Forthcoming in The World Economy.

Time, Uncertainty, and Trade Flows

José Ansón,[1] Jean-François Arvis,[2] Mauro Boffa,[3]
Matthias Helble,[4] and Ben Shepherd[5]

January 30th, 2020.

Abstract: This paper quantifies the impact of international transport time on bilateral trade flows in goods using previously unexploited information drawn from a large dataset on international parcel delivery times. In line with previous work, we find that an extra day spent in international transit reduces bilateral trade by just under one percent at the sample median. In addition, and for the first time in the literature, we examine the impact of time-related uncertainty, which requires traders to hold costly inventories or build costly redundancies into supply chains. We find that a one day increase in international transport time uncertainty reduces bilateral trade flows by just over one percent. Splitting the sample into developing and developed countries shows that international transit time matters primarily for South-South trade, whereas uncertainty is relatively more important for North-North trade. Using new data on trade in intermediate versus final goods, we also find some evidence that time and uncertainty both matter more for movements of intermediates of the type that takes place within global value chains.

JEL Codes: F13.

Keywords: Trade time; uncertainty; logistics; postal delivery; international trade.

---

[1] UPIDO AG, .
[2] World Bank.
[3] Universal Postal Union.
[4] Asian Development Bank.
[5] Developing Trade Consultants. Corresponding author: Ben@Developing-Trade.com.

1 INTRODUCTION

Trade costs are a major determinate of the observed pattern of trade and production across countries. They consist of many factors, and the best estimates available suggest that total trade costs remain high even though they have fallen substantially in recent years (Anderson and Van Wincoop, 2004; Arvis et al., Forthcoming). Applied international trade work based on the gravity model typically uses a set of proxies for bilateral trade costs, with geographical distance playing a central role as an indicator of transport costs. However, distance is a very rudimentary measure, as it neglects transshipments and geographical obstacles. One main element of trade costs that has already been identified in the literature is time (Hummels, 2001; Evans and Harrigan, 2005). For example, Djankov et al. (2010) use Doing Business data on the time taken to export—moving goods from the producer's factory to the dock—to show that an extra day's delay can decrease bilateral trade by around 1%.

Another salient feature of the current world economy is the extension of global value chains (GVCs) to sectors and countries that have not traditionally been included in them. GVCs are now apparent, at least in rudimentary form, in many parts of the world. Lead firms, often based on developed countries but sometimes also in major emerging markets, coordinate complex networks of suppliers that provide the goods and services needed to produce a final product that is then shipped to a destination market. The GVC business model relies on the swift movement of intermediate goods across borders, something that occurs numerous times during the production process. Even more important, however, is the way in which GVCs deal with risk. Clearly, delay is a major risk for the just-in-time production methods used by these business models. Basic intuition suggests that maintaining inventories would be a rational response. But doing so is costly, and the management techniques favored by GVCs try to keep inventory carrying costs to an absolute minimum. It is therefore vital that delivery of goods not only be speedy, but that the time required be certain. Indeed, businesses often report anecdotally that they can manage delay by building it into their production model, but uncertainty creates risk, which in turn increases costs and decreases their competitiveness. In the GVC context, lead firms will tend to source goods from markets that can provide a narrow window of delivery times. Countries where time delays are highly uncertain will have difficulty joining GVCs, and leveraging international trade for their development.

The importance of uncertainty as a source of costs for businesses involved in GVCs is reflected at a policy level. For example, the 21 member Asia Pacific Economic Cooperation (APEC) has adopted a Supply Chain Connectivity Framework Action Plan, in which economies committed to reduce the time, cost, and uncertainty associated with supply chain transactions by 10% by 2015. Given the prominence of the issue, it is notable that the applied international trade literature has not yet dealt with it. The key contributions on the role of time in determining bilateral trade flows—Djankov et al. (2010), and Hummels and Schaur (2013)—have focused on the central tendency of the time distribution, rather than its second moment, which would capture uncertainty.

Against this background, we build on and extend the previous literature in two main ways. First, we use a large UPU database of parcel deliveries to derive new data on bilateral international transport times for 161 exporting countries and 165 importing countries. Our data is based on individual transaction records tracked using parcel scans, and reported to the UPU by national postal authorities. As a result, our measures of time are richer than the consensus estimates from trade specialists used by Djankov et al. (2010), and the schedule data used by Hummels and Schaur (2013).

Second, we exploit the fact that the original database is recorded at the level of individual postal transactions to calculate bilateral measures of time uncertainty on all trade routes. As a proxy for uncertainty, we use the standard deviation of recorded international transit times at the transaction level. This indicator captures the dispersion of transport times around their central tendency, and can reasonably be said to be one, although not the only, proxy for the uncertainty facing firms when they make shipments. This is the first time that such a measure has been calculated and brought into contact with international trade data, and the core novelty of our paper lies in our ability to draw conclusions on the effect of time-based uncertainty on bilateral trade, in addition to average or median time.

To estimate the effects of international transit time and uncertainty on bilateral trade flows, we use a standard, theory-based gravity model. The variables of interest vary at the bilateral level, so we can control for multilateral resistance and economic size using fixed effects. We estimate by Poisson Pseudo-Maximum Likelihood to deal with heteroskedasticity and zero trade observations. The model fits the data well, and provides statistically significant results on the coefficients of interest, even with the inclusion of standard gravity model controls including distance, historical and geographical factors, and membership of a regional trade agreement.

The paper proceeds as follows. The next section discusses our dataset, focusing on the international transport time data. Section 3 presents our empirical model, implements it, and discusses results. The final section concludes and discusses possible policy implications of our findings.

2 Data and Preliminary Analysis

The dataset for this paper consists of standard bilateral trade data and gravity controls, along with exploitation of a new source on international transport times based on parcel delivery data from the Universal Postal Union (UPU). The most novel aspect of the dataset is the UPU data, so we discuss that first, in the next subsection, before presenting the more standard elements of our dataset.

2.1 International Transport Time Data

The Postal Technology Center (PTC) of the UPU collects detailed information on international postal flows. Based on scanning procedures, the PTC created the EMSEVT event messaging system. Originally, the system was developed to ensure the traceability of postal items around the world. Postal operators exchange messages containing information about every postal item that circulates in the international postal network. Based on a unique tracking number identifier, the dispatching and recipient countries communicate about events occurring to the item for three mail classes: parcels (up to 30 kg), express deliveries, and letters (up to 2 kg). Our analysis uses the data on parcel flows only, as it has the closest correspondence with trade transaction. For example, Anson et al. (2014) find a strong statistical correlation between parcel flows and international trade flows for the same commodity groups.

