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The income elasticity of import demand: A meta-survey

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Abstract

Import demand has been a major research topic in international economics for the past 80 years because of its importance for analyzing trade and evaluating trade policies. The goal of this paper is to survey the literature and conduct a meta-analysis of empirical studies on import demand with the intention of clarifying the effect of economic development on income elasticity. In particular, we test the hypothesis that higher income levels are associated with a more elastic import demand. We apply a combination of parametric and non-parametric methods on estimates from a sample of 152 papers published over the period 1975-2014 and find that this relationship is significant and robust. Specifically, kernel densities of income elasticity estimates for high-income countries in North America and Europe are shown to exceed those for poorer parts of the world. The results from quartile regressions confirm this pattern and establish its robustness when controlling for the effect of model specifications.

Keywords: trade, import demand, income elasticity, meta-analysis, survey

JEL: F10; F14

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1 Introduction

The estimation of import demand has a long history, going back to the 1940s (de Vegh, 1941; Adler, 1945). Accordingly, the empirical exercise of regressing imports on income and relative prices has developed into a sizable literature that reports estimates of income and price elasticities for countries ranging from the US (Hummels and Lee, 2018) and China (Gozgor, 2014) to Brunei (Anaman and Buffong, 2001) and Mauritius (Narayan and Narayan, 2010) and for products as diverse as peanuts (Boonsaeng et al., 2008), crude oil (Fedoseeva and Zeidan, 2018), gold (Mukherjee et al., 2017), and wooden beds (Wan et al., 2010). Moreover, the relevance of import demand elasticities is highlighted by the fact that their estimation is often conducted in the context of broader research questions exploring, among others, the effects of income inequality (Adam et al., 2012), trade liberalization (Glover and King, 2011), anti-dumping duties (Nizovtsev and Skiba, 2016), foreign exchange reserves (Arize and Osang, 2007), and European integration (Barrell and te Velde, 2002). The collapse of trade following the global financial crisis of 2008 and the growing trade tensions provoked by protectionist policies in recent years have sparked renewed interest in the topic. At the same time, the most recent surveys of the literature on import demand are dated (Sawyer and Sprinkle, 1999; Marquez, 2002) and often focus on a single country, such as the US (Sawyer and Sprinkle, 1996) or Japan (Sawyer and Sprinkle, 1997).

This paper examines the literature on import demand by conducting a meta-analysis of the corresponding elasticities estimates. In particular, we use a sample of 152 empirical studies published between 1975 and 2014 to collect a large number of estimates of the income elasticity of import demand for various countries. These estimates are then analyzed using a combination of parametric and non-parametric methods. Kernel densities are employed to visualize the entire distribution of income elasticity estimates, highlighting the modal point, while quantile regressions help us obtain parametric estimates for the conditional median and both tails of this distribution. In addition, we explore the impact of model specification, year of publication, sample composition, and sample period length on the distribution.

The main objective of the paper is twofold. First, the study of import demand is in great need of an updated survey of the literature, given that the most recent overviews were published almost two decades ago. For instance, Marquez's (2002) monograph provides a very detailed discussion of various methodological and modelling aspects and issues in the estimation of export and import demand and presents trade elasticities for the US and a small sample of Asian countries. In their book, Sawyer and Sprinkle (1999) not only review the key contributions of existing research but also report hundreds of estimates of income and price elasticities of demand for imports and exports for a large number of countries published between the 1970s and the 1990s. Such an abundance of estimates calls for a meta-analysis, which, to the best of our knowledge, has not yet been done. Ultimately, we opt for an idiosyncratic approach that combines features of a survey and meta-analysis. Specifically, we conduct a statistical investigation but are more selective in the choice of papers included in the sample than a traditional meta-analysis, while we also seek to synthesize a consensus from the existing knowledge but cover a wider range of works than is typical for a survey with a focus on seminal contributions.

The second goal of our paper narrows the scope of the empirical investigation to the income elasticity of import demand. This elasticity provides important insights into the effects of income shocks on trade patterns and is one of the key parameters estimated in the literature. At the same time, most studies produce a single preferred estimate for a given country or group of countries over a particular period. Where more than one estimate is reported, the additional results commonly serve to check for robustness rather than to reflect shifts in elasticities. In other words, it is typically assumed that the income elasticity does not change over time, at least not in any predictable ways. But there are indications that this might not be the case. Akhtar (1980) found an increase in the magnitude of income elasticity estimates for many industrial countries, arguing that rising income levels and trade openness were the cause. The notion that economic development leads to an increase in the income elasticity of import demand over time sparked a debate in the literature, whereby some studies lent support to the hypothesis (Melo and Vogt, 1984; Mah, 1999) while others rejected it (Boylan and Cuddy, 1987). More recently, Lo et al. (2007) confirmed a positive and significant relationship between income elasticity estimates and real GDP per capita for a cross-country sample, while Hummels and Lee (2018) reported a similar tendency at the micro level, suggesting that high-income households have a disproportionate effect on trade in the US. By contrast, Fajgelbaum and Khandelwal (2016) showed that growing incomes are associated with shifts away from traded manufactures, which reduces the impact of trade on high-income households across countries. Given the ambiguous nature of these findings, a meta-analysis of the literature could shed light on the issue by exploring the distribution of income elasticity estimates conditional on the countries' income levels.

