# Unconditional Quantile Estimation: An Application to the Gravity Framework.

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**Abstract**

Since its inception, the gravity model has been the cornerstone of empirical trade analysis. It has been used to estimate the marginal effects of various determinants of trade as well as to test hypothesized relationships, many of which have direct and significant policy implications. Conventional estimation methods derive the marginal effects of the covariates at the mean; or rather, only estimate the average effect of an explanatory variable on trade flows. This study applies unconditional quantile estimation (UQE), as developed by Firpo, Fortin, and Lemieux (2009), to a variant of the gravity model developed by Hallak (2006) in order to obtain income and distance elasticity estimates for imports of six differentiated agrifood products. Findings suggest that both income and distance elasticity estimates do vary across quantiles, suggesting that conventional estimation methods may limit the depth of analysis. The estimated income elasticities vary across products as well, both in terms of the underlying trends across quantiles and in magnitude, further demonstrating the capacity of UQE to identify how the underlying trend across quantiles is conditional on the product under examination.

# Introduction

Since its inception, the gravity model has been the cornerstone of empirical trade analysis. It has been used to estimate the marginal effects of various determinants of trade as well as to test hypothesized relationships, many of which have direct and significant policy implications. Conventional estimation methods derive the marginal effects of the covariates at the mean; or rather, only estimate the average effect of an explanatory variable on trade flows. This limits analysis as it fails to identify how, or if, the slope coefficients on the variables of interest change as the size of the trade flow varies. For example, a researcher may wish to test the hypothesis that the coefficient on distance becomes increasingly larger (in absolute terms) as the quantity vegetable imports increases due to the potential for spoilage; in other words, countries that are further away from each other will trade less. Results from the latter hypothetical study could then be used to demonstrate whether distance represents a larger impediment to trade in vegetables relative to other products, say wheat.

Firpo, Fortin, and Lemieux (2009) introduced an estimator they term unconditional quantile estimation (UQE), which permits the estimation of the marginal effects at various quantiles of the dependent variable. The approach involves the transformation of the dependent variable using a recentered influence function, and then estimating using a simple OLS regression. In 2011, Ker utilized UQE to estimate Engel elasticities for telecommunication expenditures. Results from the latter study demonstrated that individuals who spend less on telecommunications exhibit larger elasticities relative to those with higher expenditures. This study applies unconditional quantile estimation to a variant of the gravity model developed by Hallak (2006) in order to obtain income and distance elasticity estimates for agrifood imports. The objective of this study is to demonstrate the capacity of UQE to highlight how the marginal effects of determinants of trade may depend on the size of the trade flow, as such the main hypothesis investigates whether income and distance elasticities vary across quantiles for imports of six disaggregated agrifood products. Insight into how the covariates behave at different quantiles could provide trade economists with an applied tool to identify the key determinants of trade at different volumes – an important contribution for studies which seek to assess how trade costs influence trade in disaggregated products. In order to contrast the UQE estimates with those from conventional estimation methods, results from an OLS regression corrected for the presence of zero trade flows are included.

Six disaggregated agrifood products are examined here: wheat, rice, barley, coffee, beef and cheese. They were chosen as they represent trade in products which vary both in their sensitivity to distance and income. The first three commodities (wheat, rice and barley) are cereals representing staple foods for the majority of the world's poor, as well as intermediate inputs for livestock producers or for additional processing. They are easily stored over time implying that they can be shipped further distances with less instances of spoilage, as such our conjecture is that there will be less variability in distance coefficients on these commodities. In contrast, it is believed here that income elasticities should be substantially higher at lower quantiles then become smaller at higher quantiles, as in general as people get richer they begin to diversify their diet to include alternatives to cereals, such as dairy or meat products. In other words, as individuals become progressively richer they will first increase their consumption of cereals, and then substitute to a more diverse diet. Beef, cheese and coffee are included as they represent luxury or value-added food products. As such we expect that the magnitude of income elasticities will increase across quantiles, as the total amount of coffee, beef, and cheese imported are likely driven by the presence of individuals with larger disposable incomes. As beef and cheese are susceptible to spoilage, it is assumed that distance will have a larger impact on larger trade flows in general, and that elasticity estimates will become increasingly negative at larger trade flows.

The paper is structured as follows: the next section provides a briefly overview of UQE; the third section discusses the specification of the model, as well as highlighting any empirical issues arising during its estimation; the fourth section identifies the sources of the data used in this study; the fifth section discusses the study's findings and the final section concludes the paper.

## Unconditional Quantile Estimation

Conventional regressions involves estimation the marginal effect of a covariate at the mean of the dependent variable, holding all other covariates constant.[1] In other words, the coefficients generated by OLS can be interpreted as the change in the average of the dependent variable given a increase in the value of an explanatory variable. While in general this provides researchers with insight into the (average) relationships between an explanatory variable and the dependent variable, inference from it can be limiting in a policy context. For example, if a researcher wanted to estimate how income influences expenditure on coffee, then conventional regression approached would allow one to infer the the average Engel elasticity, but not permit one to identify differences in elasticity estimates between consumers with large expenditures relative to those with smaller ones.

[1]For example, the equation to estimate the slope parameter for a simple univariate OLS regression is:

$$\hat{\beta} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{1}$$

where $\bar{x}$ and $\bar{y}$ represent the mean of the explanatory and dependent variable respectively.

