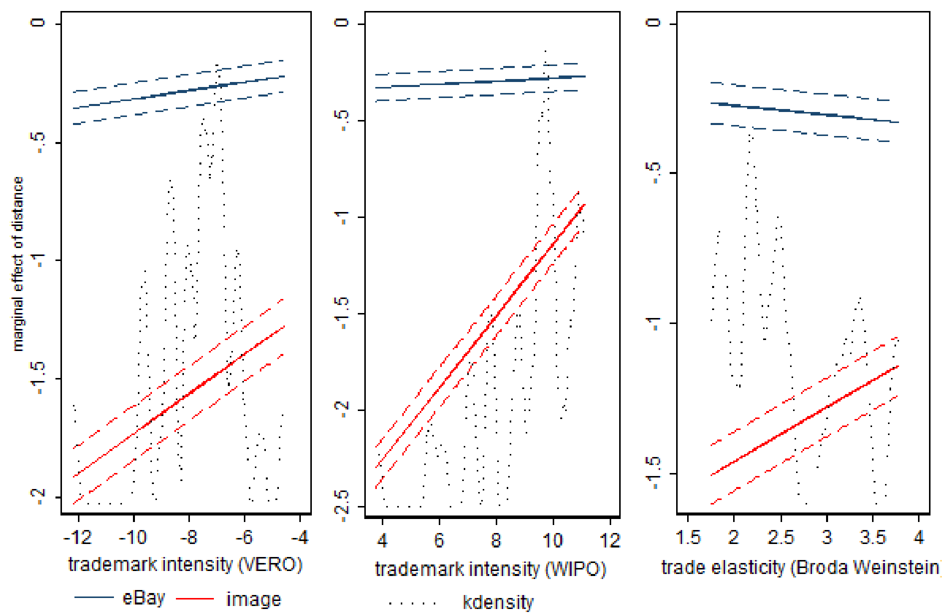
Sources: USITC and eBay

Figure 5
Distance coefficient by eBay category



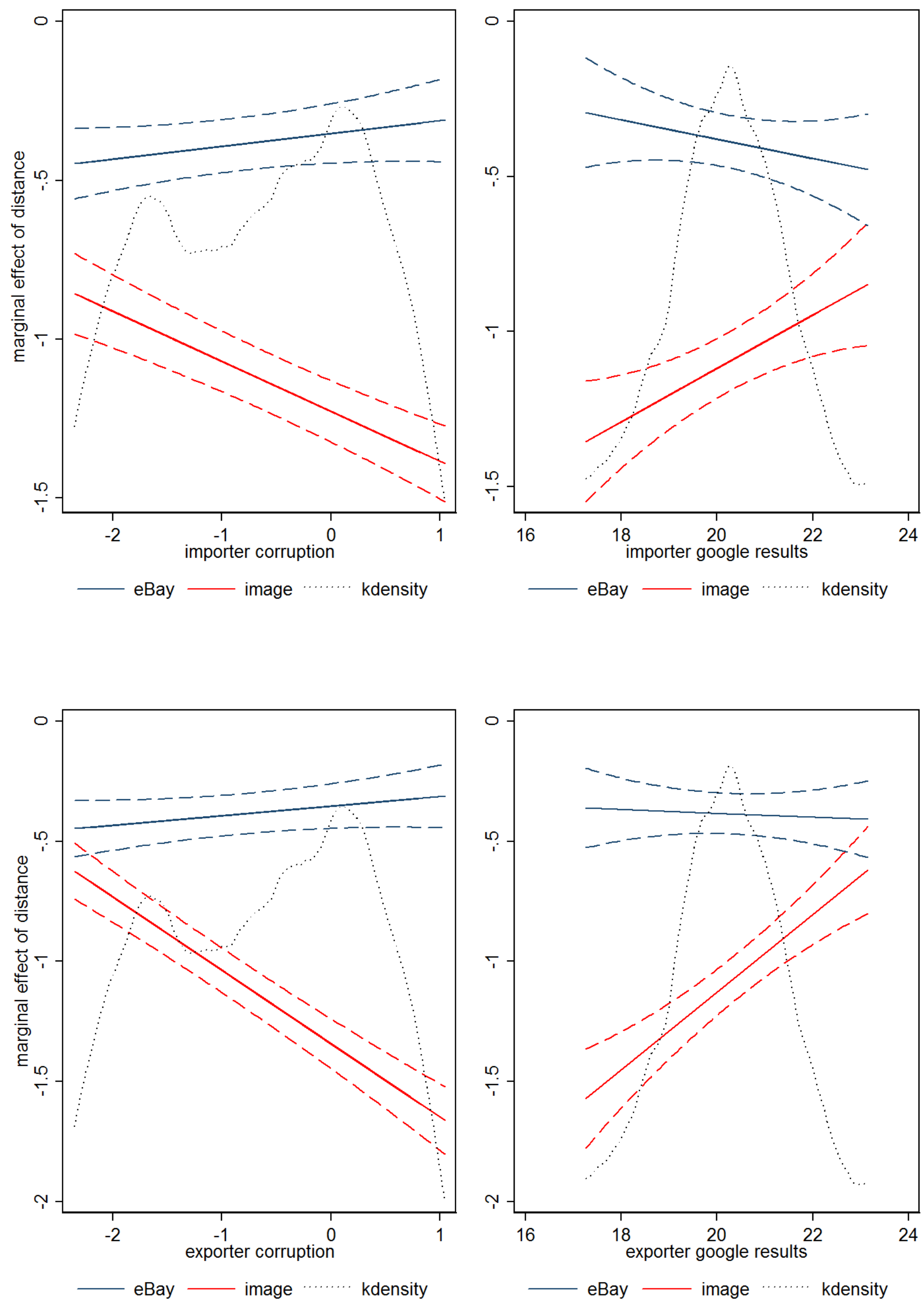
Note: The left panel reports estimates using an OLS estimator and the right panel reports estimates using a poisson estimator. Each distance coefficient is estimated in a separate regression with a specification identical to the one reported in column (2) of Table 1.