The rest of the paper is structured as follows. In the next section, we review key contributions to the empirical literature on import demand, and on income elasticity in particular. Section 3 describes the meta-analysis methodology and the sample of works included in the investigation. Section 4 presents the results, and in Section 5 we summarize our findings and draw conclusions.

2 A brief survey of the literature

The literature on import demand has always been directed at estimating income and price elasticities with the goal of addressing broader questions pertaining to trade and trade policy. But from the beginning the magnitude of these elasticities has been a matter of contention. This section will first examine various aspects of the model specification and estimation procedures before presenting an overview of the debate on the size of the elasticities in existing studies.

The theoretical foundations of aggregate import demand are derived from standard consumer demand theory (Marquez, 2002). If imports take the form of final products, then the representative consumer chooses to purchase a combination of domestic and imported goods that maximize her utility function subject to a given income level.[1] The resulting aggregate important demand function can be defined as:

[1] The import demand function can also be derived from production theory (Kohli, 1978, 1991; Kee et al., 2008). Another type of import demand function can be found in Soderbery (2015) which is derived from the work of Leamer (1981). Neither of these approaches are relevant here as they do not produce estimates of the income elasticity of import demand.

$$M_i^d = f(P_i^M, P_i, Y_i), \tag{1}$$

where M_i^d denotes the volume of country i's imports demanded; P_i^M is the domestic-currency price paid by importers in country i; P_i represents the price of domestically produced goods within country i; and Y_i is country i's nominal income. Assuming that changes in nominal variables do not affect the quantity of imports demanded, Eq. (1) can be rearranged as:

$$M_i^d = f(\frac{P_i^M}{P_i}, \frac{Y_i}{P_i}), \tag{2}$$

making import demand a function of relative import price and real income. Another common transformation takes the form of:

$$M_i^d = f(P_i^{M^*}, E, P_i, Y_i), \tag{3}$$

where the domestic-currency price of imports is broken down into the foreign-currency price of imports ($P_i^{M^*}$) and the exchange rate (E) expressed as units of foreign currency per unit of domestic currency. This model allows the exchange rate to be studied as a separate determinant of import demand.

The standard empirical specification of the aggregate demand function as defined in Eq. (1) is given by:

$$\ln M_{it}^d = \beta_0 + \beta_{PM} \ln P_{it}^M + \beta_P \ln P_{it} + \beta_Y \ln Y_{it} + \varepsilon_{it}, \tag{4}$$

where all variables are expressed in natural logs at time t. The income elasticity (β_Y) is expected to carry a positive sign, if the possibility of aggregate imports being inferior goods is excluded. The cross-price elasticity (β_P) is also predicted to have a positive effect on import demand, assuming that there are no domestic complements for imports, while the own-price elasticity (β_{PM}) is, obviously, expected to have a negative sign.[2]

The model in Eq. (4) is expanded in various ways in the literature. The relative price and the exchange rate can be incorporated into the regression as suggested by Eq. (2) and (3), respectively. Dummy variables are also often included to account for structural shifts caused, for instance, by free trade agreements or changes in the exchange rate regime. Furthermore, the time-series data used in the estimation call for a dynamic specification achieved by adding lagged variables. Accordingly, various models have been employed to assess the long-run cointegration relationship between the variables and to obtain the corresponding elasticities estimates.[3] It is worth mentioning that if estimated as a single equation, the specification in Eq. (4) suffers from simultaneity bias, which has been traditionally dealt with in the literature by assuming that the price elasticity of supply is infinite. Alternatively, studies have adopted a simultaneous-equations approach, applying various techniques that rely mostly on instrumental variables to solve the problem (e.g., 2SLS, GMM).

[2]The model presented in Eq. (1)-(4) is based on the assumption that imports are not perfect substitutes of domestic goods. Given the extent of intra-industry trade in the world, this assumption seems realistic, making the model popular in the literature, although there are also alternative specifications that assume perfect substitutes (see Goldstein and Khan (1985) for a discussion).

[3]Some of the popular models in the literature include the Autoregressive-Distributed Lag (ARDL) model, the Vector Error Correction Model (VECM), the Dynamic OLS (DOLS), and the Fully Modified OLS (FMOLS).

Once estimated, the elasticities of the import demand function have been used to measure the response of imports to changes in income and the relative price, which, in turn, can help predict shifts in the trade balance, gauge the impact of adjustments in tariffs and non-tariff barriers, and assess the implications of movements in the exchange rate. The precision of elasticities estimates is of paramount importance for the achievement of these objectives. At the same time, tensions between the theoretical predictions and empirical estimates along with the variability of estimates across model specifications have ensured that the size of the elasticities has been the subject of vigorous debates in the literature.