Firpo, Fortin, and Lemieux (2009) were the first to introduce unconditional quantile estimation (UQE) in their seminal paper. It differs from Koencker's (2005) preceding discussions of conditional quantile estimation (CQE), which estimates the effects of various quantiles on the conditional marginal distribution ($F(Y|X)$), or different quantiles on the error distribution ($F(\epsilon)$). While beneficial as a robust alternative to OLS in the presence of non-normal errors, the former approach is limited for economists as interpretation of the coefficients at various quantiles is difficult (Ker, 2011). In contrast, UQE seeks to examine the marginal effects of covariates at various quantiles of the dependent variable, or the *unconditional* marginal distribution of Y ($F(Y)$).

In order to assess how the marginal effects behave across quantiles of the dependent variable, UQE makes use of what Firpo, Fortin, and Lemieux (2009) refer to as the re-centered influence function (RIF). The RIF is obtained by adding back the distributional statistic of interest, a given quantile here, to the influence function – a function measuring the influence of an individual observation on a given a distributional statistic.[2] Equation 2 represents the influence function for a given quantile.

$$IF = \frac{\tau - I_{(-\infty, q_\tau)}}{f_Y(q_\tau)} \tag{2}$$

After adding back the quantile of interest ($q_\tau$), we get equation 3:

$$RIF_\tau = q_\tau + \frac{\tau - I_{(-\infty, q_\tau)}}{f_Y(q_\tau)} \tag{3}$$

where $I_{(-\infty, q_\tau)}$ represents a vector of dummy variables equal to one if the realization of Y is less then the value of y at the $\tau$ quantile, and $f_Y(q_\tau)$ is the density of Y evaluated at quantile $q_\tau$. The density is calculated nonparametrically using the Kernel density estimator,[3] and Silverman's rule of thumb to select the optimal smoothing parameter. Equation 3 represents the transformation of the dependent variable from which ordinary least squares can be applied. Thus, if we let $W_\tau = RIF_\tau$ then the effect of a marginal change in an explanatory variable on the outcome variable at quantile $\tau$ can be calculated by:

$$\hat{\beta}_\tau = (X^{'}X)^{-1}X^{'}W_\tau \tag{4}$$

While other methods of estimating the marginal effects have been proposed, Firpo, Fortin, and Lemieux

[2]In their paper, Firpo, Fortin, and Lemieux (2009, p. 954) focus on quantile regressions, however they mention that the approach can be extended to other statistics. The interested reader is directed to Sergio Firpo and Lemieux (2007).

[3]The standard normal was used as the kernel density function.

(2009) found that the estimates did not vary very much across methods.

# Empirical Model

## Conceptual Foundation and Specification

Since the establishment of it's theoretical foundation (e.g., Anderson (1979)), there has emerged a vast literature presenting various theoretical foundations justifying the empirical success of the gravity model. This study adopts an augmented version of Hallak's (2006) sector-level demand model. Hallak (2006) assumes a two-stage budgeting procedure, where in the first stage a representative consumer exogenously allocates the portion of their income across expenditures on spectrum of individual goods.[4] In the second stage, a Marshallian demand function for good $k$ for the representative consumer is obtained by maximizing a CES utility function subject to expenditure allocated to it in the first stage. The interested reader is encouraged to refer to Hallak (2006) for a more detailed derivation of the model.

As the conceptual foundation of the gravity model is in multiplicative form, we estimate the log-linearized transformation (equation 5).[5]

$$\begin{aligned} \ln(imp_{ijtk}) =& \beta_0 + \psi_i + \psi_j + \psi_t + \beta_4 \ln GDPpc_{ijt} + \beta_5 \ln Dist_{ij} \\ & \beta_6 Adj_{ij} + \beta_7 Lang_{ij} + \beta_8 Colony_{ij} + \beta_9 Land_i + \beta_{10} PTA_{ijt} \end{aligned} \tag{5}$$

As advocated by Anderson and van Wincoop (2003), importer and exporter fixed effects are used to control for the omission of price data. The dependent variable ($imp_{ijt}$) is the per capita quantity of imports of good $k$ in period $t$. Several variables are included to approximate the cost of engaging in trade with a particular exporter, including: distance ($Dist_{ij}$); and several dummy variables equal to one if the importing country is landlocked ($Land_i$), if the trading partners share a common official language ($Lang_{ij}$), if they had a common colonizer ($Colony_{ij}$), were adjacent to each other ($Adj_{ij}$) or if a preferential trade agreement existed between them in period $t$ ($PTA_{ijt}$).

Table 1: Frequency of Zero Trade Flows

| Commodity | Frequency of Positive Observations | Total Observations | Percentage of Zeros |
|---|---|---|---|
| Wheat | 7,041 | 170,200 | 95.9% |
| Barley | 3,901 | 170,200 | 97.7% |
| Rice | 13,231 | 170,200 | 92.2% |
| Coffee | 18,988 | 170,200 | 88.8% |
| Beef | 8,041 | 170,200 | 95.3% |
| Cheese | 13,285 | 170,200 | 92.2% |