Figure 6
Distance coefficients vs. trademark intensity and heterogeneity



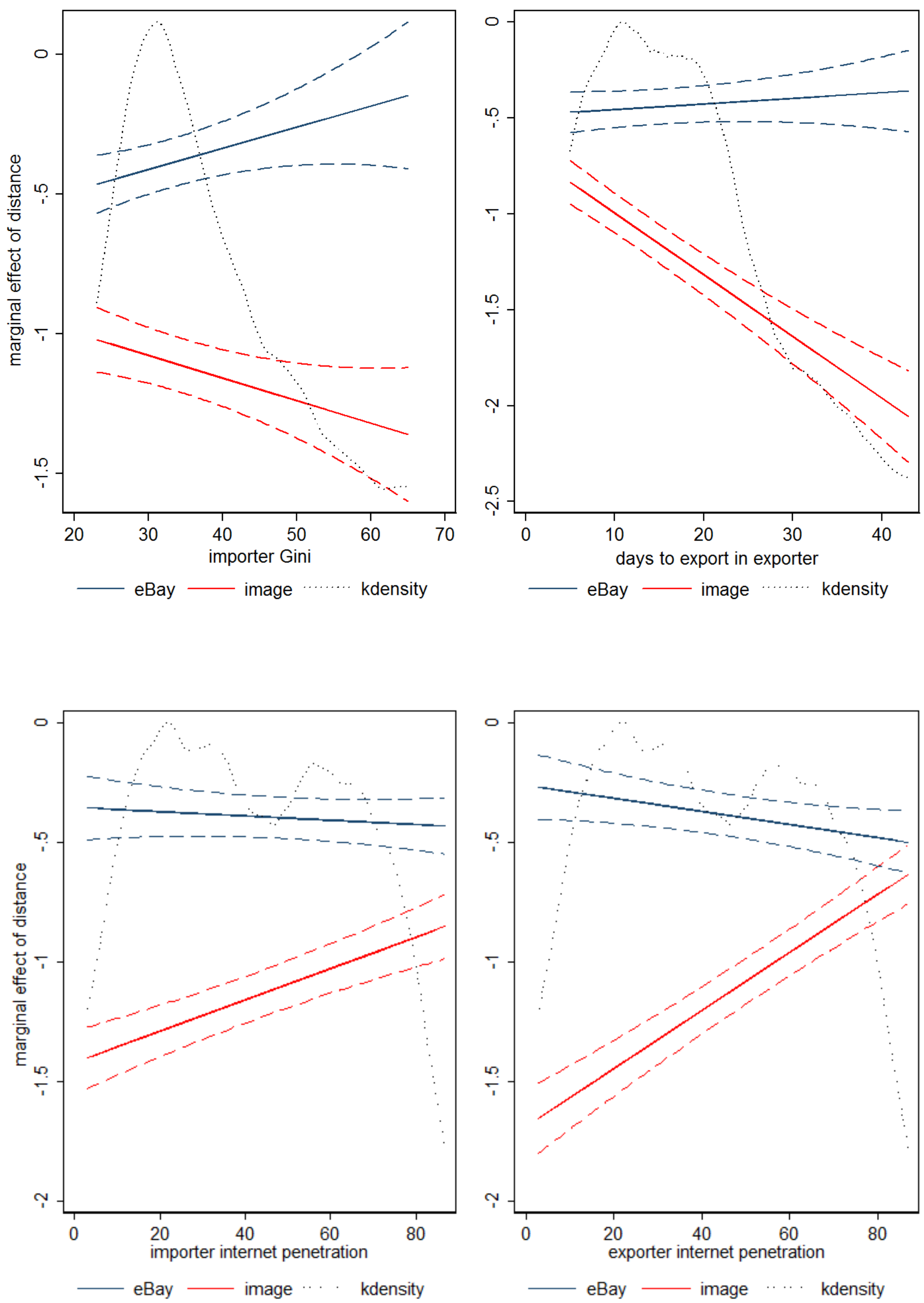
Note: These marginal effects are estimated using a specification similar to the one reported in column (3-6) of Table 5. The dotted lines give the kernel density estimate of the x axis variable. The dashed lines are the 95 percent confidence interval.