In one of the earliest seminal papers on the topic, Orcutt (1950) criticized the low price elasticities estimated in studies from the 1940s, which had shown that a depreciation of the domestic currency would not be effective in improving the trade balance. In particular, he pointed out that relating current volumes of imports to current prices in the model fails to take into account long-run adjustments in imports in response to a price change. Accordingly, long-run estimates of price elasticities are likely to be larger than short-run ones.[4] Another key argument brought forward in Orcutt's (1950) paper is that import demand is likely to be more inelastic for small than for large shifts in the price. This claim has been tested in the literature by comparing the response of imports to movements in the exchanges rate versus changes in the price, predicting that the exchange-rate elasticity would be larger in magnitude than the price elasticity. The empirical evidence is mixed. The findings of earlier studies lent support to Orcutt's hypothesis in samples of developed and

[4] Orcutt's (1950) argument can be seen as the first ever call in the literature for incorporating time lags in the empirical model for estimating the import demand function.

developing countries (Wilson and Takacs, 1979; Bahmani-Oskooee, 1986; Tegene, 1989, 1991). In a series of more recent empirical papers, Bahmani-Oskooee and his colleagues failed to detect a general pattern across various sets of countries, thus mostly rejecting the hypothesis (Bahmani-Oskooee and Kara, 2003, 2008; Bahmani-Oskooee and Ebadi, 2015a, 2015b).[5]

The size of the income elasticity of import demand, which is the focus of this paper, has also been a matter of contention. In their seminal paper, Houthakker and Magee (1969) reported income elasticity estimates for the US, which were perplexing for two reasons. First, theoretical models of consumer utility maximization postulate that, under certain assumptions, the income elasticity of import demand is 1, while the estimate ends up being 1.51, creating a trade-off between theoretical consistency and predictive accuracy (Marquez, 2002). Second, theory asserts that the income elasticity is constant, whereas an estimate larger than unity implies that income increases result in an ever larger expansion of imports. Given the robustness of these estimates across different time periods and model specifications, considerable effort has been devoted to replicating the study and solving the puzzle, known in the literature as the Houthakker-Magee asymmetry (thanks to the US income elasticity estimate with respect to exports being less than unity). Potential explanations include, among others, aggregation bias (Cardarelli and Rebucci, 2007), a large share of immigrants in the US with preference for imported goods from their home countries (Marquez, 2002), a mis-specification of the model due to the omission of product variety (Krugman, 1989; Gagnon, 2003), and the exclusion of services imports which

[5]Orcutt's hypothesis was confirmed for certain countries and commodities (e.g., Bahmani-Oskooee and Hosny, 2015).

exhibit lower income elasticity (Wren-Lewis and Driver, 1998).

For the purposes of this paper, Houthakker and Magee's (1969) work is relevant for a different but related reason. Their results suggested that the income elasticity of import demand is similar across developed countries but exceeds the level for developing ones. Updating these results with data from the 1970s, Akhtar (1980) confirmed an increase in the size of income elasticity estimates for a large sample of industrial countries. Similarly, Melo and Vogt (1984) and Mah (1999) raised the possibility that the income elasticity of import demand would tend to rise with the level of income in the case of particular countries (Venezuela and Thailand, respectively). Deyak et al. (1997) review a number of papers in the literature and provide empirical evidence that the income elasticity for the US has risen over time. By contrast, Boylan and Cuddy (1987) examined Ireland's experience but could not detect a comparable pattern. In a more recent paper, Lo et al. (2007) report a rise in income elasticity over time for a large sample of developing countries and attribute it to a shift from nonmanufactured to manufactured imports during the process of economic development.

The onset of the Great Recession has revived researchers' interest in import demand. While the crisis brought a significant fall in world output, the corresponding drop in world trade of 40% was breathtaking. The fact that changes in relative prices and exchange rates could not possibly have caused such a large decline has led to a renewed focus on the importance of income elasticity. For instance, Hummels and Lee (2018) use household data to show that income elasticities vary significantly not only across goods and time but also across income levels and are on average falling with income. Accordingly, even a uniform income shock would generate significant shifts in imports across different goods. Fajgelbaum and Khandelwal (2016) also study the unequal gains from trade across different income levels within countries using income elasticities derived from gravity models. However, they arrive at the opposite conclusion that income elasticities rise with income, causing low-income households to benefit most from trade.

While the growing attention to import demand in the literature is an exciting development, there are still large gaps in our knowledge about how the income elasticity may systematically vary among countries, regions, or levels of economic development.

3 Methodology and data

Our paper is not a traditional meta-analysis but intends to bridge the gap between survey studies that try to assess the consensus in the literature and meta-studies that use a large number of often small studies to identify the existence of publication bias and to estimate the underlying "true" coefficient.

Unlike a meta-study, our database is selective as we focus on the preferred specifications (or what we believe them to be) for each paper and drop theoretically implausible negative estimates (which are rare and usually insignificant). While this selection renders some applications of meta-studies, such as identifying a publication bias impossible, it allows a clearer view on the consensus because it removes problematic estimates that are frequently included in the original research merely to demonstrate why and how they are problematic.