Every parcel that is sent internationally through the UPU system is scanned up to twelve times, from the posting of the parcel at the local post office to the final delivery. Each scan records the exact time of the event. The EMSEVT event takes the following form:

A. Posting/Collection (EMA)
B. Arrival at outward office of exchange (EMB)
C. Departure from outward office of exchange (EMC)
D. Arrival at inward office of exchange (EMD)
E. Handed over to Customs (EME)
F. Departure from inward office of exchange (EMF)
G. Arrival at delivery office (EMG)
H. Unsuccessful delivery (EMH)
I. Final delivery (EMI)
J. Arrival at transit office of exchange (EMJ)
K. Departure from transit office of exchange (EMK)

Conceptually, there are three broad categories of events. The first segment involves all the information about the exporting procedure, from posting (EMA) at the local post office to departure from the office of exchange (EMC). The second category refers to events concerning distribution in the destination country. From arrival to the office of exchange (EMD), passing through customs (EME, EMF), up to distribution and final delivery (EMG to EMH). The third category refers to items that need an intermediate operator to reach the final destination (EMJ, EMK).

In this paper, we are concerned with international shipping times, i.e. the difference between events EMC and EMD in the EMSEVT structure.[6] This definition captures international transit time, in the sense of the amount of time taken between departure from the sending country's postal system to arrival in the recipient country's postal system. Concretely, our measure includes the time taken to move parcels from one country to another by sea, air, or in some cases, land. This element of our measurement of time introduces an important novelty into the literature, while our shipment-level unit of analysis makes it possible to go further than other work in describing the full distribution of shipment times.

Our work differs from that of Djankov et al. (2006) in that they look at time to exports in the sense of the time taken to prepare documents, move goods to the border, and clear outward procedures. They do not consider international shipping times, which are the focus of this paper. Conceptually, our analysis is of the effect of time spent between the two national borders. It is therefore closer to

[6] In additional results, available upon requests, we show that bilateral parcel flows fit well with a standard gravity model from the trade literature (R2 = 0.930; distance coefficient = -0.432, statistically significant at the 1% level).

Hummels and Schaur (2013), who use ocean shipping schedules to calculate similar measures. An important difference with that work is that our times are based on actual recorded scan data from large numbers of individual shipments, not scheduled services. As discussed below, we are therefore able to more completely characterize the sample moments of international shipping time, something that is not possible when using schedule data. Furthermore, Hummels and Schaur (2013) only study the flows that arrive in the US (by air or ocean), whereas our dataset holds transportation time for trade flows between many country pairs.

The UPU shipments dataset is very large. We start with 260 million observations, as our unit of analysis is the individual shipment. Indeed, that initial figure is already based on a restriction: we consider only observations delivered between May 2013 and April 2014. There is a considerable amount of noise in the raw data, so we adopt a number of cleaning procedures. First we selected only the tracking numbers that belong to international parcels.[7] Second, we only kept observations for which the recorded EMSEVT are chronological in the order set out above. We kept observations with some missing events but with the remainder of the message chain in chronological order. Third, we checked for the uniqueness of tracking numbers as postal operators reuse old tracking numbers after a few years. Whenever a duplicate tracking number was found, only the one with an EMD event recorded between 2013 and 2014 was kept. Our cleaning procedures do have a significant impact on data availability, reducing the effective sample from essentially all countries in the world, to 160 exporters and 119 importers.

[7]We have three mail classes in the raw data (international letters, international express mail and international parcels.)

To be able to relate the postal shipments data to trade flows, we need to work at the aggregate level. We therefore compute two time-relevant measures. The first, the sample median of the time between events EMC and EMD by (directional) country pair, is designed to capture the central tendency in the data. It is analogous to time variables used in previous research, which use one number—typically a schedule or consensus estimate—to summarize trading times. The main innovation of this paper on the data side is to supplement the median with the standard deviation of international shipments times by (directional) country pair. The standard deviation provides an indication of the uncertainty affecting shipments from one country to another.

Figure 1 presents a basic overview of the shipment time data. It identifies country group pairs, and provides the median and standard deviation of recorded international shipment times between them. Time and uncertainty are both generally decreasing in country income level, as would be expected. Perhaps the most salient feature, though, is that even in high income countries, uncertainty is substantial relative to the mean. For example, for shipments from OECD countries to other OECD countries, the mean transit time is 10.6 days, but the standard deviation is 8.2. The quantitative importance of shipment time uncertainty suggests that it may well be a neglected factor in the previous international trade literature.

Another important feature of the data is that the median and standard deviation of shipment time are correlated at the country pair level. In fact, Figure 3 shows that the relationship between the two is quite strong (rho=0.806). This result is in line with our priors: it stands to reason that longer shipping times are associated with greater absolute levels of variation. Nonetheless, it poses a potential econometric challenge as including both variables in the same regression is likely to result in inflated standard errors that bias the model against finding a statistically significant effect of time on trade. We note in passing that the Figure also suggests that the data are heteroskedastic, but little turns on this characterization, as we have used robust and cluster-adjusted estimators throughout.

In terms of the distribution of international transport times, we find that a log-normal distribution approximates the data well (Figure 4). The issue of the distribution of shipping times is an important one in terms of planning logistics activities, but it has received little attention in the international trade literature. Data like the ones we are using have real potential to open up new lines of inquiry, such as modeling the impact of transport delays on inventory holdings, and specifically introducing these processes into trade.

However, the data are somewhat skewed, which is unsurprising since they are bounded below but not above. Figure 5 shows that the distribution of average times is shifted right relative to the distribution of median times.

We emphasized above that the data have a directional quality, in the sense that export time from country i to country j is allowed to be different from export time from country j to country i. This flexibility reflects the way the data are collected, as well as the structure of our model, in which trade costs are not required to be symmetric. There are important cases in the data where this asymmetry is important. For instance, the median international transit time for exports from China to the USA is around four days, but exports going in the other direction take about 10% longer. Differences for other country pairs can be substantially larger. One potential reason is differences in connection or transit times based on different schedules for air and maritime services in the two directions. An additional factor is the product composition of trade, which differs by direction, affects modal choice, and which in turn affects speed of delivery. Indeed, the issue of product composition by country suggests that caution be exercised in interpreting our results, as some part of the observed differences in transport times is due to differences in modal choice related to product specialization in trade. This problem has previously come up in the trade and time literature: Djankov et al. (2010) similarly use data on time that are not product-specific. Although this factor suggests caution in interpreting results, we nonetheless believe that it is possible to extract some useful information from observed variations. Data on the distribution of parcel masses support that view, with an average of 6.37kg, a median of 2.72kg, and 95% weighing less than 15kg. Compared with the distribution of all internationally traded goods, this in fact suggests a relatively consistent sub-group being sent through the postal service.

When we investigate the issue of asymmetry systematically, we find that the dominant feature of international transport times is in fact their dispersion (Figure 6). When we run a non-parametric test of the null hypothesis that international transport times are asymmetric based on a comparison of medians, we cannot reject it at the 10% level. Nonetheless, we do not impose symmetry on the model, but instead let the data determine the issue through a specification that leaves asymmetry open as an option.