Figure 7
Corruption, Google popularity and the distance effect on trade



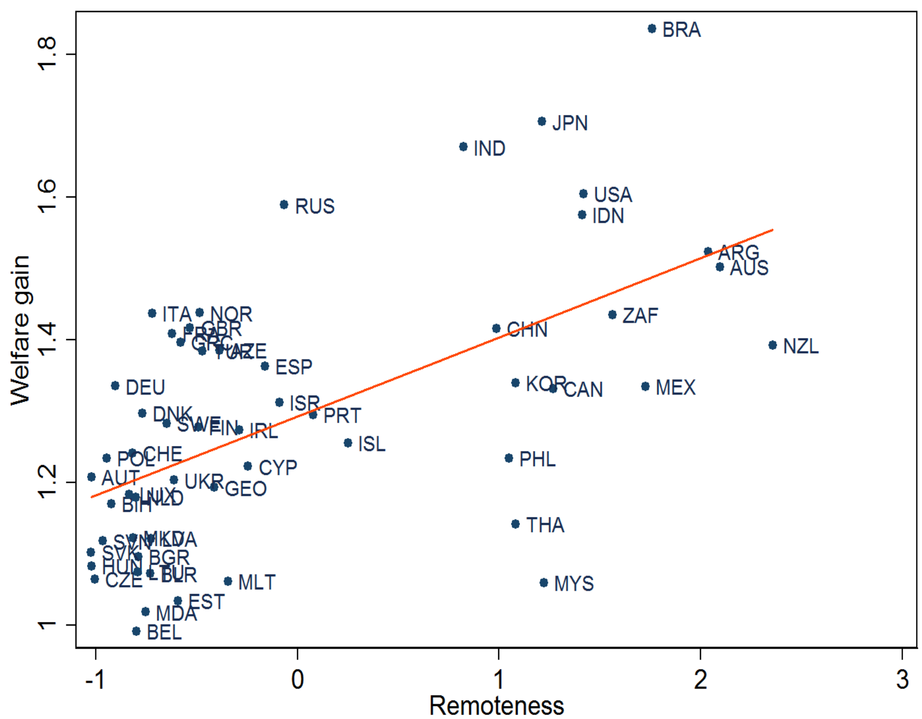
Note: The dotted lines give the kernel density estimate of the x axis variable. The dashed lines are the 95 percent confidence interval.

Figure 8
Self-selection: The role of internet penetration, importers' income inequality and exporters' GDP



Note: The dotted lines give the kernel density estimate of the x axis variable. The dashed lines are the 95 percent confidence interval.

Figure 9
Welfare gains from world flattening



Note: Remoteness is calculated as the GDP-weigthed average distance to all trading partners. The welfare gains are calculated using the Arkolakis et al. (2012) formula.

