Shipment frequency of exporters and demand uncertainty

Gábor Békés[a], Lionel Fontagné[b], Balázs Muraközy[a], Vincent Vicard[c,*]

[a] *Institute of Economics, CERS-HAS - Hungary*
[b] *PSE-Paris 1,Banque de France and CEPII - France*
[c] *Banque de France - France*

Abstract

Exporters react to the uncertainty of foreign demand by adjusting their shipment value as well as their shipment frequency. The number of shipments - here proxied by the number of months with nonzero exports - is an additional extensive margin allowing additional flexibility to firms in serving distant markets. Larger uncertainty requires firms to increase their inventory holdings in order to reduce backorder costs. Using a cross section of detailed monthly French export data we study this additional margin of trade, focusing on the role of demand volatility. We show that larger volatility is associated with both fewer and smaller shipments, but that the fall in the size of shipments is smaller reflecting increased level of inventory holdings. We also show that the impact of uncertainty is magnified by the time needed to serve the destination market from the production location. These findings are consistent with a simple stochastic inventory management model that links uncertainty of demand a firm faces in a given market to its decision on how to serve that demand.

Keywords: Gravity, transport costs, frequency of trade, inventory model, customs data
JEL classification: D40, F12, R40

PRELIMINARY DRAFT April 2013

*Corresponding author: Békés: bekes@econ.core.hu, Institute of Economics, CERS-HAS, Budaörsi út 45, Budapest, Hungary. We thank Zsuzsa Holler for excellent research assistance. The authors gratefully acknowledge financial assistance from the European Firms in a Global Economy: Internal policies for external competitiveness (EFIGE), a collaborative project funded by the European Commission's Seventh Framework Programme (contract number 225551). Békés thanks the hospitality of CEPII. This paper represents the views of the authors and should not be interpreted as reflecting those of Banque de France or the European Central Bank. The entire responsibility for errors and omissions remains on us.

1. Introduction

How many Barbie dolls should you ship from your Chinese assembly line to the UK for next Christmas? This question illustrates uncertainty on demand (children might prefer electronic devices this year) aggravated by distance (Guangzhou to Southampton is up to a 30 days sailing route) and inventory costs. Posting new orders in case of underestimation of demand will be very costly (air delivery), while ordering more than demanded means storing unsold dolls till next year. Hence, uncertainty faced by the firm is positively affected by the uncertainty of demand and the time to ship (aggravated here by the seasonality of demand). Many more examples of seasonal business could illustrate these general principle, as for example fertilizers whereby producers must build inventories to allow for timely availability during the peak season.[1] The problem for producers is always to minimize the inventory cost, while keeping the option of serving its usual consumers if the demand peaks.

Seasonality issues are an extreme case of a more general optimization problem faced by firms contemplating how to best serve their clients.[2] When deciding on serving customers, firms make decisions on the size of likely sales and on the modes and details of how to best serve clients. When clients are close to production and/or there is no need for delivery and storage, the second decision becomes less important, and a sale may be followed by another one (conditional on time to produce) after the first deal is closed. However, this is not the case when clients are far away or storage is needed to serve retail clients. Accordingly, foreign trade, where clients are located at large distance from the supplier provides a laboratory where to study such decisions made by firms in presence of demand uncertainty.

From a general economic perspective, international exchange is thus a good laboratory to study how firms adjust their sales technology in presence of uncertainty, using frequency of delivery as a margin of adjustment. From a trade perspective, shipments is another margin of exports worth studying: the question is neither whether you export (extensive firm margin), nor how much you export (intensive margin), but how often

[1] According to a report on a fertilizer company, sales vary significantly from one year to the next due to weather-related shifts in planting schedules and purchasing patterns (Industries Holdings, INC (2008) Source wikinvest.com). It is noted that when seasonal demand exceeds projections, customers may purchase from competitors, and profitability will be negatively impacted. On the other hand if seasonal demand is below expectations, the company will be left with excess inventory to be stored and paid for and/or liquidated at a low price. Very long storage is also impossible in this business.

[2] Trade technology depends on the route: air, land, maritime. According to Hummels (2009), three-quarters of world trade involves countries that do not share a border and involves mostly maritime transport. The mean cost of logistics as a percentage of the value of imports (all exporters) is in the range of 5% to 10% for an American importer. It is noticeably lower in the US (4.5%) according to Hummels (2009) calculations, than in smaller countries like Ecuador (9.2%). Part of the difference is due to the non-freight costs (e.g. insurance, warehouses), that represent only 15% of the total for the US but 55% for Ecuador.

you export, conditional on your foreign sales.[3] How uncertainty affects the number of shipments and their size is however a complex issue. Larger sales will increase the number and size of shipments (in proportion to be defined). Uncertainty on foreign demand will reduce total sales due to the storage costs afore mentioned. Uncertainty will also reduce the frequency of shipment, due to the sunk costs of shipping. Finally, uncertainty on foreign sales should reduce sales and thus the shipment size, though reducing the frequency of shipment and increasing the shipment size. What is the net effect on shipment size remains an open question.[4]

These questions are particularly relevant for international exchange since there is no just-in-time when products have to be trade internationally. When time matters, firms can optimize transport by choosing between modes of air and maritime cargo (Harrigan 2010, Hummels and Schaur, AER forthcoming).[5] Harrigan and Evans (2005) argue that an additional adjustment path is location choice: products that need to be served at a timely fashion will be produced closer to destination markets, thus affecting specialization patterns.[6] We will consider that location choices are given, and address firms' strategies conditional on these choices (we will look at export data for one exporting country only), and consider as a robustness maritime routes only.

In order to study this new margin of exports, we use the highly disaggregated nature of monthly export data for individual exporters and consider a new margin of trade: the frequency of shipments. The transaction margin has already been observed in the trade literature, but receive limited attention (Eaton et al., 2008; Ariu, 2011).[7] We use data

[3]Firms can also adjust by shipping different set of or products and/or to a different set of destinations. Iacovone and Javorcik (2010) examine how uncertainty affects trade patterns considering product level dynamics within firms for Mexico. The margin on adjustment here falls on products and uncertainty leads to product churning and limited value for new flows. In these cases, experience discussed by Araujo and Ornelas (2007) and Albornoz et al. (2012) help explain exporters' behavior. We will here focus on product-destination decisions: we assume that firms have already chosen their portfolio of exported product to each destination.

[4]We deviate from the literature (Hornok and Koren, 2012; Hummels and Schaur, forthcoming) by focusing on the supply side and firm level maximization in the presence of simple demand function. More precisely, we concentrate on logistics decisions and hence, the cost function of transportation, rather than organizational decisions.

[5]Indeed, as Hummels and Schaur (2010 JIE) demonstrated, uncertainty of demand will affect transport behavior, in the presence of higher demand uncertainty, a greater share of shipments will be taking place via air transport. We will address this issue by restricting our estimations, in a robustness, to maritime transport.

[6]Uncertainty is indeed impacting many other dimensions of individual firms decisions, like investment in presence of irreversibility (Bloom and Van Reenen, 2007), in line with the traditional real option argument (Dixit and Pindyck, 1994). We focus here on trade models.

[7]When analyzing Colombian transaction-level data, Eaton et al. (2008) show that the distribution of number of transaction is highly skewed, and that the transaction contributes to total trade significantly. Ariu (2011) also decomposes trade using the number of transactions using monthly trade data for Belgium and finds the transaction margin to be important at both the firm-level and country level

from the French Customs at individual exporter level, providing monthly firm export data by destination and product category. Products are aggregated at the 6-digit level of the Harmonized System (HS6), and shipment frequency is defined as the number of months with non-zero shipment per annum for a given firm-product-destination. We use the most recent pre-crisis year of observation (2007) and study the frequency of shipment for this cross-section for sake of tractability. However, uncertainty measurement will exploit the longitudinal dimension of the data. We limit our analysis to extra-EU exports in order to consider only relationships involving shipments of non-negligible duration.