## Zero Trade Flows

Several studies (Jayasinghe, Beghin, and Moschini (2010), Silva and Tenreyro (2006), etc.) have addressed the dilemma of how to address the prevalence of zero trade flows, as the multiplicative gravity model is conventionally estimated as log-linearized model. Zeroes can arise as a result of either missing data (a result more common when dealing with developing nations) and/or due to the reality that not all countries engage in trade with each other – an observation which become more frequent when dealing with increasingly disaggregated data. In contrast to the traditional approach, recent studies have advocated the use of a poisson-pseudo maximum likelihood estimator (PPML) as it accounts the multiplicative conceptual form instead of linear transformation of the conceptual model (Silva and Tenreyro, 2006); however, since the PPML is based off of the Poission distribution, typically used for count data, it involves estimating the data set in levels, and treats all zeros as universally the same. Due to the large dataset and correspondingly large number of countries included in the UN comtrade database, the source of the dependent variable, missing data is commonplace when dealing with a dataset of this size and disaggregation. Of the 185 countries used in this study, 116 have at least one of the five years missing, with a total of 290 missing years of data (or at least 53,360 zero observations are indicative of missing data). Since the PPML estimator intrinsically treats all zeros as corner solution, it fails to account for the fact that a large portion of the data set (approximately 30 percent of the sample) represents missing data and does not account for the sample selection bias. Furthermore, as Jayasinghe, Beghin, and Moschini (2010) argue that some zeros may represent marginal importers, or rather importers who could engage in trade, while other zeros may result as a consequence of prohibitively high trade costs. In short, the challenge is that the absence of trade between two countries in

[4] A limitation of modelling the gravity model this way is that it implicitly conceptualizes all goods as final goods, and negates the reality that many commodities are imported as intermediate goods. In this respect, one could easily derive the input factor demand equation by modelling the CES utility function as a CES production function.

[5] Silva and Tenreyro (2006) demonstrate that estimation of a log-linearized (multiplicative) gravity model can result in inconsistent estimates in the presence of heteroskedasticity. However, due to the preliminary nature of this work we do not address this issue here.

a given period, does not occur with the same probability for all country pairs. Consequentially we adopt the approach advocated by Jayasinghe, Beghin, and Moschini (2010), and estimate the probability of one country importing from another.

To correct for the prevalence of zeros in the data set, the authors employ a two-step procedure where a Probit regression is used to calculate the inverse mills ratio in the first step, which is then included as a explanatory variable in the second stage where the proposed UQE estimator is employed Heckman (1979).

$$\begin{aligned} t_{ijt} =& \beta_0 + \psi_i + \psi_j + \psi_t + \beta_4 \ln GDP_{jt} + \beta_5 \ln Pop_{jt} + \beta_6 \ln GDP_{it} + \beta_7 \ln Pop_{it} \\ &+ \beta_8 \ln Dist_{ij} + \beta_9 Adjacent_{ij} + \beta_{10} Language_{ij} + \beta_{11} Colony_{ij} \\ &+ \beta_{12} Urban_{it} + \beta_{13} PTA_{ijt} \end{aligned} \tag{6}$$

Equation 6 represents the selection equation employed in this study, where the dependent variable ($t_{ijt}$) is equal to one if the country pair exhibits a positive trade flow and zero otherwise. The selection equation is specified similar to the traditional gravity model; that is, the probability of a country importing from a given exporter is a function of their respective GDP's, population's, variables affecting trade costs and the proportion of the importer's population living in urban centres ($Urban_{it}$). The last variable is included as an exclusion restriction to account for the fact that a larger concentration of the population in urban centres likely increases the number of people who purchase food, and as such are more likely to purchase agrifood imports. As Puhani (2000) emphasizes finding an appropriate exclusion restrictions is essential to ensure that there is no collinearity between the inverse mills ratio and the other covariates.

## Endogeniety

The potential endogeniety of PTA is prevalent in the trade potential literature, many argue that the direction of causation between trade flows and a PTA is ambiguous (Baier and Bergstrand, 2007).[6] Our conjecture is that since this study is examining very disaggregated trade flows, that the magnitude of trade between two countries is likely not highly correlated with overall levels of trade (see table 2). In contrast, if we were to examine an aggregate level of trade, such as the trade in all goods and services between a country pair, that simultaneity bias is likely an issue. Intuitively, there are many countries that engage in a high level of overall trade, but not in all goods. As such it is argued here that endogeniety is not an issue, as potential gains to trade for a given commodity are unlikely to be a significant driver of a country's choice to negotiate

[6] Baier and Bergstrand (2007) argue that simultaneity bias could arise because the establishment of a PTA could be a function of the level of trade, and the level of trade is a function of the market access granted by the establishment of a PTA.

Table 2: Tradeflows – Correlation Coefficients

| | **Coffee** | **Rice** | **Cheese** | **Beef** | **Barley** | **Wheat** | **Non-oil Trade** |
|---|---|---|---|---|---|---|---|
| **Coffee** | 1 | | | | | | |
| **Rice** | 0.0399 | 1 | | | | | |
| **Cheese** | 0.1233 | 0.0553 | 1 | | | | |
| **Beef** | 0.1396 | 0.1034 | 0.4165 | 1 | | | |
| **Barley** | 0.0289 | 0.0345 | 0.2205 | 0.1822 | 1 | | |
| **Wheat** | 0.0378 | 0.1195 | 0.1542 | 0.2273 | 0.2429 | 1 | |
| **Non-oil Trade*** | 0.1352 | 0.0798 | 0.2865 | 0.2326 | 0.1090 | 0.1465 | 1 |

* Denotes a UN Comtrade product group.

a PTA. Therefore, it is argued that simultaneity bias is not present.

## Data

To examine how the income and distance elasticities vary across quantiles, we use annual import data on the per capita quantity of six commodities (wheat, barley, rice, coffee, beef and cheese) between 189 countries.[7] This results in 170,200 observations for each commodity over the period 2007-2011. Criteria for inclusion into the sample was simple, as long as all of the necessary explanatory variables were available over the sample period, the country was included. Table 5 lists all of the countries used in this study.