2.2 Other Data

Table 1 sets out the other data sources for the paper, and Table 2 presents basic summary statistics. They are standard in the gravity model literature. Trade data in value terms come from CEPII's BACI, for the year 2013. A key piece of value added of BACI relative to the raw Comtrade data is that different reports of the same flow, based on import and export data, have been reconciled. We can therefore use export data rather than mirror data, which is often necessary to deal with well-known deficiencies in reported exports. To provide a first indication of the links between time uncertainty and trade, we use aggregate data. Other data for the gravity model come from the CEPII distance dataset (historical and geographical variables), and De Sousa (2014) (the RTA dummy). We primarily work with aggregate, rather than sectoral, trade data because the UPU data do not identify the contents of shipments, although this is an area where data collection is expected to improve in the future. At the present time, it is not possible to identify shipment times for individual products.

3 Empirical Model and Results

The baseline for applied gravity modeling is Anderson and Van Wincoop (2003, 2004). Their model takes the following form:

$$X_{ij} = \frac{Y_i Y_j}{Y^w} \left(\frac{t_{ij}}{\Pi_i P_j} \right)^{1-s} e_{ij}$$

$$\Pi_i^{1-s} = \sum_j \left(\frac{t_{ij}}{P_j} \right)^{1-s} \frac{Y_j}{Y^w}$$

$$P_j^{1-s} = \sum_j \left(\frac{t_{ij}}{\Pi_i} \right)^{1-s} \frac{Y_i}{Y^w}$$

Where: Xij indicates exports from country i to country j; the Y terms are GDP in (respectively) country i, country j, and the world; tij is the trade costs function for exports from country i to country j; s is the intra-sectoral elasticity of substitution among product varieties; and e is an error term satisfying standard assumptions. Outward multilateral resistance Π_i captures the fact that i's exports to j depend on trade costs across all possible export markets. Inward multilateral resistance P_j similarly captures the dependence of j's imports on trade costs across all possible suppliers.

Before bringing the model to the data, we need to specify a form for the trade costs function in terms of observables. We follow the literature in terms of including standard trade cost determinants. We then add variables to capture the dependence of trade flows on international shipping times and their uncertainty. The function is:

$$
\begin{aligned}
t_{ij} = b_1 \log(distance_{ij}) + b_2 RTA_{ij} + b_3 CommonBorder_{ij} + b_4 CommonLanguage_{ij} \\
+ b_5 Colony_{ij} + b_6 CommonColonizer_{ij} + b_7 SameCountry_{ij} \\
+ b_8 \log(Med.Time_{ij}) + b_9 \log(SDTime_{ij}) \\
+ b_{10} \log(Med.Time_{ij}) * \log(SDTime_{ij})
\end{aligned}
$$

A gravity model in this form can be consistently estimated using fixed effects by exporter and by importer, which obviates the need to include the GDP terms and solve for the nonlinear multilateral resistance terms. By transforming the model in this way, we note that the resulting fixed effects gravity model is in fact consistent with a range of theoretical derivations (e.g., Eaton and Kortum, 2002; and Chaney, 2008); of course, interpretation of the fixed effects, as well as the trade costs coefficients, differs from one model to another. We simply emphasize the fact that ours is a very general estimating framework that does not depend on rigid adherence to a single theoretical model.

Traditionally, gravity models like ours were log linearized to facilitate estimation by ordinary least squares. Santos Silva and Tenreyro (2006) point out two major difficulties with such an approach. First, if the error term e is heterskedastic, the nonlinearity of the original model means that estimation following log linearization can lead to biased coefficient estimates, in addition to the usual problem of biased standard error estimates that is associated with heteroscedasticity. In addition, the procedure drops observations for which exports are equal to zero. Using aggregate trade data, as we do here, typically makes the problem more manageable. Indeed, only 34 zeros are observed out of a total of 23,423 observations. However, this issue combined with likely heteroskedasticity makes it important to adopt a robust estimation methodology.

The solution proposed by Santos Silva and Tenreyro (2006) is the Poisson Pseudo-Maximum Likelihood (PPML) estimator. It is equivalent to performing weighted nonlinear least squares on the nonlinear gravity model, with zeros included naturally in the estimation sample. In addition, heteroskedasticity can be dealt with easily, by using robust standard errors. By pseudo-maximum likelihood reasoning, estimates of the gravity model obtained using PPML are consistent under weak assumptions: it is enough that the conditional mean is correctly specified, and there is no requirement that the data be distributed according to a particular law. Making additional assumptions regarding the sample variance can in principle produce estimates that are more efficient than PPML, but most alternative estimators are not consistent in a similarly broad range of circumstances. We therefore use PPML as our workhorse estimator.

Table 3 presents regression results using the full country sample. Column 1 is a basic gravity model without time variables, presented to show that our results conform well with the previous literature in terms of the standard trade costs variables; to ensure comparability with other results in the Table, we limit the sample to country pairs for which we have time data. We find that most trade costs variables have coefficients with the expected signs, and which are statistically significant at the 1% level. The crucial distance coefficient is on the low side, but that is to be expected when estimating with Poisson (Santos Silva and Tenreyro, 2006).

The following columns of Table 3 progressively introduce our time variables. Column 2 includes median time only, column 3 has the standard deviation of time only, column 4 has the two preceding variables together, and column 5 includes those two variables along with their interaction. The net result that flows from Table 1 is that time is clearly important for trade, corroborating previous work like Djankov et al. (2006). The coefficient on median international shipping time is negative and statistically significant at the 5% level in column 2. A 10% increase in time is associated with a nearly 0.7% decrease in trade, which is small but nonetheless significant. Most importantly, and in an extension of existing work, we find that uncertainty over international shipping time also has the potential to hold back bilateral trade: in column 3, the coefficient on the standard deviation of shipping time is negative and also statistically significant at the 5% level. A 10% increase in uncertainty is associated with a nearly 0.8% decrease in bilateral trade, an effect that is slightly stronger than the one observed for median time. As discussed in the data section, the median and the standard deviation of time are strongly correlated, which makes identification of separate effects challenging due to inflated standard errors. Notwithstanding this difficulty, when we include both variables simultaneously in column 4, we find that both have coefficients with similar magnitudes to those observed in the stepwise regressions, and which are statistically significant at the 10% level. The evidence that shipping time uncertainty matters for trade in addition to the now well-known effect of the central tendency of time is strong. Column 5 pushes the data one step further by including an interaction term between the median and the standard deviation; however, results are not statistically significant.

We can use the joint estimates of the effects of median time and uncertainty on trade from Column 4 to provide an indication of the quantitative significance of our results. To do so, we evaluate the estimated effects at the sample median values. For international transit time, the sample median is 6.898 days, so an increase of one day would be associated with a decrease in bilateral trade of just under one percent which is very close to the result reported by Djankov et al. (2010). The sample median for uncertainty is 5.437 days, so an additional day in the standard deviation of international transit time is associated with a decrease in bilateral trade of just over one percent. The two effects are very close in magnitude, and are clearly of major economic significance. Indeed, there is some evidence that the trade depressing effect of uncertainty may be even stronger than the effect of median international transit time itself—a novel finding in the literature. We do not put undue stress on the difference in estimated effects, however, as the figures are in reality both very close to one percent.