Yet, unlike traditional surveys, we do not restrict ourselves to the milestone papers that have driven the literature and present a narrative analysis, but we borrow from classic meta-analysis and evaluate statistically a broad set of results. However, our estimation method differs. Since we are not so much interested in the “one” result or testing for bias but in understanding where the distribution of results comes from, we apply quantile regressions to estimate the conditional median and the 1^{st} and 9^{th} decile of the conditional distribution of point estimates and employ kernel density estimation to give a better visual access to the data.

3.1 The meta database

The collection of papers used in the study was derived from a two-stage process. Estimates reported prior to 1998 were obtained from the works of Stern et al. (1976) and Sawyer and Sprinkle (1999), while those published after that date resulted from querying the EconLit database. The procedure involved searching abstracts containing the term “import demand” because it identifies works with titles that do not clearly indicate the presence of import demand elasticities and ignores an extremely large number of studies where the term has been used in the body of the paper but for which no estimates are reported. The selection was completed by the end of 2018.

Our database includes 618 estimates of long-run income elasticities of import demand drawn from 152 papers published between 1975 and 2014.[6] In total, our sample covers 105 countries, whereby the number of estimates per country ranges from one (for 27 of the emerging markets covered by the sample) to 50 for the

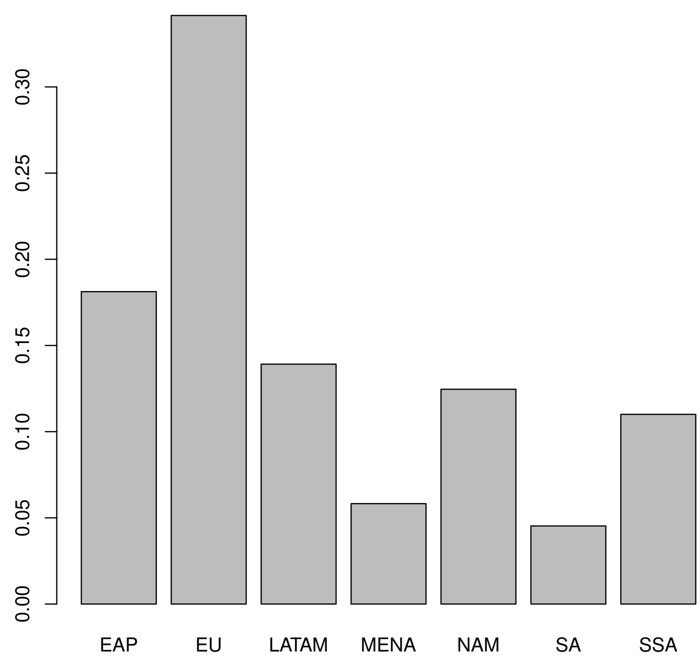
[6] The list of publications is available from the authors upon request.

US. Similarly, the distribution of countries considered per paper is highly skewed. Two-thirds of the papers in our sample are single country studies, whereas the most exhaustive individual study (Senhadji, 1998) covers 65 countries.

For the purposes of the paper, we classify countries based on two criteria. The regional dimension is based on geographic location, while the income category focuses on gross national income (GNI) per capita ranges. Both criteria adopt the classification established by the World Bank, which divides the world into regions and income groups. The seven regional entities include North America, Latin America and Caribbean, Europe and Central Asia, Middle East and North Africa (MENA), Sub-Saharan Africa (SSA), South Asia, and East Asia and Pacific (EAP). The four income categories consist of low, lower-middle, upper-middle, and high. The per-capita GNI thresholds have changed over time but, given that the majority of estimates are from the period between the 1970s and the early 1990s, we applied the earliest available classification for 1987.[7]

[7] Although the thresholds change on a regular basis, shifts across income categories occur much less often. As a result, our findings are robust across updates to income ranges by the World Bank.

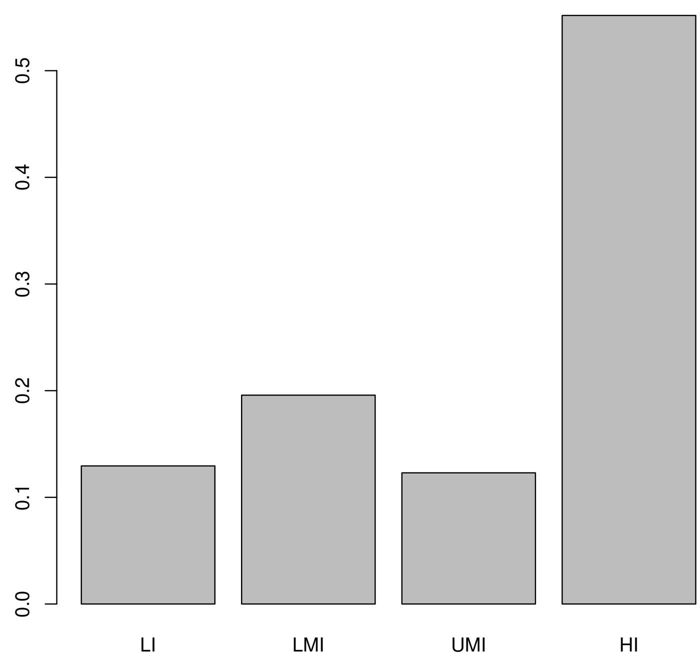
Figure 1: Income elasticity estimates by region



Note: EAP=East Asia and Pacific; EU=Europe and Central Asia; LATAM = Latin America and Caribbean; MENA = Middle East and North Africa; NAM = North America; SA = South Asia; SSA = Sub-Saharan Africa.