All annual bilateral import quantities were obtained from UN comtrade, and divided by the importing country's population in order to obtain the per capita quantity (in kgs.) of the imported commodity for a given year. As can be observed in the final column of table 1, the use of disaggregated imports coupled with the inclusion of a large and diverse sample, has resulted in a high frequency of zeros for each of the commodities examined here. As such failure to account for them would have biased results.

Data on GDP, GDP per capita, and population were obtained from the World Bank website (data.worldbank.org). Since all monetary variables are reported in USD, they were deflated using a US GDP deflator acquired from the International Monetary Fund's World Economic Outlook Database (www.imf.org).[8] All time invariant explanatory variables were obtained from the GeoDist dataset available on the CEPII website (http://www.cepii.fr). Finally, the preferential trade agreement (PTA) dummy variable was generated using the World Trade Organization's (WTO) Regional Trade Agreements Information System (RTA-IS) (www.wto.org). Only those agreements classified as either a free trade agreement or customs union were

[7] Each of these goods is defined using the SITC-3 nomenclature. We define each of the products as: wheat (Wheat/meslin – 041); rice (Rice – 042); barley (Barley grain – 043); coffee (Coffee, not roasted – 0711+ Coffee, roasted – 0712); beef (Beef, fresh/chilled/frozen – 011); and cheese (Cheese and curd – 024).

[8] The base year is 2010.

counted as an PTA, partial scope agreements were omitted due to the generally ambiguous scope of their coverage.[9] PTAs were included based on the year the agreement came into force, while only those agreements encapsulating trade in either goods, or goods and services were included in the sample.

## Results

For simplicity, the coefficients pertaining to the fixed effects and trade cost variables are not discussed here; however, all omitted explanatory variables exhibit the expected sign and are statistically significant. Tables 3 and 4 explicitly list the elasticity estimates and their standard errors for each product at each quantile.

As can be clearly observed from figures 1 and 2, both income and distance elasticity estimates vary across quantiles for all six commodities, while the OLS coefficient estimates remain constant across all quantiles (red lines). This implies that the marginal effect of income and distance on varies on imports of different sizes, and that conventional estimation methods would fail to capture the change in the marginal effects at different trade volumes.

All income elasticities are positive with the exception of rice at the $5^{th}$, $10^{th}$ and $15^{th}$ quantiles, coffee at the $10^{th}$ quantile and beef at the $5^{th}$ quantile. However, as table 3 demonstrates all negative income elasticities are statistically insignificant. The distance elasticity estimates appear to be statistically significant and negative (see table 4).

Figure 1 (panels a, b, and c) reveals that for each of the cereals (rice, barley, and wheat) that the income elasticities exhibit a common pattern across the quantiles. Initially the elasticity estimates briefly increase, peak and then begin to steadily decline. This observation echoes our earlier intuition – that income elasticities will be smaller for countries with larger annual per capita import volumes of cereals. In terms, of magnitude it appears that income elasticity estimates are less variable for rice, which ranges between -0.5 and 1.5, relative to wheat and barley which range between 0 and 3, and 1 and 4.5, respectively. Additionally the overall pattern of income elasticiities for wheat and barley appear to be quite similar, suggesting that people may view them as more homogenous relative to rice.

Smaller income elasticities at the lowest levels of per capita imports may be representative of marginal trade relationships due to lower incomes, where individuals live more agrarian communities and could be still heavily reliant on subsistence agriculture. The reason that we observe the increase in income elasticities around the $20^{th}$ quantile may be that it represents the threshold at which people/firms begin consume

[9] For several agreements, WTO records contain additional notes revealing that several members who have not notified the WTO were in practice actively involved in the agreement. While not official these countries are accounted.