The data section of this paper has shown that trade times are very different for developing and developed countries. It is therefore of interest to split the sample into two groups of countries following the World Bank classification of countries by income group: North (high income), and South (low and middle income). We can then analyze three types of trade relations: North-North, North-South, and South-South. It is plausible that time has different effects on trade according to the type of countries involved.

Estimation results for the sample limited to North-North country combinations are in Table 4, which follows the same model as the previous table in terms of the individual regressions in each column. The most important finding flowing from Table 4 is that uncertainty may play a larger role in North-North trade than in the full sample, although caution is required because of the relatively large standard errors associated with the coefficient estimates. Of the time variables in columns 2 through 4, only the standard deviation has a statistically significant coefficient (5% in column 3, and 10% in column 4). Whereas previous work has focused on the central tendency of trading times, our results suggest that for North-North trade, it is in fact uncertainty that has the main impact. The coefficient on median shipping time is not statistically significant, but the coefficient on the standard deviation indicates that a 10% increase in uncertainty is associated with a nearly 0.8% decrease in bilateral trade.

A further point of distinction with the full sample regressions is column 5. In the case of North-North trade, the interaction term has a negative and statistically significant coefficient. This result indicates that uncertainty has a particularly strong negative impact on trade for bilateral pairs that also have relatively high median shipping times.

Table 5 moves to consider North-South trade, i.e. exports from the North to the South, and from the South to the North. In this case, none of the time variables have statistically significant coefficients.

This result is surprising in light of the other results reported in this paper. A possible reason is the heterogeneity of trade flows within this sub-sample. An additional relevant factor is that the distance coefficients in the Table 5 regressions are noticeably larger in absolute value than those reported in the other regression tables. It could be that distance is capturing part of the time effect.

Results are stronger for South-South trade in Table 6. By contrast with North-North trade, where uncertainty is the main driving factor, it is median time that is most important for South-South trade. It is the only time variable that has a statistically significant coefficient (5% in columns 2 and 4, and 1% in column 5). Moreover, the quantitative significance of the effect is noticeably greater than in the other regression tables. Concretely, based on the column 5 estimates a 10% increase in median international shipping time is associated with a more than 4% decrease in bilateral trade. This effect is much larger than the one reported for the full sample, and indicates that international shipping time is a crucial determinant of bilateral trade patterns among developing countries. This is a novel finding, given that previous work has focused on transit time into US ports.

Tables 4 and 6 provide an interesting contrast in terms of the time-related factors that are significant for developed and developing country trade. In the former case, it is primarily uncertainty that matters. In the latter, it is primarily the central tendency. Aggregate regressions like the ones presented here do not allow us to draw any firm conclusions about mechanisms. However, it is plausible that North-North trade relies to a much greater degree than South-South trade on sophisticated management methods that emphasize just in time delivery and low inventories. As a result, uncertainty—which drives inventories—is the crucial factor. By contrast, South-South trade may rely on more traditional management methods, with businesses accepting some level of inventory carrying costs. Combined with longer international shipping times, this means that it is primarily the median time that matters.

Following on from this point relating to the way in which trade is organized in different country contexts, we analyze the data for possible differences in the implications of time and uncertainty for trade in global value chains (GVCs). GVCs are now active in numerous sectors, and are characterized by splitting up the production process across multiple countries. Cross-border movements of intermediate goods are particularly intense, and speed and reliability are often of the essence of these transactions because final producers use just-in-time methods and maintain low inventories to keep costs down. The OECD-WTO Trade in Value Added (TiVA) Database identifies exports of final and intermediate goods by sector, based on observed input-output relationships. We focus in on just one sector where GVC trade is particularly important: electronical goods. This sector covers consumer electronics like computers and cellular phones. We hypothesize that exports of intermediate goods in this sector are more sensitive to time and uncertainty, as measured with the parcel data, than are exports of final products in the same sector. To be clear, we are interested in comparing time coefficients across specifications for intermediate and final goods, in line with that hypothesis, and not in comparing sectoral results against the aggregate ones discussed above.

Tables 7 and 8 results for final and intermediate products respectively, using the same models as throughout the paper. The effective sample decreases due to the fact that the TiVA Database only covers 59 countries, focusing on the OECD, but also including some developing countries. Taking Table 7 first, it is clear that time and uncertainty both matter for trade in these final GVC products: the coefficients are negative and statistically significant at the 10% level in the most complete model (column 5), although the interaction is not statistically significant. In support of our hypotheses, the coefficients for intermediate goods (Table 8, column 5) are noticeably larger in absolute value than is the case for final goods. Concretely, 10% increases in time or uncertainty are associated with 1.8% increases in trade in both cases. Although the interaction term has a statistically significant coefficient, its sign is positive, which is not in line with other results in the paper. This finding suggests that uncertainty matters relatively more for connections with a short median time: a result that is plausible in the GVC context, where activity often has a strongly regional dimension, and intermediate goods are typically shipped over relatively short distances. Taking all the results together suggests that there is some evidence that time and uncertainty matter more for trade in intermediate goods, of the type frequently seen within GVCs, although the imprecision of the estimates for final goods means that the difference is not statistically significant.

4 Conclusion and Policy Implications

This paper has extended the literature on trade and time by leveraging a novel transaction level dataset of international parcel flows. The data allow us to identify bilateral international transit times based on actually recorded scans, as opposed to schedules, and moreover make it possible to characterize the second moment of the transit time distribution. As a result, we are able to analyze the effect of shipment times on trade, as well as, for the the first time, the effect of shipment time uncertainty on trade. We find that both factors are statistically and economically significant determinants of bilateral trade, in line with anecdotal evidence from international businesses, particularly those involved in GVCs. Our results are in line with an emerging policy emphasis on addressing the overall costs faced by supply chain operators, including costs linked to uncertainty.

Interestingly, we have found that the relationship between time and trade differs according to country development levels. For trade between Northern countries, it is primarily uncertainty that is a determinant of bilateral trade flows, whereas for the Southern countries, it is primarily median time. This contrast is perhaps indicative of different business models being used in the two areas, although some degree of convergence would be expected over time.

Our findings have important policy implications, particularly in the area of trade facilitation. Driven in part by data collection efforts like the Doing Business "Trading Across Borders" dataset, the emphasis in much trade facilitation work has been on reducing average border clearance times. Our results suggest two ways in which that emphasis could perhaps be retooled to reap additional advantages. First, it is not just border crossing times that matter, but also international transit times—which are a function of country-level connectivity in terms of international transport networks (e.g., Arvis and Shepherd, 2016). Second, it is important to look at the full distribution of trade-related times in order to reduce uncertainty as well as average time. Working on both factors at once will have maximum cost impact for producers, and could potentially provide a significant boost to trade, in particular in sectors where GVCs are prevalent.

REFERENCES

Anson, J., Boffa, M. and M. Helble (2014) A Short-Run Analysis of Exchange Rates and International Trade with an Application to Australia, New Zealand, and Japan. *ADBI Working Paper* , 471. Tokyo: Asian Development Bank Institute.