The share of income elasticity estimates by region in Fig. 1 shows that Europe has garnered the greatest attention in the literature. Yet, at the level of individual countries, none of the European nations match the number of estimates reported for the US. This is obfuscated by the seemingly low consideration for North America. However, according to the World Bank classification, Latin America contains all of Central America and South America, while North America only includes the US (50 estimates), Canada (27 estimates), and Bermuda (no estimates). Their exportoriented growth and trade surpluses as well as the emergence of China as a major global player have made East Asian countries also a subject of interest to previous studies. By contrast, Latin America and SSA have received less consideration, while only a few papers have reported estimates for MENA and South Asia. As for the income dimension, Fig. 2 illustrates that the overwhelming majority of existing research explored high-income countries, while other income groups featured much less prominently.

Figure 2: Income elasticity estimates by income category



Note: Countries categorized according to the World Bank's 1987 classification: LI = low income; LMI = low-middle income; UMI = upper-middle income; HI = high income.

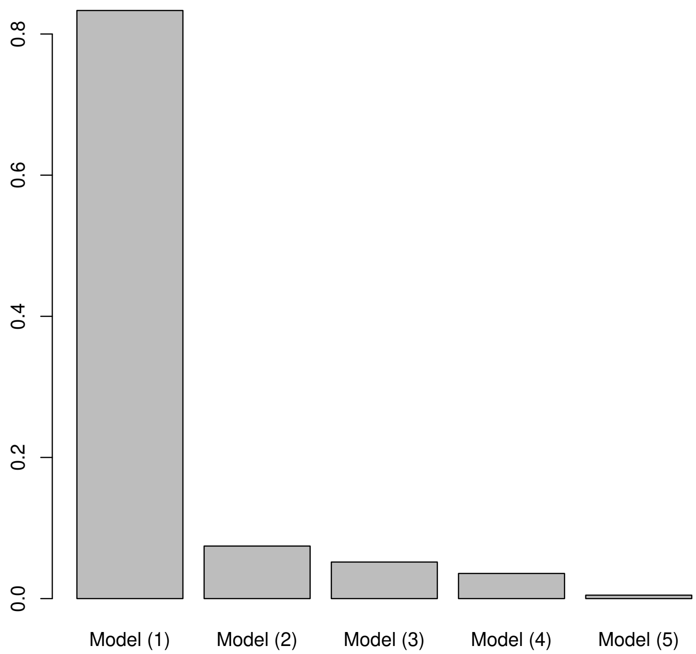
With regard to empirical specifications, we divide the models used for the estimation of import demand elasticities into five groups, all of which include the value of imports as the dependent variable and income as one of its determinants but differ in their treatment of prices and the exchange rate. Model (1) represented by Eq. (2) is the standard in the literature and incorporates the foreign and domestic prices as a ratio. Model (2) shown by Eq. (1) includes each price separately. Models (3) and (4) add the exchange rate to Models (1) and (2), respectively. Model (5), which is rare in the literature, includes the exchange rate but does not take into account any prices. Fig. 3 indicates that researchers have a revealed preference for Model (1), in spite of the fact that this specification is based upon the restrictive assumption that the demand function is homogeneous. Moreover, only a relatively small number of studies embrace the exchange rate as an independent variable in the model, and if so, there is a strong inclination to include the relative price as well (Models (3) and (4)).

3.2 Analysis

3.2.1 Kernel densities

To allow a simple visualization of the conditional distributions of estimates, we rely on kernel density estimation. We use a simple Gaussian kernel, i.e. the distribution of the data is approximated as the sum of A normal distributions, where A is the number of estimates available. The results reported in the following sections use a simple Silverman (1986) rule of thumb to pick the bandwidth. Our results are robust to different specifications, such as using an Epanechnikov kernel (which is optimal

Figure 3: Income elasticity estimates by model specification



Note: Model (1) = price ratio; Model (2) = domestic price + foreign price; Model (3) = price ratio + exchange rate; Model (4) = domestic price + foreign price + exchange rate; Model (5) = only exchange rate. All models include income as an independent variable.

when considering a squared deviation loss function) or the Sheather and Jones (1991) bandwidth rule.