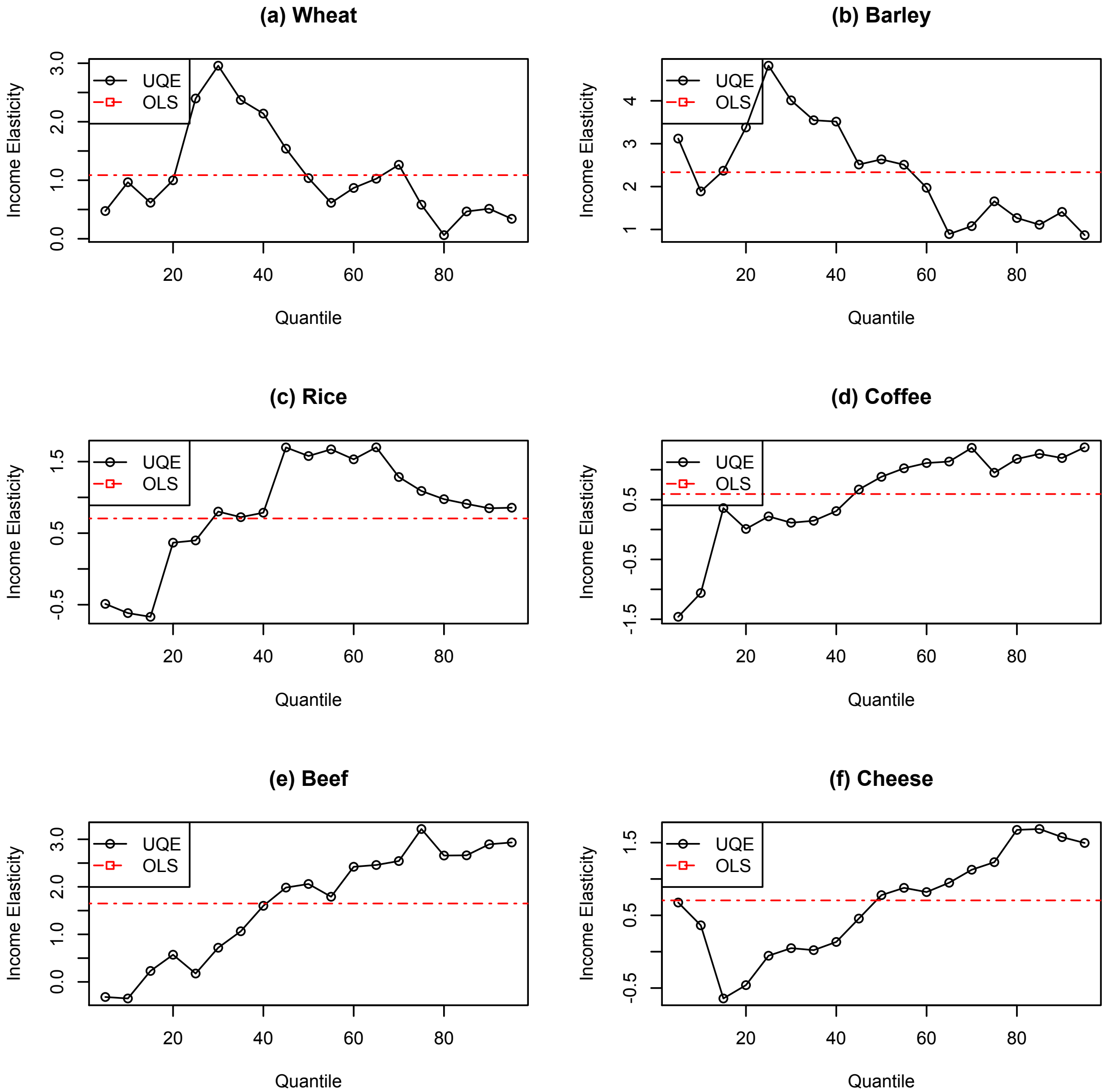


Figure 1: Individual Commodity Income Elasticities

imported cereals either for direct consumption or as inputs for in the consumption of other value-added goods. For wheat and barley the magnitude of the elasticities begin to progressively decline after peaking, with the elasticities for wheat approaching zero at the largest quantile. This decline could suggests that as nations become wealthier that imported wheat represents a more inferior good. The income elasticities for rice only experience a modest decline and then plateau at around 0.5, while despite the sustained decline barley appears to still exhibit income elasticities around unity at the highest quantiles.

The income elasticities on the luxury and value-added agrifood products are positive at all quantiles, with the few aforementioned exceptions. Beef, cheese and coffee all exhibit a consistently positive trend, where the highest income elasticity occur at the largest trade flows. A finding which remains consistent with our initial intuition; richer individuals will import (consume) more value-added or luxury goods such as coffee. The key distinction between the latter group of imports is that the imports of beef appears to be notably more responsive to income – at the $80^{th}$ quantile beef exhibits an income elasticity of roughly 2.5, while cheese and coffee has an estimate of 1.6 and 1. This implies that if income increases by a percent, that the amount of beef, cheese and coffee imported will increase by 2.5, 1.6 and 1 percent, respectively. Unlike it's counterparts, cheese is unique in that the fifth and tenth appear to exhibit large income elasticities in excess of one. This could be attributable to niche trade in artisan cheeses.

For wheat and barley, it appears that distance has the equivalent of an inverted relationship that import volume had with income. At lower quantiles distance appears to have the smallest impact, however as one moves across quantiles distance appears to have an increasingly negative impact on import volume until after the $60^{th}$ quantile where the elasticity begins to increase in magnitude to -2. This could be indicative that larger trade flows are more indicative of systemic relationships, and therefore are not as sensitive to higher trade costs as marginal importers, which could explain why the distance elasticities begin to rebound after the initial decline. The distance elasticities on coffee exhibit a similar pattern - initially decreasing and then increasing after the $80^{th}$ quantile, but are less variable ranging more modestly between -0.6 and -1.6

Distance appears to have a generally increasingly negative effect on per capita imports of rice. The interesting finding is that rice has a distance elasticity near zero, although statistically insignificant, at the $5^{th}$ quantile. Beef and cheese both demonstrate a generally monotonically decreasing trend in distance elasticities which range from -1.28 to -3 and -0.5 to -3.3, respectively.

Results from the distance elasticities appear to be generally consistent with our original hypothesis that the (negative) effect of distance on per capita trade flows would increase with trade volume. A finding which may provide some support for the notion of the regionalization of trade is disaggregated agrifood products.