One important issue here is how to best measure uncertainty faced by exporters. We consider that due to stochastic demand, firms are unaware of the final demand and hence, face uncertainty. This definition is related to business dynamics, although all aspects of a market may influence certainty of sales. To this end, we measure uncertainty by averaging volatility of firms' past (annual) sales changes for each product-destination markets before the year considered, meaning over the period 1999-2006. Several studies considered uncertainty, stemming from productivity shocks (Bloom et al. 2012), price volatility (Hummels and Schaur 2010 JIE) or instability of political-institutional variables (Handley and Limao 2012). Our approach to uncertainty is somewhat different, as we directly consider volatility of sales, and its use will complement existing approaches.

We firstly run firm-product-destination level regressions in a simple gravity framework to study how this margin of trade is used by firms to smooth the impact of business conditions on their different markets. We observe the adjustment of the number of shipments and the size of shipments using firm-product fixed effects. Accordingly, we control for the composition effect as firms endogenously choose destinations and products to ship. We observe that the adjustment to market size is roughly channeled half trough the number of shipment and half trough their size.

In a second step, we study the impact of uncertainty on sales, number and size of shipments. We find that: i) firms adjust on both margins to an increase in demand, and this is mirrored in the (similar) elasticity of trade frequency and value per shipment with respect to demand; ii) higher uncertainty reduces export value, the number of shipments and has an ambiguous impact on the average value of shipments; iii) holding export value fixed, higher uncertainty reduces the number of shipment and increases the average value per shipment; iv) the effect of uncertainty is magnified by shipment time: uncertainty only matters if transport is timely.

Finally, we show that these stylized facts are fully consistent with a simple theoretical setting fitting inventory costs. Inventory models have been long used in logistic theory. More recently, they have been shown to be useful frameworks when explaining the impact of large demand shocks in presence of transaction and inventory costs (Alessandria et al., 2011). The models in Alessandria et al. (2010) and Alessandria

decompositions.

et al. (2011) were designed to explain time series evidence after large trade shocks. They consider a dynamic version of problem when the importer has to decide about importing or not. They compare non-importers and importers in terms of reaction to fluctuation of condition, on the basis that importers take more time to adjust. Instead, our simple and tractable approach will reflect the inventory decisions of a firm exporting to many markets, and predict differences across markets and products.[8]

Against this background, we show that a simple model focusing on uncertainty, where firms pay per shipment cost to reach their foreign clients, and pay a storage cost to store goods and serve clients as they appear, will easily reproduce our stylized facts. Note that inventory model's predictions that shipment frequency will depend on sales, fixed costs and inventory costs are not unique. In Hornok and Koren (2011), consumers have heterogeneous preferences for the arrival time of a non-storable product and firms compete by selecting the time of their shipment. Per shipment costs reduce shipment frequency and increase the shipment size and the product price. The preferred shipment time of the consumer also contributes to inventory costs. In case of demand uncertainty, a firm may sell some amount with doing another shipment if and only if the first batch is sold. Also, on explicit modeling of trade technology, see Behrens and Picard (2011) or Kleinert and Spies (2011).

In what follows, in Section 2 we first introduce our data, then provide some basic statistics on shipment frequency as a margin of trade. The next section addresses the impact of uncertainty on these export margins. We then rely on main alternative measurement strategies and results in a robustness section (additional robustness checks are relegated to the Appendix). Finally, a simple model of inventory management is presented offering some testable predictions in Section 5. The last section concludes.

2. Data and descriptive stats

2.1. Data

We use detailed firm export data from the French Customs for 2007, providing monthly firm export value by destination and product category at the 6-digit HS level[9]. Two different thresholds apply to the collection of French exports, depending on their country of destination. All extra EU export shipments over 1000 Euros are to be declared to the French Customs whereas for exports to other EU Member states the declaration is compulsory if the yearly cumulated value of exports to the other 26 EU

[8]Inspired by the Great Recession, Novy and Taylor (2013) also investigates the role of macro uncertainty on trade volumes. They relate a real option model of stochastic inventory management to the trade reaction model of Bloom (2009) emphasizing the role of imported intermediate inputs. Using monthly US import and industrial production data, they suggest a link between uncertainty and macro-economic cyclicality.

[9]We excluded Ships and Aircraft because these items are not exported through usual transport technology but through self-propulsion.

Member states taken together is larger than 150,000 Euros. We therefore restrict our sample to extra-EU exports.

Annual GDP data are from the World Bank and distance come from CEPII Trade Dataset. Data on the mode of transport at the frontier are from Comext, which details the mode of transport of extra-EU trade by destination and HS6 digit level and differentiate between sea, rail, road, air, postal consignment, fixed transport installations, inland water transports or own propulsion. We use the information on the main mode of transport by market (product $\times$ destination) to identify shipments by sea from other modes of transport.

2.2. Descriptive statistics

How frequently do firms export? We compute the number of months for which a shipment was recorded in a cell firm-HS6 product category-destination. Considering only non-zero observations, the median is two shipments per year (Table 1).[10] Interestingly, the upper quartile is corresponding to five shipments only: choosing when to export is really a choice to be made by firms. The corresponding strategy has many dimensions worth looking at.

Table 1: Descriptive statistics: median, mean, first and last quartile of the number of shipments (2007)

	Mean	p25	Median	p75
Total	3.7	1	2	5
UE27	4.6	1	3	8
extra UE	2.3	1	1	2
Large countries (GDP)	4.2	1	2	7
Small countries (GDP)	2.8	1	1	3
Large firms	4.3	1	2	7
Small Firms	2.8	1	1	3
Intermediate goods	3.8	1	2	6
Other goods	3.6	1	2	5

Firstly, different destinations will be served differently: in EU destinations that will be disregarded in our econometric exercise, the frequency is higher: the median is 3 shipments compared to one for extra-EU trade relationships). This higher frequency can be driven by proximity (authorizing less costly shipments), by market size (large markets can be served more frequently), by type of products exported, or even by the composition of exporters. Considering market size, we observe that destinations with

[10]This does not exclude indeed more than one shipment in a month for a given firm, but we will loosely associate month in which a shipment is recorded to "shipment".

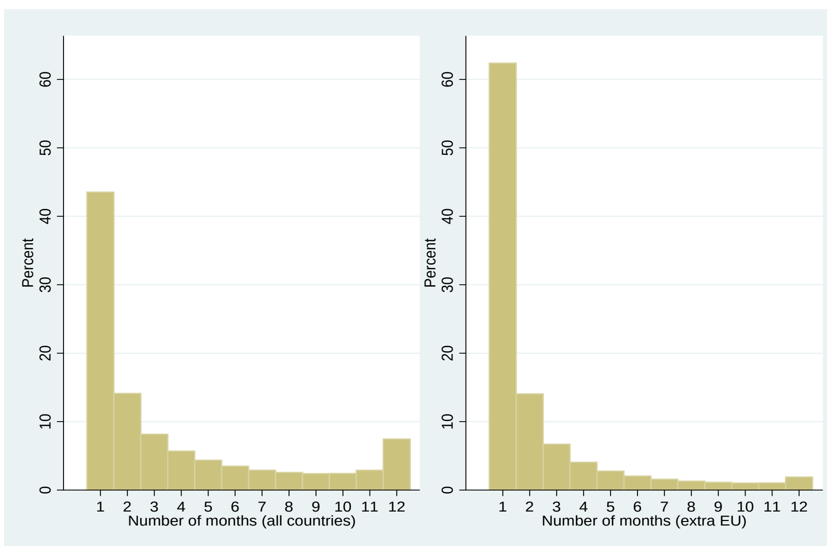
above the median GDP receive more frequent shipments than destinations below the median.

Big players ship their products more often, which is in line with the predictions of our model. This is confirmed by the data and even more visible in the last quartile where the mean number of shipments is seven for the large firms.