Arvis, J.F., Duval, Y., Shepherd, B., Utoktham, C., and Raj, A. (Forthcoming) "Trade Costs in the Developing World: 1996-2010," *World Trade Review*.

Arvis, J.F. and B. Shepherd (2016) "Measuring Connectivity in a Globally Networked Industry: The Case of Air Transport," *The World Economy* 39(3), pp. 369-385.

Chaney, T. (2008) "Distorted Gravity: the Intensive and Extensive Margins of International Trade," *American Economic Review* 98(4), pp. 1707–1721.

Djankov, S., Freund, C., and Pham, C. (2010) "Trading on Time," *The Review of Economics and Statistics*, 92(1), pp. 166-173.

Eaton, J. and S. Kortum (2002) "Technology, Geography, and Trade," *Econometrica*, 70(5), 1741-1779.

Evans, C. L. and J. Harrigan. (2005) "Distance, Time, and Specialization: Lean Retailing in General Equilibrium," American Economic Review, 95(1), pp. 292-313.

Hummels, D. (2001). "Time as a trade barrier", Purdue University, July 2001.

Hummels, D. and G. Schaur (2013) "Time as a Trade Barrier," *American Economic Review,* 103(7), pp. 2935-59.

Santos Silva, J. M. C. and S. Tenreyro (2006) "The Log of Gravity," *The Review of Economics and Statistics*, 88(4), pp. 641-658.

TABLES

Table 1: Variables and sources.

Variable	Definition	Source
Colony	Dummy variable equal to unity if one country in a pair was once a colony of the other.	CEPII.
Common Border	Dummy variable equal to unity for country pairs that share a common land border.	CEPII.
Common Colonizer	Dummy variable equal to unity for country pairs that were colonized by the same power.	
Common Language	Dummy variable for country pairs that share a common language (ethnographic basis).	CEPII.
Exports	Value of exports from the exporting country to the importing country.	BACI (CEPII).
Log(Distance)	Logarithm of the great circle distance between the main cities in the exporting and importing countries.	CEPII.
Log(Med. Time)	Logarithm of the median international transport time reported for parcel shipments from the exporting country to the importing country.	UPU.
Log(SD Time)	Logarithm of the standard deviation of international transport times reported for parcel shipments from the exporting country to the importing country.	UPU.
RTA	Dummy variable equal to unity for country pairs that are members of the same regional trade agreement.	De Sousa (2014).

Table 2: Summary statistics.

Variable	Observations	Mean	Std. Dev.	Min.	Max.
Colony	21,389	0.016	0.126	0	1
Common Border	21,389	0.020	0.139	0	1
Common Colonizer	21,389	0.088	0.283	0	1
Common Language	21,389	0.151	0.358	0	1
Exports	23,423	846.846	7866.172	0	460007.7
Log(Distance)	21,389	8.683	0.828	3.190	9.894
Log(Med. Time)	8,743	2.031	0.893	-1.482	5.673
Log(SD Time)	7,727	1.679	1.282	-8.077	7.301
RTA	19,201	0.203	0.402	0	1

Table 3: PPML regression results using the full sample.

	(1)	(2)	(3)	(4)	(5)
Log(Distance)	-0.597 ***	-0.598 ***	-0.601 ***	-0.600 ***	-0.605 ***
	(0.032)	(0.032)	(0.034)	(0.034)	(0.034)
RTA	0.450 ***	0.422 ***	0.412 ***	0.389 ***	0.392 ***
	(0.071)	(0.071)	(0.073)	(0.073)	(0.073)
Common Border	0.375 ***	0.369 ***	0.383 ***	0.375 ***	0.379 ***
	(0.111)	(0.110)	(0.116)	(0.116)	(0.115)
Common Language	0.060	0.053	0.082	0.078	0.082
	(0.103)	(0.103)	(0.100)	(0.101)	(0.100)
Colony	0.348 ***	0.340 ***	0.325 ***	0.315 ***	0.315 ***
	(0.110)	(0.107)	(0.112)	(0.108)	(0.109)
Common Colonizer	0.652 ***	0.646 ***	0.619 ***	0.622 ***	0.624 ***
	(0.178)	(0.172)	(0.185)	(0.178)	(0.177)
Same Country	-0.212	-0.247	-0.293 *	-0.312 *	-0.321 **
	(0.170)	(0.170)	(0.157)	(0.159)	(0.159)
Log(Med. Time)		-0.068 **		-0.064 *	-0.002
		(0.029)		(0.034)	(0.056)
Log(SD Time)			-0.076 **	-0.058 *	-0.011
			(0.031)	(0.033)	(0.044)
Log(Med. Time)*Log(SD Time)					-0.028
					(0.022)
Constant	-4.000 ***	8.992 ***	5.080 ***	5.290 ***	5.203 ***
	(1.213)	(0.479)	(0.619)	(0.631)	(0.627)
Observations	8743	8743	7727	7727	7727
R2	0.882	0.883	0.890	0.889	0.890

Note: The dependent variable is Exports in all cases. Estimation is by PPML with fixed effects by exporter and importer, and robust standard errors clustered by country pair. Standard errors appear below coefficient estimates. Statistical significance is indicated as follows: * (10%), ** (5%), and *** (1%).

Table 4: PPML regression results using the North-North sample.

	(1)	(2)	(3)	(4)	(5)
Log(Distance)	-0.543 ***	-0.547 ***	-0.544 ***	-0.547 ***	-0.559 ***
	(0.060)	(0.061)	(0.064)	(0.066)	(0.068)
RTA	0.464 ***	0.430 **	0.398 **	0.381 **	0.388 **
	(0.168)	(0.177)	(0.172)	(0.184)	(0.186)
Common Border	0.534 ***	0.516 ***	0.608 ***	0.590 ***	0.579 ***
	(0.122)	(0.123)	(0.128)	(0.136)	(0.138)
Common Language	0.072	0.069	0.063	0.066	0.086
	(0.162)	(0.164)	(0.159)	(0.161)	(0.162)
Colony	0.184	0.175	0.147	0.140	0.137
	(0.140)	(0.141)	(0.151)	(0.155)	(0.154)
Common Colonizer	1.097 ***	1.080 ***	1.139 ***	1.124 ***	1.142 ***
	(0.295)	(0.288)	(0.285)	(0.285)	(0.283)
Same Country	0.433	0.413	0.234	0.236	0.205
	(0.273)	(0.270)	(0.252)	(0.253)	(0.251)
Log(Med. Time)		-0.049		-0.025	0.080
		(0.042)		(0.053)	(0.080)
Log(SD Time)			-0.085 **	-0.078 *	0.008
			(0.035)	(0.041)	(0.060)
Log(Med. Time)*Log(SD Time)					-0.053 *
					(0.030)
Constant	12.433 ***	12.574 ***	2.011 ***	2.105 ***	2.084 ***
	(0.661)	(0.705)	(0.691)	(0.750)	(0.756)
Observations	1700	1700	1588	1588	1588
R2	0.913	0.913	0.917	0.916	0.917

Note: The dependent variable is Exports in all cases. Estimation is by PPML with fixed effects by exporter and importer, and robust standard errors clustered by country pair. Standard errors appear below coefficient estimates. Statistical significance is indicated as follows: * (10%), ** (5%), and *** (1%).