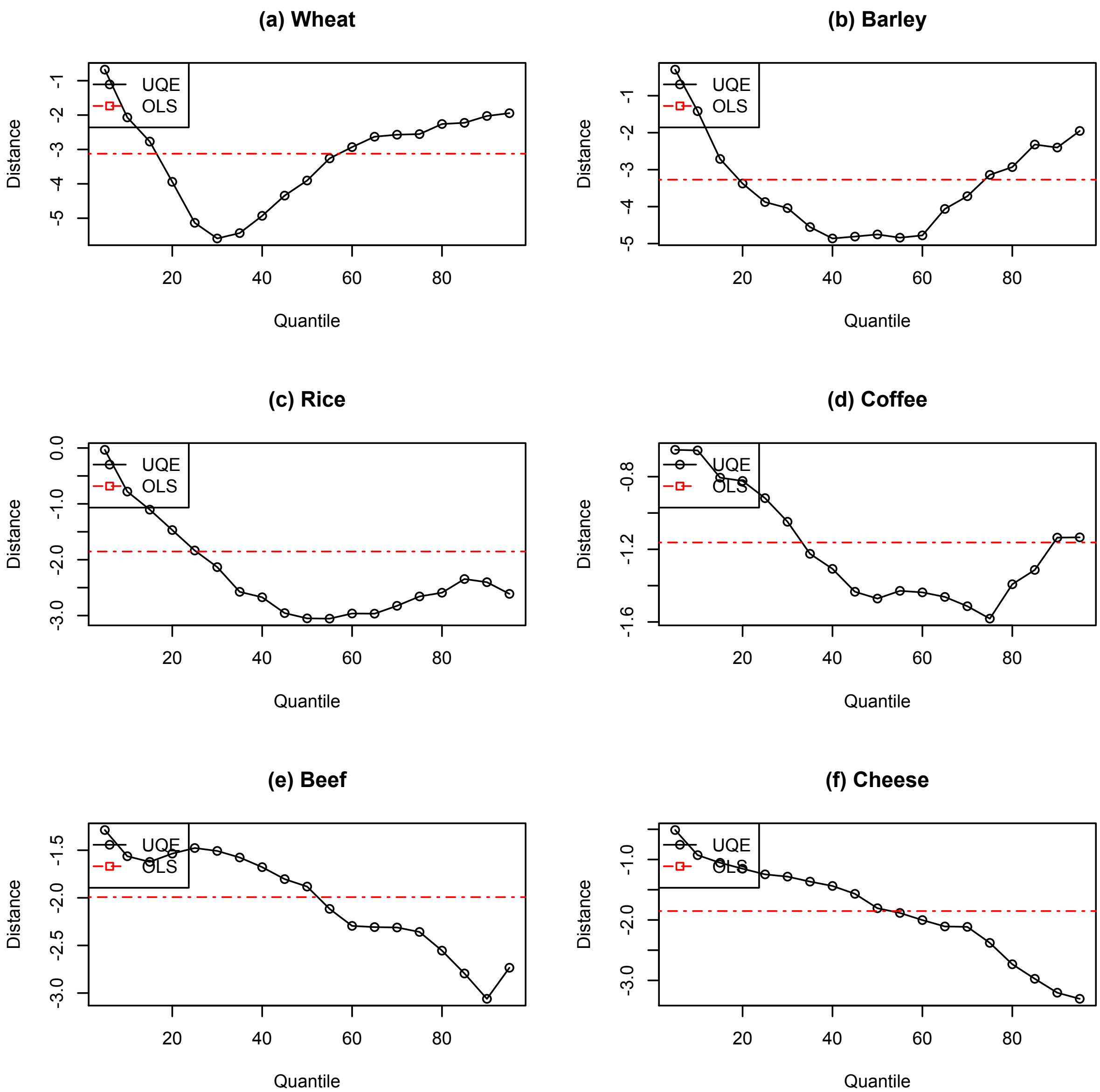


Figure 2: Individual Commodity Distance Elasticities

Perhaps the most surprising artifact is that the distance elasticities are larger in absolute terms for wheat and barley than for the value-added products beef and cheese, which are more susceptible to spoilage relative to the former commodities.

## Conclusion

This paper applied unconditional quantile estimation to the gravity model to estimate the income and distance elasticities for six disaggregated agrifood products. To account for the presence of zeros, usually in excess of 90 percent of the sample, we employ a two-stage estimation procedure where the inverse mills ratio is estimated in the first stage using a Probit model, and then included in the regression in the second stage. This was done as it accounts for the sample selection bias arising zeros resulting from data missing from the UN comrade database, and its ability of the approach to approximate the probability that two countries will engage in trade (Jayasinghe, Beghin, and Moschini, 2010). Furthermore, prices and other country-specific heterogeneity is controlled for using exporter, importer and year fixed effects.

Income elasticities for wheat and barley initially increase and then declined, rice again increases but then begins to decline modestly. The general pattern of increase and then decline is likely attributable to fact that wealthier individuals have a tendency to diversify their diet as they become richer. As predicted the income elasticities increase at higher quantiles for the luxury or value-added products of coffee, cheese and beef. This is likely due to the fact that as individuals become richer they can afford to consume these products. All of the distance elasticities are negative and statistically significant. For all products examined here all of the distance elasticities become increasingly negative at higher quantiles. However, for wheat and barley, and to a lesser extent coffee, the distance coefficients rebound become slightly smaller in absolute terms.

Our results remain consistent with our original justification for its application – revealing that estimates of the marginal effects for income (per capita GDP) and distance vary across quantiles. An additional benefit of UQE highlighted in this study is the fact that products also behave differently across quantiles.

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Table 3: Income Elasticity Estimates by Commodity (2007-2011)