Just-in-time strategies embraced by many producers, combined with global value chains, should lead intermediate products to be exported more often. This difference is only weakly in the data.

In order to focus on non-neighboring countries, we stick to non-EU destinations. We can observe in Figure 1 that Extra-EU destinations (remote, more uncertain) exhibit a different distribution of the frequency of shipments, with a much larger concentration on single shipments.

Figure 1: Frequency of shipments, number of months, 2007, all and extra-EU



Notes: firm-destination-product (HS6) level. Source: French Customs, authors' calculation.

2.3. Simple gravity of the frequency to export

We can now use a simple gravity framework to decompose the different margins of exports at the firm-product level. Our aim her is to describe how this new margin of trade behaves. It is important as this margin is used by firms to smooth the impact of different business conditions on their different markets.[11]

Our first dependent variable is the log value of firm-product exports to each destination, for 2007. It is decomposed into the number of shipments per firm-product on each destination, and the mean value of these shipments for this firm-product. We have 568,131 observations for 315,659 firm-products.[12] Remind that we consider only extra-EU destinations. In this elementary gravity framework simply aiming at providing a decomposition of the margins at stake, we consider only market size (GDP of the destination country) and distance from France (distances were taken from the CEPII database) as determinants of the value of firm-products exports. Indeed unobserved product and firm characteristics have to be controlled for, which is done in columns (2), (4) and (6) with firm-product fixed effects. All variables are taken in logarithm and the estimated coefficients on the mean value and the number of shipments add to the coefficient on the total value in column (1). We cluster by destination-product. All estimated parameters are significant at the 1% level.

Comparing columns (1) and (2), Table 2, we observe the traditional sorting of firms on remote destinations: when firm-product characteristics are not controlled, distance has a positive impact on the value of exports, which channels through the average value of the shipments in column (5). Big and more efficient players export their better products on remote markets. Indeed, this composition effect disappears when controlling for firm-product characteristics in Columns (2) and (6). Demand has ultimately a positive impact on firm-product exports.

This simple framework makes it possible to decompose the two margins we are interested in: the number of shipments (more precisely the number of months a shipment was recorded for a given firm-product to a destination within a year) and the mean value of each shipment (more precisely of monthly exports of a given firm-product to a destination within that year). Considering the fixed-effects specification, we observe that more than half of the increase in exports to larger markets channels through the mean value of shipments, less than half of impact of demand channeling through the number of shipments. Larger markets offer economies of scale in terms of logistics, as the number of shipments increase less than demand. As for the impact of distance, three fourth fall on the number of shipments, and one fourth on their mean value.

[11]This baseline regression result (Table 2) is presented for the same sample as used for the rest of the paper to ease comparability. Estimation details will be presented in section 3.

[12]We use here the censored dataset, as in the follow up of the paper.

Table 2: Gravity variables and export margins

	(1)	(2)	(3)	(4)	(5)	(6)
	value (log)		nbr of shipments (log)		avg value (log)	
GDP (log)	0.032***	0.167***	0.013***	0.070***	0.019***	0.097***
	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
distance (log)	0.087***	-0.099***	0.009***	-0.075***	0.078***	-0.025***
	(0.006)	(0.004)	(0.002)	(0.002)	(0.006)	(0.003)
Constant	7.724***	5.705***	0.042	-0.780***	7.683***	6.485***
	(0.096)	(0.099)	(0.051)	(0.051)	(0.072)	(0.059)
Firm*product fixed effect	-	Yes	-	Yes	-	Yes
Observations	568,131	568,131	568,131	568,131	568,131	568,131
Number of id		315,659		315,659		315,659
R-squared	0.006	0.045	0.002	0.041	0.005	0.026

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Clustered by destination/product

3. Uncertainty and trade margins

This section studies how uncertainty affects export sales and the related margins – number and mean size of shipment – at the firm-product-destination level.

An important issue is accordingly the definition of uncertainty. Our preferred uncertainty variable is a proxy for the variance of the distribution of demand from our model. It captures the average uncertainty of sales faced by French firms on a specific market (j, k) when deciding to ship, i.e. the distribution of sales variations over time on the market.

More specifically, uncertainty is measured as the cross-firm average standard deviation of firms' yearly export growth at the product and destination level over the period 1999-2006. High uncertainty reflects a higher volatility of the demand addressed to firms and may be related to both variations in overall annual demand on the market and/or the process of reallocation of market shares across firms.

equation here

Robustness estimations with alternative measures of uncertainty are provided in the next section.

3.1. Estimation strategy

In terms of methodology, let us emphasize a few important issues: restriction of countries, panel structure, using fixed effects and dummies to instead of cost estimates and censoring. Robustness checks will be discussed in a separate section.

Restriction of countries. Importantly, we dropped all EU countries from the sample for two reasons. First, shipments within the EU are recorded differently, and we loose many smaller shipments. Second, transport within the EU is mostly swift and time and distance plays a much smaller role. A robustness check including EU countries is presented in available on request.

Panel structure In particular we will relate uncertainty to (1) total (annual) shipment value (val_tot), (2) shipment frequency ($freq$), (3) average shipment value (val_avg). All dependent variables (value, number of shipments and average value) are presented in logs and estimate model at the at firm-product-destination (i, j, k) level yields:

$$Value_{ijk} = \alpha + \beta_{1v} Y_k + \beta_{2v} Dist_k + \beta_{3v} Uncert_{jk} + \theta_{ij} + \epsilon_{ijk} \tag{1}$$

$$NbrShip_{ijk} = \alpha + \beta_{1f} Y_k + \beta_{2f} Dist_k + \beta_{3f} Uncert_{jk} + \theta_{ij} + \epsilon_{ijk} \tag{2}$$

$$AvgVal_{ijk} = \alpha + \beta_{1a} Y_k + \beta_{2a} Dist_k + \beta_{3a} Uncert_{jk} + \theta_{ij} + \epsilon_{ijk} \tag{3}$$

Our data is firm-product-destination level panel (for one year). These equations may be estimated by OLS but we included θ_{ij} product-firm fixed effects to control for composition effects as well as unobserved cost characteristics. Selection is really important as more productive firms self-select into different countries, as they are the ones that can pay the sunk of exports to harder markets (Mayer and Ottaviano, 2011; Arkolakis, 2010). Furthermore, Békés and Muraközy (2012) argue that more productive firms will more likely export at a permanent (and hence, more frequent) fashion. Note that adding firm-product FE implies that single-product, single-destination (outside the EU) exporters are not considered.

To handle the fact that error terms may be correlated we cluster standard errors by the dimension of our key uncertainty variable (product * destination). To control for unobserved country characteristic, for several estimations, GDP and distance are replaced with country dummies. This allows us to focus on product-country level uncertainty.

Parameters and dummies This paper focuses on the impact of uncertainty on shipment behavior[13]. Per shipment fixed costs may include per container costs, administrative cost at the border, insurance and distribution. Inventory cost would include warehouse costs that are shaped by size and weight, specific conditions for perishable goods, as well as firm specific effects (e.g. financial strength that may affect the discount rate). Both per shipment costs and storage costs are very hard to measure - and instead, we'll argue that firm-product fixed effects will also control for these costs.

[13] An earlier working paper version includes a greater set of variables.

At a later stage, we introduce destination specific fixed effects that shall pick costs associated with destination market interest rates, as well as doing business types of costs of each shipment. As the identification is on the cross section, these fixed effects shall control for most variables of the model apart from the product-destination specific uncertainty, the effect of which we look for[14].

Censoring As presented in section 2.2, the number of shipments is censored at twelve (months). One of our concerns is that the number of months is a noisy proxy of the number of shipments in a given year. While it is a reliable approximation for low frequency exports, it may be biased for frequent exporters. To handle this problem, we opted for the simplest treatment and dropped the upper tail of the distribution focusing on firm-product-destination observations for 1-9 shipments. In terms of generality, this is not a very serious problem, as this requires dropping only 6 percent of observations.