Table 1
Trade cost and gravity online and offline

	(1) eBay	(2) eBay	(3) eBay	(4) eBay	(5) offline	(6) offline	(7) offline	(8) offline
Distance	-0.549***	-0.383***	-0.382***	-0.299***	-1.393***	-1.107***	-1.092***	-0.663***
	(0.0323)	(0.0419)	(0.0435)	(0.0925)	(0.0353)	(0.0475)	(0.0483)	(0.0456)
No common legal sys.		-0.304***	-0.237***	-0.272***		-0.577***	-0.578***	-0.379***
		(0.0547)	(0.0536)	(0.102)		(0.0536)	(0.0537)	(0.0591)
No colony		0.146	0.0940	-0.287**		-0.418***	-0.422***	0.0300
		(0.135)	(0.133)	(0.125)		(0.158)	(0.157)	(0.109)
No common language		-0.475***	-0.486***	-0.933***		-0.195*	-0.200*	0.218**
		(0.0937)	(0.0938)	(0.139)		(0.106)	(0.105)	(0.0956)
No border		-0.153	-0.137	-0.762***		-0.366**	-0.333**	-0.285***
		(0.124)	(0.122)	(0.137)		(0.144)	(0.144)	(0.0895)
No FTA		-0.161**	-0.181**	-0.359**		-0.320***	-0.297***	-0.430***
		(0.0796)	(0.0795)	(0.151)		(0.0872)	(0.0876)	(0.0830)
Shipping costs			0.0527				-0.0835	
			(0.0708)				(0.0687)	
Observations	3,763	3,763	3,733	3,763	3,763	3,763	3,733	3,763
R-squared	0.874	0.877	0.882		0.851	0.859	0.859	

Note: All regressions are estimated using an importer and exporter fixed effect linear model, except for columns (4) and (8) which use a poisson pseudo maximum likelihood estimator. The figures in brackets are robust standard errors, and * stands for statistical significance at the 10 percent level, ** for statistical significance at the 5 percent level and *** for statistical significance at the 1 percent level.

Table 2

Testing differences in gravity coefficients

	Distance	No common legal system	No colony	No common language	No border	No FTA
Gravity coefficient	-1.119***	-0.584***	-0.408*	-0.210	-0.353*	-0.314***
	(0.100)	(0.0945)	(0.222)	(0.175)	(0.206)	(0.110)
Interaction with eBay dummy	0.711***	0.318*	0.596*	-0.239	0.231	0.107
	(0.136)	(0.167)	(0.318)	(0.240)	(0.273)	(0.204)

Note: The dependant variable is log imports. Regression estimated using importer-eBay and exporter-eBay fixed effect linear model. The figures in brackets are robust standard errors, and * stands for statistical significance at the 10 percent level, ** for statistical significance at the 5 percent level and *** for statistical significance at the 1 percent level.

Table 3

Robustness checks: Trade cost and gravity for different types of eBay flows

	(1) eBay total	(2) offline total	(3) New goods	(4) Used goods	(5) Auctions	(6) Non-auctions	(7) Consumer sellers	(8) PowerSellers	(9) Non-PowerSellers
Distance	-0.446***	-1.352***	-0.408***	-0.573***	-0.490***	-0.335***	-0.535***	-0.355***	-0.461***
	(0.0306)	(0.0495)	(0.0393)	(0.0470)	(0.0287)	(0.0327)	(0.0574)	(0.0362)	(0.0393)
No common legal sys.	-0.143***	-0.569***	0.0295	-0.165***	-0.114***	-0.0567	-0.460***	-0.251***	-0.324***
	(0.0372)	(0.0554)	(0.0475)	(0.0580)	(0.0343)	(0.0397)	(0.0703)	(0.0456)	(0.0481)
No colony	-0.341***	-0.325*	0.00399	-0.238*	-0.375***	-0.131	-0.180	-0.330***	-0.269**
	(0.0937)	(0.170)	(0.122)	(0.131)	(0.0851)	(0.102)	(0.175)	(0.123)	(0.113)
No common language	-0.366***	-0.340***	-0.432***	-0.245***	-0.339***	-0.379***	-0.498***	-0.268***	-0.297***
	(0.0656)	(0.113)	(0.0850)	(0.0936)	(0.0587)	(0.0728)	(0.128)	(0.0738)	(0.0868)
No border	-0.275***	-0.243*	-0.362***	-0.102	-0.265***	-0.345***	-0.133	-0.258**	-0.268***
	(0.0845)	(0.146)	(0.107)	(0.124)	(0.0752)	(0.0936)	(0.156)	(0.107)	(0.104)
No FTA	-0.122**	-0.191**	-0.0598	-0.228**	-0.0546	-0.126**	0.0337	-0.264***	-0.0681
	(0.0545)	(0.0932)	(0.0728)	(0.0895)	(0.0566)	(0.0588)	(0.101)	(0.0699)	(0.0716)
Observations	3,778	3,778	3,740	3,740	3,740	3,740	3,763	3,778	3,778
R-squared	0.913	0.799	0.881	0.818	0.920	0.910	0.791	0.893	0.871