| Quantile | Wheat (a) | Barley (b) | Rice (c ) | Coffee (d) | Beef (e) | Cheese (f) |
|---|---|---|---|---|---|---|
| 5 | 0.23 | 3.13 | -0.03 | 0.23 | -0.54 | 1.40 |
| | (1.5909) | (1.9570) | (0.9659) | (0.8549) | (1.2407) | (0.9500) |
| 10 | 0.86 | 1.88 | -0.44 | -0.16 | 0.05 | 0.96 |
| | (1.3003) | (1.6125) | (0.7661) | (0.6520) | (1.0635) | (0.7740) |
| 15 | 0.44 | 2.87** | -0.66 | 0.89 | 0.36 | 0.29 |
| | (1.2511) | (1.4168) | (0.6842) | (0.5878) | (0.9428) | (0.6740) |
| 20 | 0.87 | 3.82*** | 0.28 | 0.27 | 0.33 | 0.01 |
| | (1.2154) | (1.3485) | (0.6329) | (0.5297) | (0.7885) | (0.5708) |
| 25 | 1.80 | 5.41*** | 0.22 | 0.26 | 0.70 | 0.55 |
| | (1.2669) | (1.3160) | (0.5723) | (0.4773) | (0.6974) | (0.5160) |
| 30 | 2.32* | 4.80*** | 0.47 | 0.18 | 1.12* | 0.60 |
| | (1.2333) | (1.2940) | (0.5591) | (0.4610) | (0.6637) | (0.4672) |
| 35 | 1.98* | 4.11*** | 0.24 | 0.31 | 0.85 | 0.51 |
| | (1.1133) | (1.2862) | (0.5519) | (0.4310) | (0.6194) | (0.4356) |
| 40 | 1.72* | 4.11*** | 0.26 | 0.46 | 1.50** | 0.48 |
| | (1.0205) | (1.2956) | (0.5438) | (0.4277) | (0.5862) | (0.4107) |
| 45 | 1.39 | 3.05** | 1.08** | 0.69* | 2.12*** | 0.79* |
| | (0.8662) | (1.3000) | (0.5156) | (0.4062) | (0.5629) | (0.4050) |
| 50 | 0.96 | 3.08** | 0.96* | 0.80** | 2.26*** | 1.31*** |
| | (0.7623) | (1.2980) | (0.4963) | (0.3769) | (0.5578) | 0.3868) |
| 55 | 0.59 | 2.78** | 1.12** | 0.89** | 2.00*** | 1.20*** |
| | (0.6612) | (1.1963) | (0.4894) | (0.3742) | (0.5295) | (0.3965) |
| 60 | 0.84 | 1.97* | 1.01** | 0.91*** | 2.27*** | 1.20*** |
| | (0.5860) | (1.1895) | (0.4796) | (0.3517) | (0.5201) | (0.3854) |
| 65 | 1.12** | 0.89 | 1.09** | 0.96*** | 2.33*** | 1.11*** |
| | (0.5614) | (1.0165) | (0.4782) | (0.3465) | (0.5171) | (0.3917) |
| 70 | 1.37** | 1.23 | 0.63 | 1.29*** | 2.40*** | 1.36*** |
| | (0.5494) | (0.9436) | (0.4742) | (0.3414) | (0.5042) | (0.3853) |
| 75 | 0.63 | 1.64* | 0.53 | 1.02*** | 2.63*** | 1.27*** |
| | (0.5620) | (0.8645) | (0.4613) | (0.3539) | (0.4970) | (0.3839) |
| 80 | 0.17 | 1.13 | 0.47 | 1.02*** | 2.36*** | 1.64*** |
| | (0.5826) | (0.8357) | (0.4465) | (0.3657) | (0.4786) | (0.3967) |
| 85 | 0.49 | 0.96 | 0.43 | 1.04*** | 2.29*** | 1.52*** |
| | (0.5794) | (0.8430) | (0.4287) | (0.3782) | (0.4696) | (0.4244) |
| 90 | 0.57 | 0.98 | 0.23 | 1.10*** | 2.44*** | 1.36*** |
| | (0.6443) | (0.8653) | (0.4636) | (0.3933) | (0.4869) | (0.4524) |
| 95 | 0.41 | 0.45 | 0.44 | 1.08** | 2.64*** | 1.21** |
| | (0.6178) | (0.9281) | (0.5893) | (0.4410) | (0.5819) | (0.4713) |

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Distance Elasticities by Commodity (2007-2011)