Results for the uncensored sample are presented in the Appendix[15] According to uncesnored results, our benchmark censored results, apart from reducing the effect of the bias, also reduce the strength of the transaction adaptation channel. Hence, censored results show more conservative estimates.

3.2. How margins adjust to uncertainty

The first two stylized facts that we will show refer to the margins of trade and the impact of uncertainty. This is also shown in Table 2.

Table 3 presents results for our baseline regressions for OLS (cols 1,3 and 5) as well as firm-product fixed effects regressions (columns 2,4 and 6). The dependent variable for the first two columns is the log of annual sales, followed by two columns on log number of shipments (months) and then, log average value.

Results show that estimated GDP coefficient is approximately equally divided between frequency and average size: 0.016 vs 0.018 for the OLS and 0.071 vs 0.096 for the firm-product FE model. Note that relationship is also present in Table (12) where we use the broadest possible sample and present simple uncensored results (0.038 vs 0.046 for the OLS and 0.102 vs 0.135 for the FE model). Accordingly, our first stylized facts is that firms equally adjust the number of shipments and their size to observable changes in demand.

The second stylized fact is that higher uncertainty reduces shipment value as well as the shipment frequency. This is illustrated in three specifications: pooled OLS (columns 1,3,5 of Table 3), firm-product fixed effects (columns 2,4,6 of Table 3), and

[14]One can expect that products with high depreciation rate (perishables) react differently. Unfortunately food items, which is a clear candidate, is also seasonal and as France ships little raw food overseas, is not a convincing candidate. Fast fashion is hardly distinguishable at 6-digit level. Instead we tried intermediate goods (by BEC category) as shipping these goods are rather time sensitive. There was no apparent difference.

[15]All results presented are confirmed (available on request) when we restrict sample for 10 and below or 8 and below shipments as well.

Table 3: Baseline regressions

	(1)	(2)	(3)	(4)	(5)	(6)
	value (log)		nbr of shipments (log)		avg value (log)	
GDP (log)	0.034***	0.167***	0.016***	0.071***	0.018***	0.096***
	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
distance (log)	0.087***	-0.100***	0.010***	-0.075***	0.078***	-0.025***
	(0.006)	(0.004)	(0.002)	(0.002)	(0.005)	(0.003)
uncert (log)	-0.068***	-0.023**	-0.146***	-0.055***	0.078***	0.032***
	(0.013)	(0.009)	(0.006)	(0.004)	(0.010)	(0.007)
Constant	7.699***	5.694***	-0.013	-0.807***	7.712***	6.501***
	(0.095)	(0.101)	(0.046)	(0.051)	(0.073)	(0.060)
Firm*product FE	-	Yes	-	Yes	-	Yes
Observations	568,131	568,131	568,131	568,131	568,131	568,131
Number of id		315,659		315,659		315,659
R-squared	0.006	0.045	0.009	0.042	0.006	0.026

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Clustered by destination/product

firm-product fixed effects as well as destination dummies (table 4). Note that the measured effect of uncertainty is very different when we control for the composition effect.(i.e. the difference between OLS and firm-product FE). The coefficient of the total volume falls substantially (by about two-thirds) when we control for firm and product characteristics. This is then affects both shipment frequency and average size, about equally in magnitude.

Considering our preferred destination FE specification (Table 4), a firm facing a 10% higher uncertainty for a given product at a given market is selling 0.7% less at that market, with most of the hit taken through fewer (0.5% less) number of shipments.

Note that the full effect on average shipment size is negative but this result is strongly dependent of specification and control. The relationship between uncertainty and average value can go either way depending on relative size of various types of costs.

Comparing Table 4 to Table 3, the impact on sales and number of transactions remain in the same magnitude as before. The coefficient of the average shipment size becomes negative suggesting that the effect of declining overall sales is not fully passed through on the size of shipments, when additional controls are employed. The destination FE specification is our preferred model, and hence, from now on, all specifications will include firm-product as well as destination fixed effects unless otherwise indicated.

Table 4: The role of uncertainty: destination fixed effects

	(1)	(2)	(3)
	value (log) full sample	avg value (log) full sample	nbr of shipments (log) full sample
uncert (log)	-0.072***	-0.020***	-0.053***
	(0.009)	(0.007)	(0.004)
Firm*product FE	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes
Observations	568,131	568,131	568,131
Number of id	315,659	315,659	315,659
R-squared	0.060	0.050	0.058
Clustered by destination/product			

Both Table 3 and table 4 presented results on the censored sample. As we will show in the next sub-section, all variable estimates are on the conservative side, with estimated coefficients on both total value and number of shipments typically doubled when using the full sample.

3.3. Adjustment of margins conditional on sales

So far we have considered unconstrained models. The number of shipments will also fall because even for the same amount of sales, firms will choose to send fewer shipments when uncertainty is high (exactly the opposite for package size). We run the same regression as before, but for this constrained version, we control for the total value, and 2 becomes:

$$NbrShip_{ijk} = \alpha + \beta_{1f} Y_k + \beta_{2f} Dist_k + \beta_{3f} Uncert_{jk} + \beta_{4\_} Value_{ijk} + \theta_{ij} + \epsilon_{ijk} \quad (4)$$

Results in Table 5 confirm this: when we compare two shipments controlling for the annual total volume, the product-destination market with 10% higher uncertainty is associated with 0.3% less transactions. (Coefficients on the average size is exactly opposite when total sales are controlled for.) Thus, we can see that the about half of the drop in transport frequency come from the firm's optimization effort yielding less overall sales, while the other half comes from less frequency for less the same sales (0.03% vs 0.053%).

Table 5: Role of uncertainty conditional on sales

	(1)	(2)	(3)
	avg value (log)	nbr of shipments (log)	nbr of shipments (log)
	full sample	full sample	Maritime only
uncert (log)	0.030***	-0.030***	-0.028***
	(0.003)	(0.003)	(0.003)
total value (log)	0.684***	0.316***	0.325***
	(0.001)	(0.001)	(0.001)
Constant	2.202***	-2.202***	-2.235***
	(0.016)	(0.016)	(0.032)
Firm*product FE	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes
Observations	568.131	568,131	300,906
Number of id	315.659	315,659	170,273
R-squared	0.811	0.495	0.499
Clustered by destination/product			

Of course, total sales is fully endogenous as a control for number of shipments. To treat this endogeneity, we instrument value by market size - measures as the global imports to a given product-destination pair using data from the COMTRADE dataset[16].

[16]Our data coming from French customs is 86% correlated with COMTRADE data on imports from

Results hold when instrumenting value by total imports, or even when simply replacing them.

3.4. Impact of uncertainty magnified by distance

Table 6 tests the argument that distance (travel time) magnifies the effect of uncertainty. To test this, we interact our distance and uncertainty variables, so add a cross term of uncertainty and distance to equation and and 2 becomes:

$$NbrShip_{ijk} = \alpha + \beta_{1f} Y_k + \beta_{2f} Dist_k + \beta_{3f} Uncert_{jk} + \beta_4 Dist_k * Uncert_{jk} + \theta_{ij} + \epsilon_{ijk}. \quad (5)$$

Columns 1-2 present basic results, columns 3-4 includes the control of total values as well. Our model is specified for maritime travel in mind, involving a great deal of time for a shipment. However, we have analyzed the whole sample (of non-EU countries) so far. However, even for overseas (or far away countries that may be reached both by road and shipping, such as Russia), some part of the transport is carried out by air or road. This may explain the lack of results in column 1.

Fortunately, for 52% of our sample, we know that transport include maritime transportation - with rest including air, road, and unidentified. Indeed, this instance, the travel mode distinction becomes important, as the cross term is estimated to be non-zero only for the maritime (ie certainly time consuming) modes of transport. The coefficient of uncertainty is estimated to be positive, but for all markets beyond 7000km, the combined effect is negative. A possible non-linearity of this relationship is tested by employing three dummy variables in columns 5 with results suggesting the negative effect to be in place for 8000km and beyond.