Table 5: PPML regression results using the North-South sample.

	(1)	(2)	(3)	(4)	(5)
Log(Distance)	-0.761 ***	-0.755 ***	-0.758 ***	-0.747 ***	-0.748 ***
	(0.053)	(0.052)	(0.053)	(0.052)	(0.052)
RTA	0.595 ***	0.583 ***	0.598 ***	0.580 ***	0.584 ***
	(0.090)	(0.090)	(0.091)	(0.090)	(0.090)
Common Border	0.563 ***	0.562 ***	0.547 ***	0.552 ***	0.561 ***
	(0.156)	(0.156)	(0.157)	(0.156)	(0.156)
Common Language	0.102	0.111	0.113	0.124	0.129
	(0.101)	(0.099)	(0.103)	(0.101)	(0.101)
Colony	0.702 ***	0.691 ***	0.697 ***	0.677 ***	0.686 ***
	(0.117)	(0.116)	(0.117)	(0.116)	(0.116)
Common Colonizer	0.405 **	0.409 **	0.427 **	0.443 **	0.445 **
	(0.194)	(0.192)	(0.191)	(0.184)	(0.184)
Same Country	-0.615 ***	-0.628 ***	-0.591 ***	-0.607 ***	-0.601 ***
	(0.148)	(0.149)	(0.152)	(0.152)	(0.152)
Log(Med. Time)		-0.041		-0.077	0.017
		(0.042)		(0.047)	(0.092)
Log(SD Time)			0.010	0.027	0.085
			(0.037)	(0.038)	(0.069)
Log(Med. Time)*Log(SD Time)					-0.037
					(0.035)
Constant	3.891 ***	3.935 ***	0.385	0.468	0.289
	(0.566)	(0.567)	(0.537)	(0.533)	(0.535)
Observations	4918	4918	4443	4443	4443
R2	0.969	0.969	0.969	0.969	0.969

Note: The dependent variable is Exports in all cases. Estimation is by PPML with fixed effects by exporter and importer, and robust standard errors clustered by country pair. Standard errors appear below coefficient estimates. Statistical significance is indicated as follows: * (10%), ** (5%), and *** (1%).

Table 6: PPML regression results using the South-South sample.

	(1)	(2)	(3)	(4)	(5)
Log(Distance)	-0.622 ***	-0.578 ***	-0.635 ***	-0.585 ***	-0.560 ***
	(0.107)	(0.107)	(0.116)	(0.115)	(0.114)
RTA	0.491 ***	0.445 ***	0.457 ***	0.414 ***	0.414 ***
	(0.143)	(0.146)	(0.149)	(0.151)	(0.147)
Common Border	0.088	0.131	0.055	0.111	0.105
	(0.180)	(0.170)	(0.185)	(0.176)	(0.173)
Common Language	0.318 **	0.252 *	0.306 **	0.224	0.260
	(0.152)	(0.151)	(0.156)	(0.155)	(0.160)
Colony	0.646 ***	0.612 ***	0.612 **	0.590 ***	0.581 ***
	(0.237)	(0.220)	(0.239)	(0.222)	(0.223)
Common Colonizer	0.593 **	0.603 **	0.555 **	0.590 **	0.573 **
	(0.244)	(0.235)	(0.259)	(0.246)	(0.237)
Same Country	-0.068	-0.092	-0.071	-0.109	-0.069
	(0.296)	(0.303)	(0.295)	(0.297)	(0.290)
Log(Med. Time)		-0.198 **		-0.213 **	-0.437 ***
		(0.085)		(0.088)	(0.134)
Log(SD Time)			-0.027	0.024	-0.145
			(0.063)	(0.060)	(0.101)
Log(Med. Time)*Log(SD Time)					0.087
					(0.061)
Constant	-3.191 ***	-3.434 ***	6.784 ***	7.088 ***	7.468 ***
	(1.230)	(1.221)	(1.376)	(1.363)	(1.330)
Observations	2125	2125	1696	1696	1696
R2	0.850	0.852	0.851	0.854	0.857

Note: The dependent variable is Exports in all cases. Estimation is by PPML with fixed effects by exporter and importer, and robust standard errors clustered by country pair. Standard errors appear below coefficient estimates. Statistical significance is indicated as follows: * (10%), ** (5%), and *** (1%).

Table 7: PPML regression results using exports of final electrical goods.

	(1)	(2)	(3)	(4)	(5)
Log(Distance)	-0.359 ***	-0.632 ***	-0.633 ***	-0.636 ***	-0.632 ***
	(0.112)	(0.045)	(0.046)	(0.047)	(0.046)
RTA	0.470 ***	0.342 ***	0.353 ***	0.335 ***	0.330 ***
	(0.156)	(0.069)	(0.071)	(0.070)	(0.069)
Common Border	0.529 ***	0.141	0.106	0.105	0.093
	(0.168)	(0.114)	(0.112)	(0.112)	(0.110)
Common Language	0.011	0.017	0.028	0.022	0.010
	(0.171)	(0.098)	(0.097)	(0.098)	(0.099)
Colony	0.009	0.072	0.051	0.048	0.041
	(0.145)	(0.117)	(0.118)	(0.114)	(0.111)
Common Colonizer	0.699 **	0.486 *	0.448 *	0.444 *	0.441 *
	(0.297)	(0.251)	(0.268)	(0.259)	(0.258)
Same Country	-0.113	-0.514 ***	-0.499 ***	-0.513 ***	-0.514 ***
	(0.205)	(0.167)	(0.165)	(0.166)	(0.166)
Log(Med. Time)		-0.064 *		-0.044	-0.151 *
		(0.038)		(0.042)	(0.087)
Log(SD Time)			-0.076 **	-0.061	-0.126 *
			(0.038)	(0.042)	(0.069)
Log(Med. Time)*Log(SD Time)					0.043
					(0.034)
Constant	4.795 ***	9.502 ***	9.441 ***	9.536 ***	9.637 ***
	(1.159)	(0.462)	(0.468)	(0.477)	(0.467)
Observations	3361	2836	2703	2703	2703
R2	0.779	0.968	0.971	0.970	0.971

Note: The dependent variable is Exports in all cases. Estimation is by PPML with fixed effects by exporter and importer, and robust standard errors clustered by country pair. Standard errors appear below coefficient estimates. Statistical significance is indicated as follows: * (10%), ** (5%), and *** (1%).

Table 8: PPML regression results using exports of intermediate electrical goods.