| Quantile | Wheat (a) | Barley (b) | Rice (c ) | Coffee (d) | Beef (e) | Cheese (f) |
|---|---|---|---|---|---|---|
| 5 | -0.68 | -0.30 | -0.03 | -0.65*** | -1.29*** | -0.51** |
| | (0.5188) | (0.5283) | (0.3006) | (0.1485) | (0.2765) | (0.2294) |
| 10 | -2.07*** | -1.42*** | -0.78*** | -0.66*** | -1.56*** | -0.93*** |
| | (0.4299) | (0.4829) | (0.2438) | (0.1138) | (0.2470) | (0.1873) |
| 15 | -2.77*** | -2.71*** | -1.10*** | -0.81*** | -1.62*** | -1.05*** |
| | (0.4087) | (0.4590) | (0.2153) | (0.1007) | (0.2285) | (0.1690) |
| 20 | -3.94*** | -3.38*** | -1.47*** | -0.82*** | -1.54*** | -1.15*** |
| | (0.4072) | (0.4319) | (0.1995) | (0.0903) | (0.1876) | (0.1453) |
| 25 | -5.13*** | -3.88*** | -1.84*** | -0.92*** | -1.48*** | -1.25*** |
| | (0.4336) | (0.4304) | (0.1878) | (0.0877) | (0.1643) | (0.1295) |
| 30 | -5.59*** | -4.04*** | -2.13*** | -1.05*** | -1.51*** | -1.28*** |
| | (0.4443) | (0.4143) | (0.1823) | (0.0834) | (0.1599) | (0.1192) |
| 35 | -5.43*** | -4.55*** | -2.58*** | -1.23*** | -1.58*** | -1.37*** |
| | (0.4191) | (0.4199) | (0.1777) | (0.0823) | (0.1532) | (0.1152) |
| 40 | -4.93*** | -4.86*** | -2.67*** | -1.31*** | -1.68*** | -1.44*** |
| | (0.3868) | (0.4470) | (0.1708) | (0.0811) | (0.1476) | (0.1137) |
| 45 | -4.34*** | -4.81*** | -2.96*** | -1.43*** | -1.80*** | -1.57*** |
| | (0.3300) | (0.4400) | (0.1717) | (0.0802) | (0.1470) | (0.1084) |
| 50 | -3.90*** | -4.75*** | -3.05*** | -1.47*** | -1.88*** | -1.81*** |
| | (0.3100) | (0.4350) | (0.1701) | (0.0754) | (0.1494) | (0.1054) |
| 55 | -3.26*** | -4.84*** | -3.06*** | -1.43*** | -2.12*** | -1.88*** |
| | (0.2737) | (0.4117) | (0.1692) | (0.0732) | (0.1458) | (0.1046) |
| 60 | -2.93*** | -4.78*** | -2.96*** | -1.44*** | -2.30*** | -2.00*** |
| | (0.2227) | (0.4027) | (0.1717) | (0.0718) | (0.1430) | (0.1058) |
| 65 | -2.63*** | -4.06*** | -2.97*** | -1.46*** | -2.31*** | -2.11*** |
| | (0.2372) | (0.3987) | (0.1698) | (0.0729) | (0.1416) | (0.1166) |
| 70 | -2.57*** | -3.72*** | -2.83*** | -1.51*** | -2.31*** | -2.11*** |
| | (0.2300) | (0.3469) | (0.1702) | (0.0755) | (0.1379) | (0.1178) |
| 75 | -2.55*** | -3.14*** | -2.66*** | -1.58*** | -2.36*** | -2.38*** |
| | (0.2515) | (0.3287) | (0.1724) | (0.0769) | (0.1426) | (0.1209) |
| 80 | -2.26*** | -2.93*** | -2.59*** | -1.39*** | -2.56*** | -2.73*** |
| | (0.2617) | (0.3413) | (0.1833) | (0.0831) | (0.1456) | (0.1293) |
| 85 | -2.23*** | -2.32*** | -2.35*** | -1.31*** | -2.80*** | -2.97*** |
| | (0.2759) | (0.3539) | (0.1825) | (0.0819) | (0.1537) | (0.1536) |
| 90 | -2.03*** | -2.40*** | -2.40*** | -1.14*** | -3.06*** | -3.20*** |
| | (0.2956) | (0.3766) | (0.2002) | (0.0905) | (0.1662) | (0.1912) |
| 95 | -1.95*** | -1.95*** | -2.61*** | -1.13*** | -2.73*** | -3.31*** |
| | (0.3269) | (0.4773) | (0.2797) | (0.1087) | (0.2242) | (0.2237) |

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: List of Sample Countries

| | | | |
|---|---|---|---|
| Afghanistan | Ecuador | Lithuania | Samoa |
| Albania | Egypt | Luxembourg | Sao Tome and Principe |
| Algeria | El Salvador | Macao | Saudi Arabia |
| Angola | Equatorial Guinea | Macedonia | Senegal |
| Antigua and Barbuda | Eritrea | Madagascar | Serbia |
| Argentina | Estonia | Malawi | Seychelles |
| Armenia | Ethiopia | Malaysia | Sierra Leone |
| Australia | Fiji | Maldives | Singapore |
| Austria | Finland | Mali | Slovakia |
| Azerbaijan | France | Malta | Slovenia |
| Bahamas | Gabon | Marshall Islands | Solomon Islands |
| Bahrain | Gambia | Mauritania | South Africa |
| Bangladesh | Georgia | Mauritius | South Korea |
| Barbados | Germany | Mexico | Spain |
| Belarus | Ghana | Micronesia | Sri Lanka |
| Belgium | Greece | Moldova | Sudan |
| Belize | Grenada | Mongolia | Suriname |
| Benin | Guatemala | Montenegro | Swaziland |
| Bhutan | Guinea | Morocco | Sweden |
| Bolivia | Guinea-Bissau | Mozambique | Switzerland |
| Bosnia Herzegovina | Guyana | Myanmar | Tajikistan |
| Botswana | Haiti | Namibia | Tanzania |
| Brazil | Honduras | Nepal | Thailand |
| Brunei Darussalam | Hong Kong | Netherlands | Timor-Leste |
| Bulgaria | Hungary | New Zealand | Togo |
| Burkina Faso | Iceland | Nicaragua | Tonga |
| Burundi | India | Niger | Trinidad and Tobago |
| Cambodia | Indonesia | Nigeria | Tunisia |
| Canada | Iran | Norway | Turkey |
| Cameroon | Iraq | Oman | Turkmenistan |
| Cape Verde | Ireland | Pakistan | Tuvalu |
| Central African Republic | Israel | Palau | Uganda |
| Chad | Italy | Panama | Ukraine |
| Chile | Jamaica | Papua New Guinea | United Arab Emirates |
| China | Japan | Paraguay | United Kingdom |
| Colombia | Jordan | Peru | United States |
| Comoros | Kazakhstan | Philippines | Uruguay |
| Costa Rica | Kenya | Poland | Uzbekistan |
| Cote d'Ivoire | Kiribati | Portugal | Vanuatu |
| Croatia | Kuwait | Qatar | Venezuela |
| Cyprus | Kyrgyzstan | Republic of Congo | Vietnam |
| Czech Republic | Laos | Romania | Yemen |
| Democratic Republic of Congo | Latvia | Russia | Zambia |
| Denmark | Lebanon | Rwanda | Zimbabwe |
| Djibouti | Lesotho | St. Kitts and Nevis | |
| Dominica | Liberia | St. Lucia | |
| Dominican Republic | Libya | St. Vincent and the Grenadines | |