4. Robustness

We analyze here the robustness of our findings using alternative estimation methods, alternative measures of uncertainty and finally tackling more minor issues.

4.1. Alternative estimation methods

Robustness results are presented in Table 7. Regression results here include country dummies with additional robustness checks with GDP and distance relegated to the Appendix. Column (1) reproduces column (3) from Table 4 to ease comparability. Column (2) shows baseline results for whole sample, ie. including observations with shipments 10-12. The estimated coefficient is higher (-0.053 vs -0.088), and this remains true for other specifications. In the Appendix we present a Table 12 with full sample results for selected models, and additional results are available on request.

France.

Table 6: Uncertainty and distance

	(1)	(2)	(3)	(4)	(5)
Dep var:			nbr of transactions (log)		
Sample	full sample	Maritime only	full sample	Maritime only	Maritime only
uncert (log)	-0.039	0.061	-0.052	0.120***	-0.012*
	(0.049)	(0.058)	(0.037)	(0.041)	(0.006)
distance (log) * uncert (log)	-0.002	-0.014**	0.003	-0.017***	
	(0.006)	(0.007)	(0.004)	(0.005)	
total value (log)			0.316***	0.325***	0.325***
			(0.001)	(0.001)	(0.001)
dum 7000 * uncert (log)					-0.012
					(0.008)
dum 8000 * uncert (log)					-0.030***
					(0.008)
Constant	0.526***	0.618***	-2.202***	-2.230***	-2.233***
	(0.023)	(0.051)	(0.016)	(0.032)	(0.032)
Firm*product FE	Yes	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes	Yes
Observations	568,131	300,906	568,131	300,906	300,906
Number of id	315,659	170,273	315,659	170,273	170,273
R-squared	0.058	0.052	0.495	0.499	0.499

This is followed by two random effect effect models - one simple way to treat potential over-specification (Matyas, Hornok, Pus 2012). Results confirm earlier results while showing a coefficient estimate somewhat larger than before. We carried out truncation in this case as well, with no apparent change. In the in column (5) we present results with a Tobit model, in which all observations with more than 8 months are treated as censored[17]. Once again, the key negative relationship between shipment frequency and uncertainty is confirmed.

Table 7: Different estimators

	(6)	(7)	(8)	(9)	(10)
	nbr of shipments (log)				
	OLS Fixed Effects		OLS Random effects		Tobit RE
Sample	Baseline	All transactions	Baseline	All transactions	All transactions
uncert (log)	-0.053***	-0.088***	-0.130***	-0.197***	-0.118***
	(0.004)	(0.005)	(0.008)	(0.009)	(0.003)
Constant	0.526***	0.626***	0.548***	0.629***	0.537***
	(0.023)	(0.028)	(0.018)	(0.023)	(0.010)
Firm*product FE	Yes	Yes	-	-	-
Destination FE	Yes	Yes	Yes	Yes	Yes
Observations	568,131	595,809	568,131	595,809	595,809
Number of id	315,659	319,068	315,659	319,068	319,068
R-squared	0.058	0.096			

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Clustered by destination/product

Looking at results at Table 7 as well as Table 12 we can see that point estimates of the uncertainty variable vary between -0.053 (our baseline estimate) and -0.217 suggesting that presenting results on the truncated sample with destination fixed effects is a rather conservative approach.

To reflect the potential inconsistency resulting from heteroscedasticity in data, we use Poisson pseudo maximum likelihood estimator proposed by Santos Silva and Tenreyro (2006). This methodology is consistent with average value of shipment estimation and the number of shipments proxied by the number of non-zero monthly exports - at the firm-destination-product level. Poisson PML results - with destination fixed effects are presented in Table 9 and Table 10 of the Appendix confirm key results (with the effect of uncertainty on the total value being not significant).

[17]Changing the censoring limit to 8 or 10 months does not change the results importantly.

4.2. Alternative measures of uncertainty

Our benchmark measure looked at dynamics in a given (i, j) (i.e. product-destination country) market. In this subsection, let us consider alternative measures to our uncertainty variable.

First, we consider uncertainty based on variation of demand over time. Firms may look at demand uncertainty from the vantage point of overall demand fluctuations based on past experience. To capture this, we created the $uncert_agg$ variable as the relative standard deviation of quarterly sales (j, k) for 32 quarters (1999-2006). We added zeros to quarters when annual sales that year were non zero and applied a simple seasonal adjustment by calculating quarter dummies as deviations from a trend.

Both our benchmark and the $uncert_agg$ variables may be endogenous to the (i, j, k) shipment. To avoid this, our second alternative variable $uncert_agg_ita$ replaces relative standard deviation overtime of French Firms, calculated by those experienced by Italian firms. Of course, this means a great deal of loss of observations, as we can only observe markets served by both French and Italian firms.

Our third alternative measure is a firm's experience in a given market. As local experience helps a firm know its market better, it can reduce uncertainty. A firm's experience in a given market (i, j, k) is simply the number of years with non-zero exports since 1991. Of course this variable captures firm age and overall export experience. However, given our firm-product fixed effect specification, this shall be partially out. Please note that this variable has the opposite expected sign as all other, as a greater number represents more certainty while for other variables, it implies greater uncertainty.

Results, looking at both total value and the number of shipments, are presented in Table 8, comparing the effect to the benchmark case, one by one, and finally taking the benchmark, the aggregate and firm experience variables all together. Table 8 presents results: Panel A for total value, Panel B for number of shipments, Panel C repeats the exercise for average number of shipments. All results presented before are confirmed as all uncertainty variables behave the similar way as our benchmark.

4.3. Additional robustness checks

We made several additional robustness checks: looking at a smaller sample of firms, dropping small markets, and focusing on a set of products whereas classification has been stable.

Firms We considered robustness from another angle: the sample of shipments considered. As discussed before, the first point was to reduce the sample for maritime shipments, than we considered manufacturing firms only, and finally incumbent firms, ie those who exported the same product to the same destination. Results, presented in the Appendix (Table 12), confirm earlier results.

Market sizen About 1/3 of product-destination markets are served by only one firm at a time. In this case, volatility is identified from past sales of this firm. As robustness check, we dropped all observations to these markets (reducing sample size from 595K to 522K), and repeated all regressions. We found marginally higher estimated uncertainty coefficients, and hence, if anything, we have underestimated the impact of uncertainty. Results available on request.

HS6 coding stability. There has been many coding changes in the HS6 classification. This is is not random, as more technology related products are recoded. Hence, we dropped all codes that went through any change between 1999 and 2007 - affecting about 20% of total observation. Results suggesting that this had no effect, are available on request.

Table 8: Alternative uncertainty measures

	Panel A				
Dep	value (log)				
uncert (log)	-0.066***				
	(0.011)				
uncertagg (log)		-0.241***			
		(0.010)			
uncertaggita (log)			-0.033***		
			(0.005)		
Experience by dest*prod					0.076***
					(0.001)
Constant	8.629***	8.480***	8.631***		8.254***
	(0.057)	(0.058)	(0.056)		(0.057)
R-squared	0.057	0.063	0.057		0.081
	Panel B				
Dep	nbr of shipments (log)				
uncert (log)	-0.052***				
	(0.005)				
uncertagg (log)		-0.145***			
		(0.005)			
uncertaggita (log)			-0.020***		
			(0.002)		
Experience by dest*prod					0.044***
					(0.001)
Constant	0.507***	0.418***	0.509***		0.290***
	(0.029)	(0.031)	(0.029)		(0.029)
R-squared	0.058	0.066	0.058		0.094
	Panel C				
Dep	avg value (log)				
uncert (log)	-0.014*				
	(0.008)				
uncertagg (log)		-0.096***			
		(0.007)			
uncertaggita (log)			-0.012***		
			(0.004)		
Experience by dest*prod					0.032***
					(0.001)
Constant	8.121***	8.062***	8.122***		7.964***
	(0.036)	(0.036)	(0.035)		(0.036)
R-squared	0.048	0.050	0.048		0.056

For all panels, a unified sample is used: number of observation is 507,930, number of id is 291,127.
Robust standard errors in parentheses, clustered by destination/product.
Product-firm FE and destination dummies always included.