3.2.2 Quantile regression

Rather than using the standard least square approach employed in most meta-studies, we apply quantile regressions that allow us to predict conditional quantiles of the distribution rather than the mean. Namely, we estimate the coefficients for:

$$P(\eta_i < \alpha + \sum_{j=1}^{J-1} \beta_j R_j + \sum_{k=1}^{K-1} \gamma_k I_k + \sum_{n=1}^{N-1} \theta_n M_n) = \tau, \tag{5}$$

where η_i is the estimated income elasticity for observation i, yr_i is the number of years that the estimation covers; J, K, and N are the total number of regions, income groups, and models, respectively. $R_{i,j}$, $I_{i,k}$, and $M_{i,n}$ are the corresponding region, income group, and model dummies.

The inclusion of the inverse sample length serves to control for the uncertainty of individual estimates in the absence of sufficient data on standard errors. This approach is borrowed from the meta-study literature and usually serves a twofold purpose. First, it helps to test for publication bias. If uncertain studies are clustered in one tail of the distribution, this reflects a tendency to prefer outliers in one direction rather than outliers in the other direction. In our case, the interpretation of a significant coefficient β as proof of publication bias is problematic, since we omit negative estimates, thereby cutting one tail. The second objective is to correct said publication bias and obtain a point estimate that corresponds to 'no uncertainty' or, in our case, an infinitely large sample. By controlling for uncertainty, we can thus compensate the bias that would be introduced by our truncation of the data. We set the base categories to North America, high income, and the standard model specification (represented by Eq. (2) which includes the price ratio rather than individual prices). In other words, the constant term can be interpreted as estimate for the respective bias-corrected quantile for US and Canadian estimates of the income elasticity of import demand.

Borrowing from the meta-literature for the purposes of our "meta-survey" again, we also run a robustness test where the same specification is estimated using weighted quantile regressions with the inverse sample size as weight. That is, observations coming from very small samples are considered less important in the loss function that is minimized to obtain our estimates.

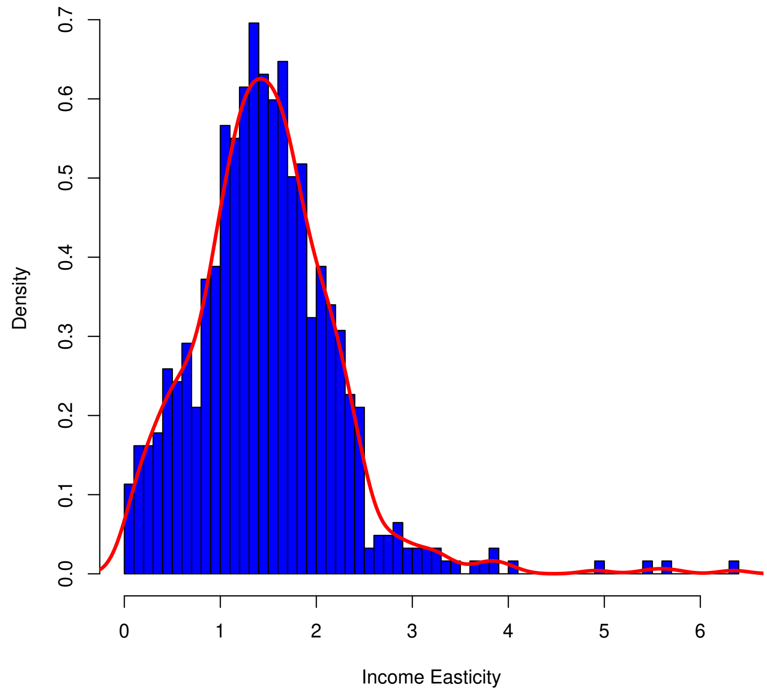
While most applications of quantile regressions focus on the point estimates for the different quantiles, we are also interested in the quantile difference between the tails, to see whether a particular region, income group or model specification exhibits higher uncertainty. Since the quantiles are independently estimated but their errors are obviously related, our assessment of quantile differences is not based on the covariance matrices (which assume independence) but on a simple bootstrap. Specifically, we randomly draw 1000 artificial samples (with replacement) from our original sample and reestimate the quantile regression for the tail quantiles based on those artificial samples.

4 Results

4.1 Kernel densities

The analysis begins with the distribution of income elasticity estimates of import demand across publications shown in Fig. 4. The probability mass is concentrated in the range between 0 and 2.5 with the highest density achieved around the value of 1.5, which corresponds to Houthakker and Magee's (1969) estimate for the US. Given their low probability, income elasticities exceeding 2.5 are likely outliers that arise from errors in the estimation procedure.