Note: All regressions are estimated using an importer and exporter fixed effect linear model. The figures in brackets are importer- and exporter-clustered standard errors, and * stands for statistical significance at the 10 percent level, ** for statistical significance at the 5 percent level and *** for statistical significance at the 1 percent level.

Table 4

Testing differences in gravity coefficients for PowerSellers

	Distance	No common legal system	No colony	No common language	No border	No FTA
Gravity coefficient	-0.461***	-0.324***	-0.269**	-0.297***	-0.268***	-0.0681
	(0.0393)	(0.0481)	(0.113)	(0.0868)	(0.104)	(0.0716)
Interaction with PowerSeller dummy	0.106**	0.0731	-0.0611	0.0291	0.00982	-0.195*
	(0.0534)	(0.0663)	(0.167)	(0.114)	(0.149)	(0.100)

Note: The dependant variable is log of eBay imports. Regression estimated using importer-PS and exporter-PS fixed effect linear model. The figures in brackets are robust standard errors, and * stands for statistical significance at the 10 percent level, ** for statistical significance at the 5 percent level and *** for statistical significance at the 1 percent level.

Table 5

Product information and distance effects online and offline

	(1) ebay	(2) offline	(3) ebay	(4) offline	(5) ebay	(6) offline	(7) ebay	(8) offline
Distance	-0.299***	-1.552***	-0.380***	-2.045***	-0.240***	-0.123***	-0.356***	-0.999***
	(0.0105)	(0.0306)	(0.0118)	(0.0322)	(0.0117)	(0.0280)	(0.0126)	(0.0279)
No common legal sys.	-0.279***	-0.988***	-0.287***	-0.907***	-0.280***	-0.857***	-0.315***	-0.790***
	(0.0138)	(0.0409)	(0.0150)	(0.0412)	(0.0148)	(0.0351)	(0.0161)	(0.0361)
No colony	-0.0419	-0.758***	-0.0460	-0.814***	-0.0650*	-0.834***	-0.0297	-0.848***
	(0.0359)	(0.0885)	(0.0390)	(0.0901)	(0.0388)	(0.0804)	(0.0421)	(0.0830)
No common language	-0.638***	1.198***	-0.715***	0.710***	-0.729***	0.374***	-0.728***	-0.170***
	(0.0268)	(0.0725)	(0.0297)	(0.0745)	(0.0293)	(0.0657)	(0.0326)	(0.0656)
No border	-0.619***	-0.300***	-0.617***	-0.442***	-0.605***	-0.629***	-0.559***	-0.688***
	(0.0320)	(0.0746)	(0.0351)	(0.0764)	(0.0342)	(0.0676)	(0.0371)	(0.0699)
No FTA	0.0165	0.388***	0.0147	0.259***	0.00741	0.105**	0.000187	-0.211***
	(0.0176)	(0.0535)	(0.0191)	(0.0534)	(0.0188)	(0.0467)	(0.0200)	(0.0466)
Distance × TM-complaint			-0.0145***	-0.0711***				
			(0.000375)	(0.00104)				
Distance × TM-WIPO					-0.00604***	-0.143***		
					(0.000336)	(0.000740)		
Distance × sigma							0.0272***	-0.148***
							(0.00107)	(0.00200)
Constant	6.265***	20.81***	6.039***	20.66***	6.292***	20.07***	6.110***	19.16***
	(0.0795)	(0.223)	(0.0871)	(0.228)	(0.0861)	(0.198)	(0.0940)	(0.202)
Observations	107,302	107,302	88,744	88,744	90,977	90,977	76,410	76,410
R-squared	0.055	0.046	0.069	0.097	0.061	0.302	0.065	0.138

Note: All regressions are estimated using deviations from the importer-category and exporter-category means. The figures in brackets are robust standard errors, and * stands for statistical significance at the 10 percent level, ** for statistical significance at the 5 percent level and *** for statistical significance at the 1 percent level.