5. Modeling shipment frequency

We illustrate here that the stylized facts afore mentioned can be reproduced using a simple model of steady state behavior. One can easily describe how trade frequency (the number of shipments per year by a firm from one product to a given country) changes with demand parameters and uncertainty about demand with explicitly accounting for logistical/operation management decisions of firms. In this setup firms consider external demand at each of their (product-destination) markets and optimize their shipment process based on available cost information as well as uncertainty about demand.

We consider here the total logistics cost, which includes transportation cost, per-shipment costs as well as warehouse expenses. We investigate a direct exporter, and assume that the firm pays all transportation costs and sells to foreign clients directly from its warehouse in the foreign country. Hence, retailers play no role in our framework.

In this section, let us first review a baseline deterministic model followed by a stochastic version. This will be based on the review of Zipkin (2000). Having discussed costs of inventory management, we turn to firm maximization and then summarize predictions for the empirical work.

5.1. Deterministic demand

The starting point of our framework is the idea of inventory management, where firms optimize inventory decisions under different circumstances. The simplest such models investigate the optimal policy under a constant demand rate, and hence, are deterministic in nature.

In the deterministic framework, the firm faces a demand of λ in each time period, has to pay a per-shipment cost of k each time when placing an order, the variable cost of transportation is τ, and holding one unit of inventory costs h per unit of time. Inventory cost shall include all costs related to storage such as rent, running cost of facilities and personnel. Furthermore, it includes the cost of capital that covers the value of stored goods, which may be affected by the financial position of the firm. In the simplest case, the firm has to hold enough inventory to satisfy the demand of all customers from its holdings, hence quantity sold is exogenously determined.

The main decision variable is the average shipment size, which also determines the number of shipments per period. The tradeoff the firm faces is between more shipments implying higher per-shipment costs and more inventory holding implying higher inventory costs. Under such circumstances, the firm minimizes its total logistic cost:

$$C(q) = \tau\lambda + k\lambda/q + 1/2hq$$

where q is the average shipment size. Note that it is assumed that goods will be depleted linearly and hence, average value of goods kept abroad is half the shipment quantity. The optimal shipment size is:

$$q^* = \sqrt{\frac{2k}{h}\lambda}$$

while the optimal number of shipments is:

$$f^* = \sqrt{\frac{h}{2k}\lambda}$$

Hence both the number of shipments and the quantity/shipment increases in proportion to the square root of demand intensity, λ. It is optimal to adjust to larger market size on two margins: logistics costs are minimized when the firm increases both the number of shipments and shipment size in proportion to the square root of demand, as both margins has a similarly increasing marginal cost schedule[18].

Now we can express the total logistics cost (per period) of the firm:

$$C^* = \tau\lambda + \sqrt{2k\lambda}$$

which takes the general form of $B\lambda + C\sqrt{\lambda}$. As we will see, this general form remains valid in more realistic inventory models as well. Note that this formula suggests that - in contrast to iceberg trade costs - there are economies of scale in logistics thanks to the presence of per-shipment costs.

A simple modification of this model enables firms to serve some customers with delay. In the inventory literature this is called a *planned backorder*. Such planned backorders are costly to the firm either because consumer satisfaction is lower or because serving these customers requires some extra spending. We assume that the firm faces a penalty cost of b per backordered unit. It can be easily shown that the main results of the previous model are preserved in this case. First, both optimal shipment size and frequency are proportional to $\sqrt{\lambda}$:

$$q^* = \sqrt{\frac{2k\lambda}{h}}\sqrt{\frac{1}{\omega}}; f^* = \sqrt{\frac{h\omega}{2k}\lambda}$$

where $\omega = \frac{b}{b+h}$ is the relative size of the backorder penalty. The total optimal logistics cost also takes the form of $B\lambda + C\sqrt{\lambda}$:

$$C^* = \tau\lambda + \sqrt{2k\omega\lambda} \tag{6}$$

One empirical prediction of this extension is that it allows one to analyse differences across perishable (food, fashion goods) and non-perishable products. The relative backorder cost of perishable products is much larger, leading to more frequent shipments, and also, ceteris paribus, to higher logistics costs.

[18]The model has a similar mechanics to the well known Baumol-Tobin model.

5.1.1. Stochastic inventory models

While deterministic inventory models are able to capture a number of important aspects of real-world inventory problems, one of our main aims is to investigate the role of demand uncertainty explicitly. For this, one has to turn to stochastic inventory models.

In such models demand follows a stochastic process. While the models are able to handle very general processes, we will concentrate on a normal approximation here. Assume that the demand (D) in a period with a length of T can be approximated with a normal distribution with a mean $\upsilon = E(D) = \lambda T$ and variance $\sigma^2 = Var(D) = \psi^2 \lambda T$. [19] Note that the expected value of this process does not depend on time, hence it is suitable to describe steady state behavior. Describing other situtations, like dynamic adjustements to a large permanent shock may require other stochastic models.

As we will see, the key measure of uncertainty for the firm is the variability of demand between the actions of the firm and the arrival of the shipment. This is the product of the time required for the shipment to arrive and the volatility of demand. Note that if the shipment arrives instantly or demand is deterministic, then we are back to deterministic models - hence deterministic models can do a better job in describing trade frequency between nearby countries than between far away trading partners.

The time needed for the inventory to arrive will be denoted by L. λ will show the (now stochastic) intensity of demand, while ψ^2, the asymptotic variance-to-mean ratio represents the relative variability of demand.

We will also specify an inventory policy describing the behavior of the firm. A widely used policy is the (r,q) model. This means that the firm always sends q units whenever the inventory declines below the re-order point, r. The optimization requires firms to to choose q and r optimally to minimize the expected logistics cost. In this decision the tradeoff between inventory costs and per-shipment costs is complicated by the fact that low inventory levels may lead to larger expected backorder costs.

Unfortunately such models do not have a closed form solution in general. It can be shown, however, that in important respects the optimal policy is very similar to that in the deterministic case.[20] In particular, the behavior of lower and upper bounds for q^*, f^* and C^* provides important clues about the shape of optimal policy[21].

First, we have the following bounds for q^*:

$$\sqrt{\frac{2k}{h\omega}\lambda} \leq q^* \leq \sqrt{\frac{2k\omega + b\psi^2 L}{h\omega^2}\lambda} \tag{7}$$

[19] This can be interpreted as an approximation of a Poisson demand process, with mean and variance λT.

[20] See subsection 6.5.3 of Zipkin (2000).

[21] An important difference relative to the deterministic case is that these are expected values.

Taking logs[22]:

$$\frac{1}{2}\ln\frac{2k}{h\omega}+\frac{1}{2}\ln\lambda \le \ln q^* \le \frac{1}{2}\ln\lambda+\frac{1}{2}\ln\frac{2k}{h\omega}+\frac{1}{2}\ln(1+\frac{b}{k\omega}\psi^2 L) \le \frac{1}{2}\ln\lambda+\frac{1}{2}\ln\frac{2k}{h\omega}+\frac{b}{2k\omega}\psi^2 L \tag{8}$$

One observation is that both bounds increase proportionally with $\sqrt{\lambda}$, hence it is a good approximation that q^* increases linearly with $\sqrt{\lambda}$. Second, while the lower bound is independent of $\psi^2 L$, the upper bound increases in it. The intuition of this result is that the larger uncertainty is, the larger shipments the firm sends in order to reduce the expected value of backorders, leading to a smaller expected number of shipments conditional on λ. The above formula shows that this effect is zero when $b = h$, and becomes stronger as the cost of backorders increases relative to inventory costs. All in all, it is possible to approximate $\ln q^*$ with a relatively simple functional form:

$$\ln q^* \approx A_q + \frac{1}{2}\ln\lambda + C_q\psi^2 L \tag{9}$$

where A_q, C_q depend on b, h and k. Similarly, the optimal expected frequency, $f^* = \frac{\lambda}{q^*}$ can be approximated by

$$\ln f^* \approx -A_q + \frac{1}{2}\ln\lambda - C_q\psi^2 L \tag{10}$$

One can see that the important result of the deterministic case, that both frequency and batch size increases linearly to the square root of demand.