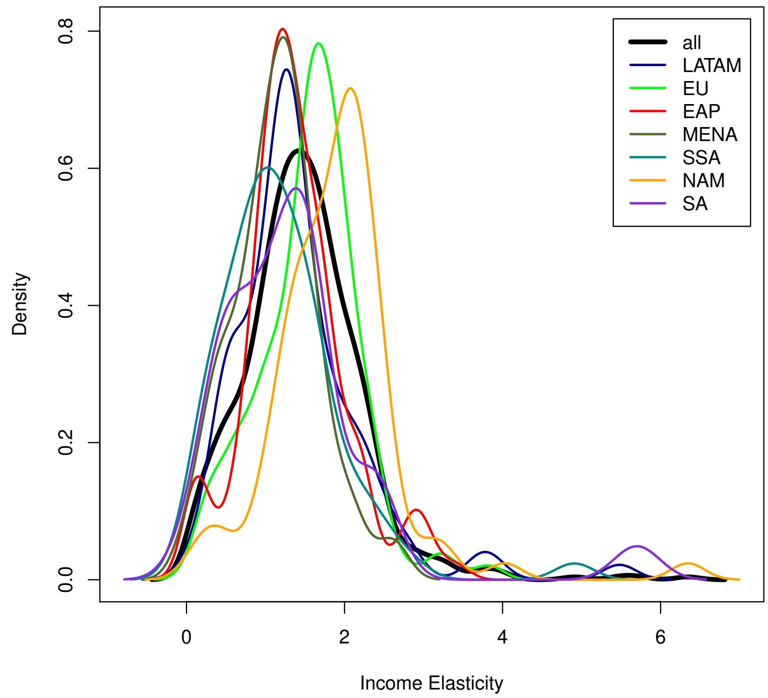
Figure 4: Distribution of income elasticity estimates



4.1.1 Regional dimension

The distributions of income elasticity estimates by region are presented in Fig. 5. The major mode of the distributions for North America, and to a lesser extent for Europe, lies clearly to the right of all the others, suggesting that imports in these wealthy regions are indeed much more sensitive to changes in their income than the rest of the world. By comparison, regions at lower levels of economic development, such as SSA, MENA, Latin America, and South Asia, are clustered on the left side of the distribution. In terms of variance, the distributions for South Asia and SSA are wider and exhibit more modes at the higher levels of income elasticity.

Figure 5: Distribution of income elasticity estimates by region

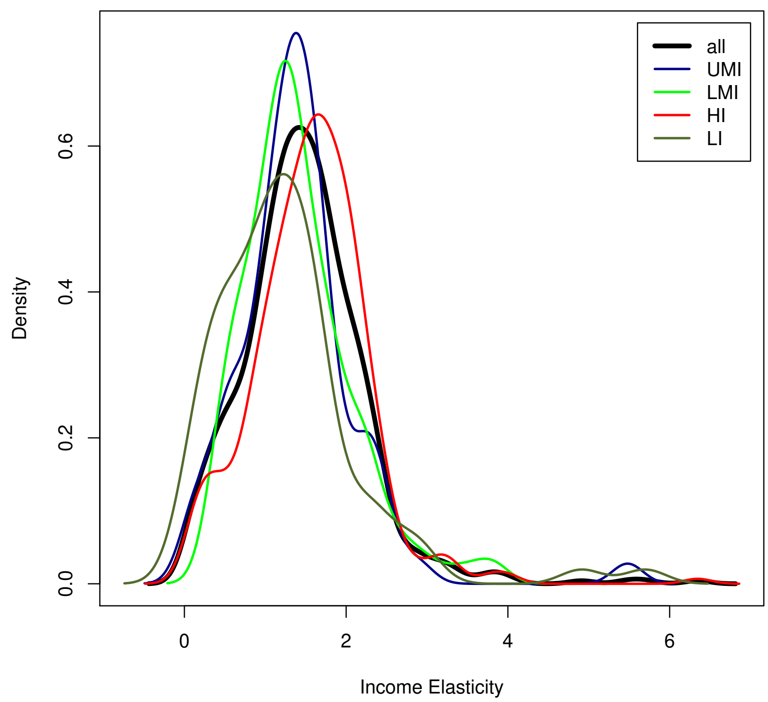


Note: EAP=East Asia and Pacific; EU=Europe and Central Asia; LATAM = Latin America and Caribbean; MENA = Middle East and North Africa; NAM = North America; SA = South Asia; SSA = Sub-Saharan Africa.