Table 6

Disentangling the mechanisms

	(1) ebay	(2) ebay	(3) ebay	(4) ebay	(5) offline	(6) offline	(7) offline	(8) offline
Distance	-0.353***	-0.353***	-0.225	0.246	-1.342***	-1.227***	-4.356***	-2.836***
	(0.0478)	(0.0482)	(0.471)	(0.523)	(0.0531)	(0.0493)	(0.572)	(0.572)
No common legal sys.	-0.320***	-0.320***	-0.306***	-0.311***	-0.456***	-0.514***	-0.541***	-0.558***
	(0.0555)	(0.0548)	(0.0555)	(0.0555)	(0.0545)	(0.0542)	(0.0543)	(0.0544)
No colony	0.138	0.138	0.142	0.130	-0.354**	-0.386**	-0.337**	-0.374**
	(0.135)	(0.136)	(0.136)	(0.136)	(0.155)	(0.157)	(0.158)	(0.159)
No common language	-0.460***	-0.460***	-0.474***	-0.472***	-0.315***	-0.256**	-0.214**	-0.204*
	(0.0938)	(0.0939)	(0.0945)	(0.0948)	(0.104)	(0.104)	(0.106)	(0.106)
No border	-0.162	-0.162	-0.152	-0.147	-0.297**	-0.331**	-0.391***	-0.382***
	(0.124)	(0.124)	(0.125)	(0.125)	(0.133)	(0.138)	(0.142)	(0.143)
No FTA	-0.156*	-0.156*	-0.160**	-0.158**	-0.362***	-0.342***	-0.339***	-0.330***
	(0.0807)	(0.0806)	(0.0805)	(0.0804)	(0.0860)	(0.0880)	(0.0876)	(0.0882)
Distance × exporter corruption	0.0399				-0.306***			
	(0.0275)				(0.0262)			
Distance × importer corruption		0.0403				-0.157***		
		(0.0260)				(0.0238)		
Distance × exporter Google popularity			-0.00787				0.161***	
			(0.0231)				(0.0280)	
Distance × importer Google popularity				-0.0312				0.0859***
				(0.0258)				(0.0282)
Constant	-1.178**	-1.185**	-0.757	-0.814*	13.69***	12.08***	10.70***	10.54***
	(0.596)	(0.597)	(0.489)	(0.488)	(0.551)	(0.517)	(0.452)	(0.449)
Observations	3,763	3,763	3,763	3,763	3,763	3,763	3,763	3,763
R-squared	0.910	0.910	0.910	0.910	0.905	0.902	0.902	0.901

Note: All regressions are estimated using an importer and exporter fixed effect linear model. The figures in brackets are robust standard errors, and * stands for statistical significance at the 10 percent level, ** for statistical significance at the 5 percent level and *** for statistical significance at the 1 percent level.

Table 7
Selection effects?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ebay	ebay	ebay	ebay	offline	offline	offline	offline
Distance	-0.383***	-0.485***	-0.354***	-0.262***	-1.107***	-0.674***	-1.418***	-1.687***
	(0.0423)	(0.0666)	(0.0690)	(0.0704)	(0.0479)	(0.0711)	(0.0672)	(0.0762)
No common legal sys.	-0.304***	-0.317***	-0.290***	-0.328***	-0.577***	-0.472***	-0.547***	-0.528***
	(0.0552)	(0.0576)	(0.0556)	(0.0558)	(0.0541)	(0.0568)	(0.0552)	(0.0555)
No colony	0.146	0.179	0.160	0.102	-0.418***	-0.343**	-0.375**	-0.380**
	(0.136)	(0.138)	(0.139)	(0.134)	(0.159)	(0.156)	(0.160)	(0.156)
No common language	-0.475***	-0.507***	-0.514***	-0.448***	-0.195*	-0.266**	-0.252**	-0.281***
	(0.0946)	(0.100)	(0.0955)	(0.0961)	(0.107)	(0.108)	(0.108)	(0.107)
No border	-0.153	-0.102	-0.175	-0.204	-0.366**	-0.254*	-0.326**	-0.285**
	(0.125)	(0.107)	(0.127)	(0.125)	(0.145)	(0.137)	(0.142)	(0.138)
no FTA	-0.161**	-0.107	-0.163**	-0.154*	-0.320***	-0.323***	-0.319***	-0.318***
	(0.0804)	(0.0837)	(0.0810)	(0.0816)	(0.0880)	(0.0876)	(0.0882)	(0.0873)
Distance × importer Gini	0.121***				0.167***			
	(0.00922)				(0.00697)			
Distance × exporter days to export		0.00291				-0.0321***		
		(0.00333)				(0.0036)		
Distance × importer internet penetration			-0.000892				0.00652***	
			(0.00110)				(0.00107)	
Distance × exporter internet penetration				-0.00274**				0.0121***
				(0.00119)				(0.00115)
Constant	-4.910***	-0.529	-0.886	-1.462**	4.565***	12.01***	12.22***	13.96***
	(0.670)	(0.526)	(0.618)	(0.618)	(0.551)	(0.482)	(0.561)	(0.587)
Observations	3,763	3,519	3,641	3,641	3,763	3,519	3,641	3,641
R-squared	0.910	0.908	0.911	0.910	0.901	0.906	0.902	0.904