The effect of uncertainty is less obvious. The main effect of increasing uncertainty is that the expected cost of backorders increases for each level of inventories. Hence, when uncertainty increases, it is optimal to increase average inventory levels in order to reduce expected backorder costs. Optimizing firms do it on two margins: they increase both their reorder points and the average shipment size. Larger shipments result in less frequent deliveries for the same demand intensity.

Uncertainty also affects total logistic costs on three channels. First, it leads to larger expected backorder costs. Second, as firms increase their inventory levels, inventory costs also increase. These two effects are somewhat mitigated by a fall in per-shipment costs. Total logistics costs can be approximated by lower and upper bounds:

$$\tau\lambda + \sqrt{(2kh\omega + b^2\Upsilon^2(\omega)\psi^2 L)\lambda} \le C^* \le \tau\lambda + \sqrt{2kh\omega\lambda} + b\Upsilon(\omega)\sqrt{\psi^2 L\lambda}$$

where $\Upsilon(\omega) = \frac{\phi(\Phi^{-1}(1-\omega))}{1-\omega}$ and Φ, ϕ are the cdf and the density function of the Normal distribution, respectively. Assuming that σ is relatively large[23], we can approximate

[22] And applying the formula $\ln(1 + x) \le x$

[23] Zipkin (2000) p.219 provides numerical simulations showing that this approximation is valid even for relatively small values of σ.

the cost function as

$$C^* \approx \tau\lambda + (C_1 + C_2\sqrt{\psi^2 L})\sqrt{\lambda} \tag{11}$$

where $C_1 = \sqrt{(2kh\omega)}$ and $C_2 = b\Upsilon(\omega)$.

This result shows that in the stochastic case the cost function remains similar to the one in the deterministic case in the sense that it is a linear function of λ and $\sqrt{\lambda}$. The new element is that the coefficient of $\sqrt{\lambda}$ increases in demand uncertainty thanks to larger expected backorder costs and the required increase in inventory levels: total logistics cost is increasing in uncertainty, but less then proportionally.

Also, uncertainty is the product of the variance of demand (ψ^2) and the time to ship (L): if either of them is small, than logistics cost is not effected significantly by the other one. This result is highly intuitive: the effective uncertainty the firm faces is the variability of demand between its actions and the arrival of the shipment.

These observation lead to the important consequence that firms' transportation costs can feature strong economies of scale. While this is true in the deterministic case, the stochastic case shows that uncertainty even increase this nonlinearity through its effect on the desired inventory level. The model predicts that both transportation costs and the economies of scale increase in demand uncertainty and distance.

The model is also able to capture the role of perishability resulting from non-durability of foods or fashion goods. One may assume that these goods depreciate quicker then durable goods, hence h is higher for these goods than for durable goods. For simplicity, we may also assume that the backorder cost is also higher for these goods to a similar degree (hence ω is the same for the two type off goods). In such a case, both the lower and upper bound goes down in 7. Hence firms send such goods more frequently but in smaller shipments. Perishability, however, is quite distinct from uncertainty of demand in this framework.

5.2. Firm maximization

The previous models assumed that λ, (expected) quantity is given. When applying the model to real data, however, one has to take into account that market size and uncertainty affect the quantity choice of firms through changes in its marginal cost schedule. Higher uncertainty, for example, leads to an upward shift in the marginal cost curve, implying smaller quantity sold.

Let we denote the market size in country i as M_i. The demand curve the firm faces in this country is $\lambda_i = M_i D(p_i)$; $\frac{\partial D}{\partial \lambda_i} < 0$. The cost function of the firm is the sum of its production ($c_i\lambda_i$) and logistic costs:

$$C(\lambda_i) = c_i\lambda_i + \tau\lambda_i + (C_1 + C_2\sqrt{\psi^2 L})\sqrt{\lambda} \tag{12}$$

As noted above, this function features economies of scale, which are increasing in uncertainty. The firm maximizes its profit:

$$\Pi_i = D{-}1(\frac{\lambda_i}{M_i})\lambda_i - C(\lambda_i) \tag{13}$$

To get an intuition of comparative statics, note that the marginal cost schedule is:

$$MC_i = c_i + \tau + \frac{1}{2}(C_1 + C_2\sqrt{\psi^2 L})\frac{1}{\sqrt{\lambda}} \tag{14}$$

The marginal cost functions of two similar markets with different volatility is depicted on Figure [2]: market 2 is more uncertain, hence marginal costs are higher on it for all quantity levels. As a comparison, the horizontal line represents the iceberg transportation cost case, when marginal costs are constant.

Let us analyze first the effect of increase in market size, shown in Figure 3. Here, the increasing returns of logistics leads to a larger change in the quantity sold and smaller increase in price by the firm than under iceberg transportation costs. Hence, taking account inventory costs predicts a larger than proportional reaction of quantity to market size. As the elasticity of both shipment size and the number of shipments with respect to quantity is 1/2 in our framework, their elasticity with respect to market size can be somewhat larger than 1/2 thanks to the increasing returns of logistics.

Second, an increase in demand uncertainty tilts the marginal cost schedule. This is illustrated on (Figure 3), which compares two similar markets with different levels of uncertainty. Uncertainty reduces quantity sold, and the effect depends on the elasticity of demand and the slope of the marginal cost curve.

When analyzing the effect of uncertainty on shipment size and the number of shipments, we should combine this observation with the previous result that - with fixed quantity - uncertainty leads to larger and less frequent shipments. Hence, we expect that uncertainty leads to a decrease in frequency on two channels: first, it leads to a fall in quantity, and hence, to a decrease in frequency; second, it leads to less frequent shipments even when quantity is unchanged. An increase in uncertainty also leads to a fall in shipment size, which is mitigated to some extent by the direct effect of uncertainty on inventory decisions. The net effect depends on the shape of the demand and marginal cost functions.

In the empirical section of the paper we have shown a series of stylized fact on how uncertainty affects exporters' decisions. In the simple framework used here, we consistently showed that:

1) The elasticities of trade frequency and value per shipment with respect to demand are similar.

2) Higher uncertainty (a) reduces export value, (b) reduces the number of shipments but (c) has an ambiguous impact on the average value of shipments.

3) Holding export value fixed, higher uncertainty reduces the number of shipment

(and increases the average value per shipment).

4) Shipment time magnifies the impact of uncertainty.

Uncertainty indeed increases logistic costs reducing total sales, which directly tends to reduces the number of shipment and the average value. Firms however hold larger average inventories when demand is uncertain in order to decrease the expected value of backorder costs. This indirectly reinforce the negative impact of uncertainty on the number of shipments. Regarding the average value per shipment, the direct and indirect effects go in opposite directions, so that the impact of uncertainty is ambiguous. For a given value exported, only the indirect impact of uncertainty through the level of inventory holding works, so that the impact is unambiguous: uncertainty reduces the number of shipment and increases the average value per shipment.

6. Conclusion

Understanding the role of shipment frequency and showing that it is a new margin does not only matter for its own sake. Instead, firms may use this margin to adjust to different business conditions at various (product-destination) markets. When there is high uncertainty creating high potential costs, firms may mitigate these costs by flexibly adjusting their shipment frequency. In other words, the option to use shipment frequency as a margin of adjustment increase overall volume and is hence, rather beneficial. As long as trade liberalization, technological development or better infrastructure reduces the time required to ship, it leads to lower logistics costs and more trade.