	(1)	(2)	(3)	(4)	(5)
Log(Distance)	-0.313 **	-0.672 ***	-0.677 ***	-0.678 ***	-0.668 ***
	(0.141)	(0.039)	(0.041)	(0.040)	(0.040)
RTA	0.356	0.279 ***	0.257 ***	0.253 ***	0.259 ***
	(0.218)	(0.074)	(0.079)	(0.076)	(0.075)
Common Border	0.634 ***	0.130	0.082	0.080	0.071
	(0.194)	(0.109)	(0.107)	(0.107)	(0.106)
Common Language	0.085	0.037	0.051	0.050	0.032
	(0.224)	(0.101)	(0.097)	(0.098)	(0.097)
Colony	-0.046	0.089	0.049	0.048	0.049
	(0.198)	(0.143)	(0.143)	(0.143)	(0.134)
Common Colonizer	0.090	0.265	0.142	0.145	0.156
	(0.326)	(0.213)	(0.222)	(0.224)	(0.222)
Same Country	0.398	-0.563 ***	-0.560 ***	-0.567 ***	-0.579 ***
	(0.388)	(0.200)	(0.204)	(0.201)	(0.196)
Log(Med. Time)		-0.011		-0.007	-0.178 **
		(0.045)		(0.049)	(0.087)
Log(SD Time)			-0.069	-0.067	-0.179 ***
			(0.042)	(0.045)	(0.068)
Log(Med. Time)*Log(SD Time)					0.075 **
					(0.035)
Constant	3.016 **	6.560 ***	4.191 ***	4.212 ***	3.548 ***
	(1.447)	(0.497)	(0.723)	(0.727)	(1.043)
Observations	3361	2836	2703	2703	2703
R2	0.462	0.960	0.963	0.963	0.964

Note: The dependent variable is Exports in all cases. Estimation is by PPML with fixed effects by exporter and importer, and robust standard errors clustered by country pair. Standard errors appear below coefficient estimates. Statistical significance is indicated as follows: * (10%), ** (5%), and *** (1%).