Note: All regressions are estimated using an importer and exporter fixed effect linear model. The figures in brackets are robust standard errors, and * stands for statistical significance at the 10 percent level, ** for statistical significance at the 5 percent level and *** for statistical significance at the 1 percent level.

Table 8
The welfare gains from world flattening

country	welfare gain	country	welfare gain
BRA	83.6%	IRL	27.4%
JPN	70.5%	ISL	25.5%
IND	67.0%	CHE	24.1%
USA	60.4%	POL	23.4%
RUS	58.8%	PHL	23.4%
IDN	57.5%	CYP	22.2%
ARG	52.3%	AUT	20.7%
AUS	50.2%	UKR	20.3%
NOR	43.7%	ROM	19.4%
ITA	43.7%	GEO	19.3%
ZAF	43.5%	LUX	18.3%
GBR	41.6%	NLD	18.0%
CHN	41.5%	BIH	17.0%
FRA	40.8%	THA	14.2%
GRC	39.7%	MKD	12.3%
NZL	39.2%	LVA	12.1%
AZE	38.5%	SVN	11.8%
TUR	38.4%	SVK	10.2%
ESP	36.2%	BGR	9.6%
KOR	34.0%	HUN	8.3%
DEU	33.5%	LTU	7.5%
MEX	33.5%	BLR	7.2%
CAN	33.1%	CZE	6.4%
ISR	31.2%	MLT	6.2%
DNK	29.7%	MYS	6.0%
PRT	29.4%	EST	3.4%
SWE	28.3%	MDA	1.8%
FIN	27.8%	BEL	-0.9%

Note: Welfare gains estimated using formula in Arkolakis et al. (2012).

Table 9

Matching eBay categories and HS codes

eBay category	HS codes
Antiques	9701 9702 9703 9706
Baby	6111 6209 9501 9502 9503 490300 871500 940490
Books, Comics and Magazines	4901 4902 970200
Business, Office and Industrial	85 8201 8304 8459 8460 8461 8462 8463 8465 8517 9018 481960 852020 940600
Auto - Parts	8803 8714 8708
Clothes, Shoes and Accessories	61 62 64 65 420221 420222 420229 630900
Coins	490700 7118
Collectables	9705
Computing	8471
Consumer Electronics - Other	853110 8507 8506
Dolls, Doll Houses	9502
Hobbies and Crafts	4203 4414 4817 340600 701610 731910 960330 960340
Home and Garden	57 3922 6303 8450 9103 9105 9405 230910 392610 481960 830300 850910 851610 851660 940310 940330 940340
Jewellery and Watches	7101 7102 7103 7113 7114 7116 7117 9101 9102
DVDs, Film and TV	3706 852490
Music	8524
Photography	9006
Pottery and Glass	6911 7013
Sporting Goods	9506
Sports Memorabilia	9705
Stamps	490700 970400
Toys and Games	9501 9502 9503 9505 9506
Musical Instruments	92
Mobile and Home Phones	8517
PC and Video Gaming	950410 950430
Consumer Electronics - Audio	8518 8519 8521 8528 9007
Art	9701 9702 9703
Health and Beauty	3301 3303 3304 3305 3306 330730 330790

Note: When aggregated into a basket, HS categories that fit into many eBay categories are added only once.