We presented a simple inventory management model that reproduces the stylized facts present in the French data. It links uncertainty of demand a firm faces in a given market to its decision on how to serve that demand. Firms react by adjusting their shipment value as well as their shipment frequency. The number of shipments - measured as the number of months with nonzero exports - is an additional extensive margin allowing additional flexibility to firms in serving distant markets. Our empirical analysis confirms that firms respond to demand uncertainty by reducing the number of their shipments and increasing the average value per shipment for a given value exported in a year. We also show that the impact of uncertainty is magnified by the time needed to serve the destination market from the production location. A novel prediction of this model is that decreasing time to ship increases more the number of shipments and total exports to more distant and uncertain markets.

7. Appendix

Table 9: Poisson PML

	Panel A							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		value (log)				avg value (log)		
Sample	baseline	maritime	manuf	Incumbent	baseline	maritime	manuf	Incumbent
uncert (log)	-0.072***	-0.088***	-0.072***	-0.114***	-0.020***	-0.032***	-0.019***	-0.035***
	(0.009)	(0.010)	(0.009)	(0.011)	(0.007)	(0.008)	(0.007)	(0.008)
total value (log)								
Constant	8.623***	8.759***	8.622***	8.940***	8.098***	8.144***	8.092***	8.188***
	(0.045)	(0.100)	(0.046)	(0.050)	(0.028)	(0.064)	(0.029)	(0.030)
Firm*product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	568,131	300,906	542,205	332,365	568,131	300,906	542,205	332,365
Number of id	315,659	170,273	300,415	156,363	315,659	170,273	300,415	156,363
R-squared	0.060	0.065	0.060	0.065	0.050	0.060	0.051	0.059

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Clustered by destination/product

Table 10: Poisson PML

	Panel B							
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	number of shipments (log)							
Sample	baseline	maritime	manuf	Incumbent	baseline	maritime	manuf	Incumbent
uncert (log)	-0.053***	-0.056***	-0.053***	-0.079***	-0.030***	-0.028***	-0.030***	-0.040***
	(0.004)	(0.005)	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)	(0.004)
total value (log)					0.316***	0.325***	0.316***	0.338***
					(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.526***	0.615***	0.530***	0.752***	-2.202***	-2.235***	-2.194***	-2.274***
	(0.023)	(0.052)	(0.024)	(0.027)	(0.016)	(0.032)	(0.016)	(0.018)
Firm*product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	568,131	300,906	542,205	332,365	568,131	300,906	542,205	332,365
Number of id	315,659	170,273	300,415	156,363	315,659	170,273	300,415	156,363
R-squared	0.058	0.052	0.059	0.057	0.495	0.499	0.495	0.522

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Clustered by destination/product

Table 11: Effect of uncertainty - restricted sample

	(1)	(2)	(3)	(4)	(5)
	nbr of shipments (log)				
	OLS Fixed Effects		OLS Random effects		Tobit RE
Sample	Baseline	All shipments	Baseline	All shipments	All shipments
GDP (log)	0.071***	0.101***	0.016***	0.030***	0.051***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)
distance (log)	-0.075***	-0.108***	0.010***	0.005**	-0.058***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.001)
uncert (log)	-0.055***	-0.092***	-0.146***	-0.217***	-0.122***
	(0.004)	(0.005)	(0.006)	(0.007)	(0.003)
Constant	-0.807***	-1.227***	-0.013	-0.243***	-0.463***
	(0.051)	(0.066)	(0.046)	(0.050)	(0.013)
Firm*product FE	Yes	Yes	-	-	-
Observations	568,131	595,809	568,131	595,809	595,809
Number of id	315,659	319,068	315,659	319,068	319,068
R-squared	0.042	0.072			

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Clustered by destination/product

Table 12: Uncensored sample

	(1)	(2)	(3)	(4)	(5)	(6)
Dep var:	nbr of shipments (log)					
Sample	full sample	full sample	full sample	full sample	full sample	Maritime only
GDP (log)	0.030***	0.101***				
	(0.002)	(0.002)				
distance (log)	0.005**	-0.108***				
	(0.003)	(0.003)				
uncert (log)	-0.217***	-0.092***	-0.088***	-0.037***	-0.058	0.117***
	(0.007)	(0.005)	(0.005)	(0.003)	(0.037)	(0.039)
distance (log) * uncert (log)					0.002	-0.018***
					(0.004)	(0.005)
total value (log)				0.335***	0.335***	0.343***
				(0.001)	(0.001)	(0.001)
Constant	-0.243***	-1.227***	0.626***	-2.319***	-2.319***	-2.338***
	(0.050)	(0.066)	(0.028)	(0.016)	(0.016)	(0.032)
Firm*product FE	-	Yes	Yes	Yes	Yes	Yes
Destination FE	-	-	Yes	Yes	Yes	Yes
Observations	595,809	595,809	595,809	595,809	595,809	315,298
R-squared	0.016	0.072	0.096	0.577	0.577	0.576
Number of id	-	319,068	319,068	319,068	319,068	172,043

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Figure 2: Marginal cost functions with different volatility

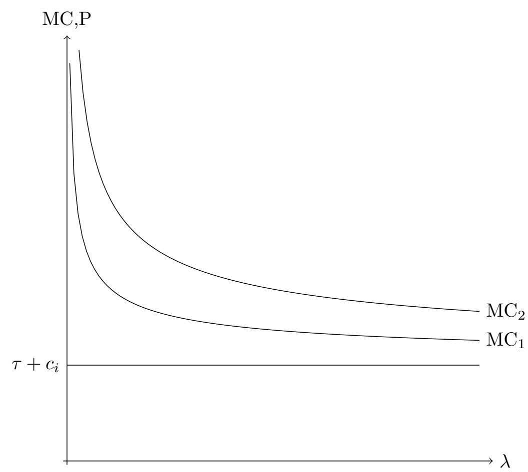


Figure 3: The effect of an increase in market size

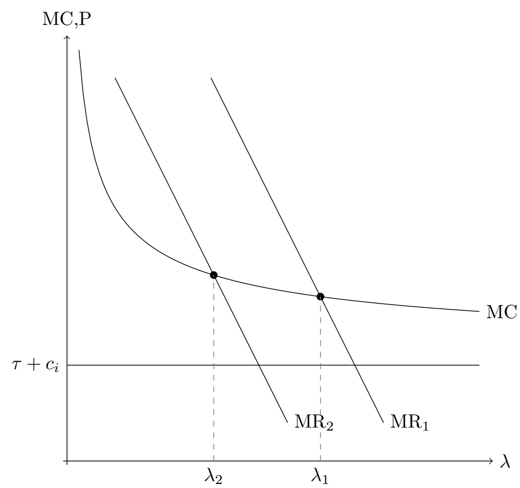
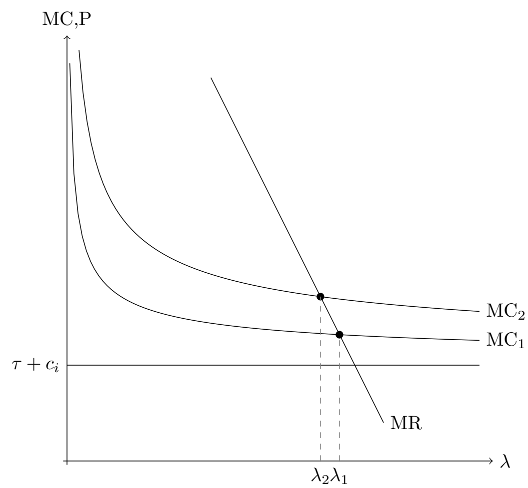


Figure 4: The effect of an increase in demand uncertainty



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