FIGURES

Figure 1 UPU EMSEVT Event Workflow

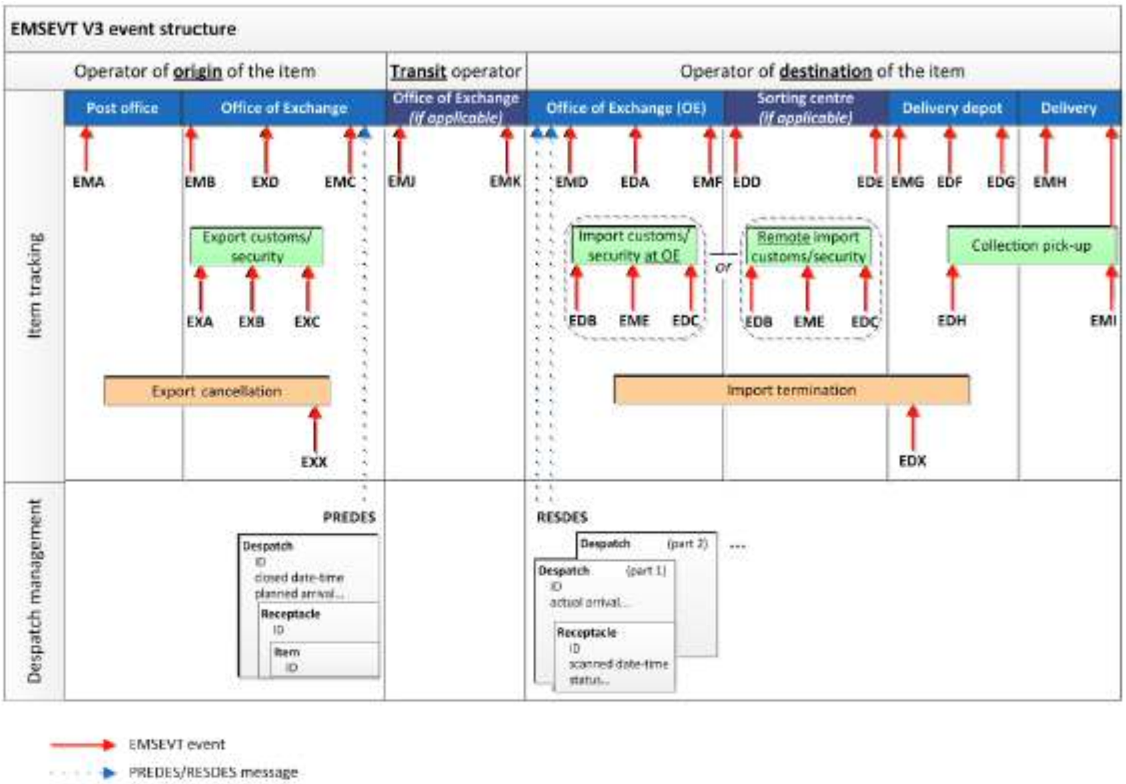

Figure 2 : Overview of Transit by Income Class, Parcels

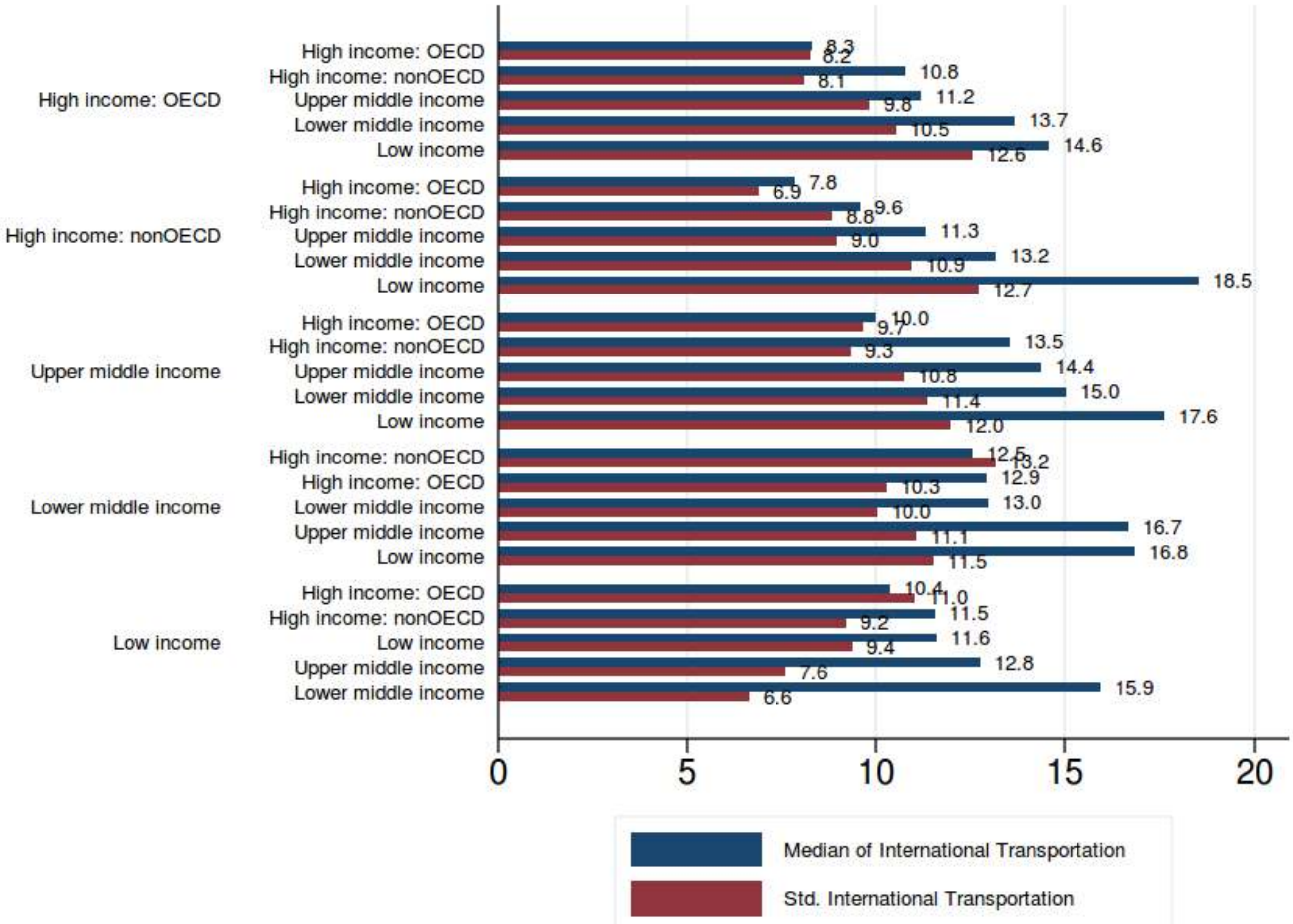

Figure 3: Association between median shipment time and uncertainty.

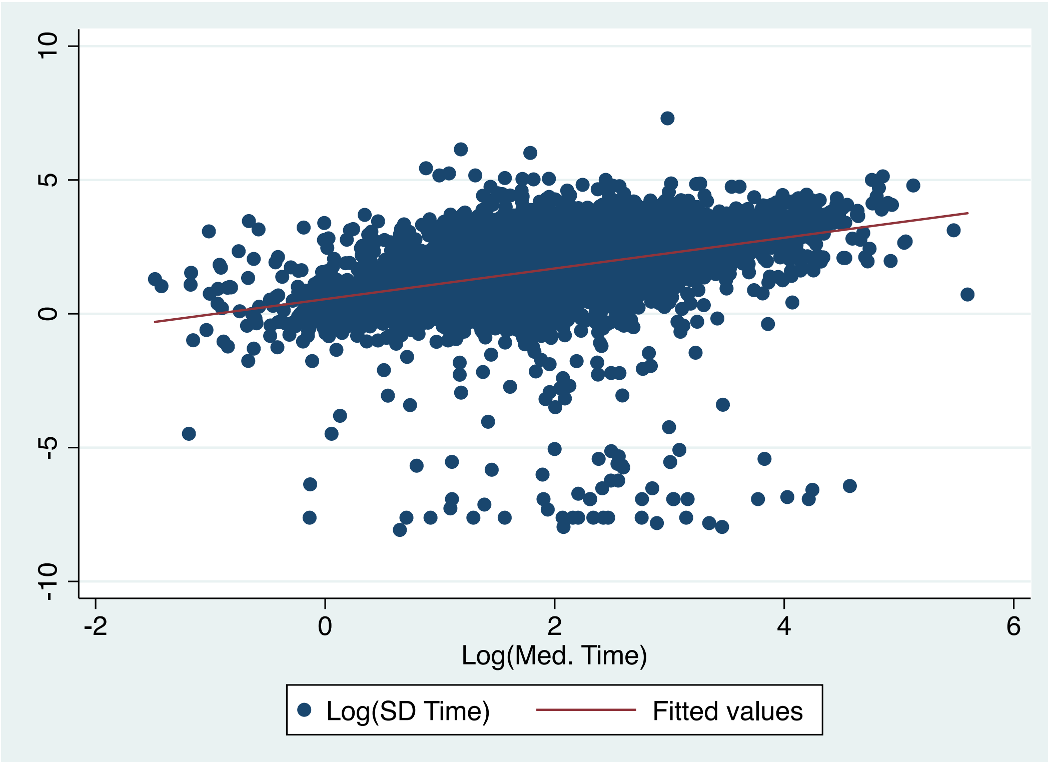

Figure 4: Quantile-quantile plot of the log(median time).

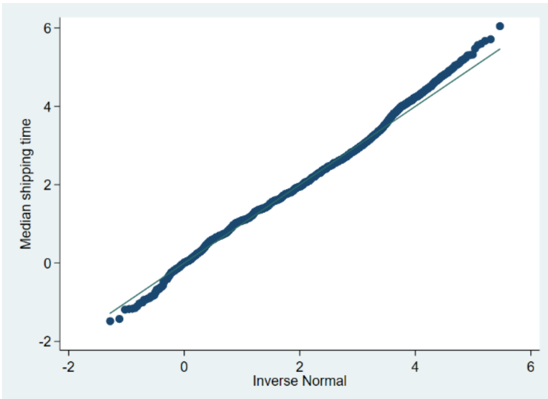

Figure 5: Distributions of average and median transport times.

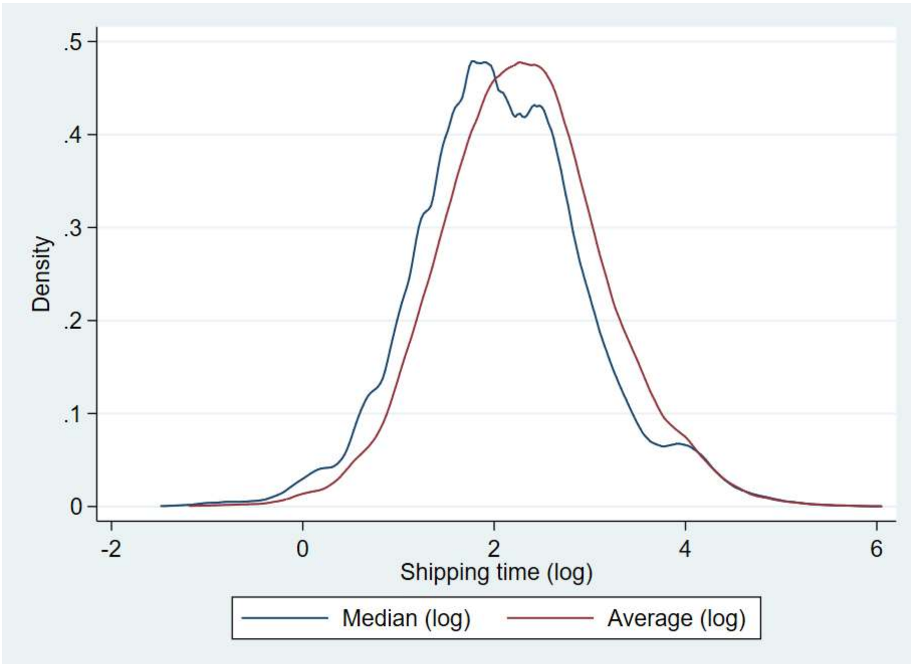

Figure 6: Comparison of international transport times by direction of movement..