4.1.2 Income categories

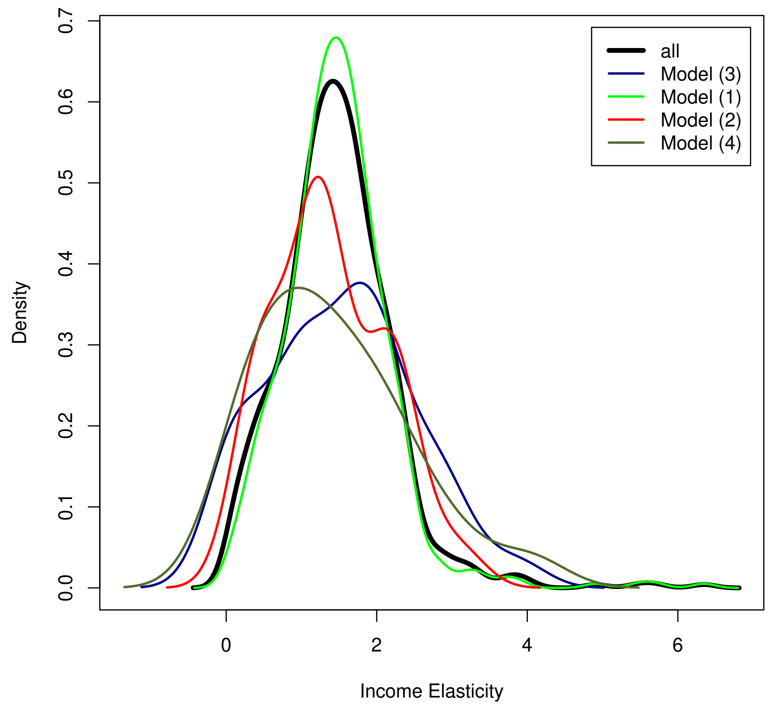
The emphasis on the developed world in the literature (see Fig. 2) is understandable given that most of the trade is concentrated there. In other words, research on import demand elasticities appears to be positively correlated with both the volumes of trade emanating from developed countries and the concomitant level of economic development. The distributions in Fig. 6 concur with those in Fig. 5 but show more clearly the evolution of the magnitude of income elasticity during the transition from low- to high-income levels. The probability mass for low-income countries is clustered to the left of the average around the value of 1, while middle-income countries exhibit modes concentrated around 1.5. The high-income distribution occupies the place further to the right, approaching the value of 2. Furthermore, the range of estimates at both ends of the income scale is considerably wider than in the middle.

Figure 6: Distribution of income elasticity estimates by income category



Note: Countries categorized according to the World Bank's 1987 classification: LI = low income; LMI = low middle income; UMI = upper middle income; HI = high income.

Figure 7: Distribution of income elasticity estimates by model specification



Note: Model (1) = price ratio; Model (2) = domestic price + foreign price; Model (3) = price ratio + exchange rate; Model (4) = domestic price + foreign price + exchange rate. All models include income as an independent variable.

4.1.3 Method specifications

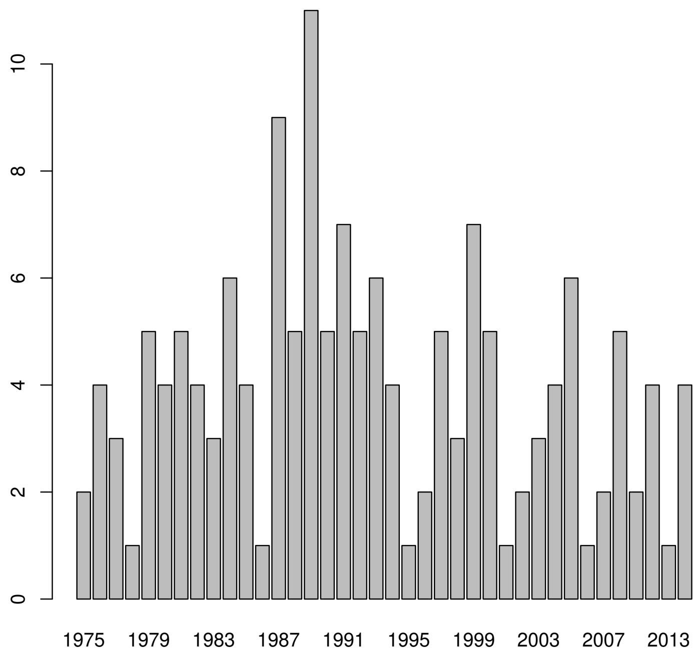
Fig. 7 provides limited evidence that the model specification may have a nontrivial impact on the estimated income elasticity. The standard equation (Model (1)) has the highest mode located in the range between 1.5 and 2. Once the price ratio is broken down (Model (2)), the distribution of estimates widens dramatically, indicating a decline in the precision of the estimate. When the exchange rate is added to the model, the distributions widen even further, whereby the probability mass for Model (3) is concentrated closer to the value of 2, while Model (4) leans towards 1. In summary, the decomposition delivers information that is being masked by the use of the price ratio; however, this comes at the cost of a potentially less accurate estimate of income elasticity.

4.1.4 Time dimension

The number of publications by year shown in Fig. 8 reveals the evolution of the literature on import demand across time. The subject was a popular topic in the 1970s as a nexus of data availability, computing power, and econometric modeling came together. Models that decomposed the price ratio into foreign prices, domestic prices, and the exchange rate became widely studied in the 1980s, when the largest number of publications was achieved. In addition, advances in time-series econometrics led to new empirical investigations that emphasized the lagged responses of import to its determinants. Further increases in research output can be detected in the late 1990s and early 2000s, but over the last two decades the levels have generally been declining despite several surges in recent years.

The year of publication has also affected the distribution of income elasticity estimates as indicated by Fig. 9. The earliest estimates from the 1970s and the most recent ones from the 2010s are highly concentrated around the value of 1.5. This pattern might be explained by the tendency of earlier researchers to focus on relatively simple empirical specifications that yielded similar estimates. Interestingly, the most recent empirical work has moved back to these comparatively straightfor-

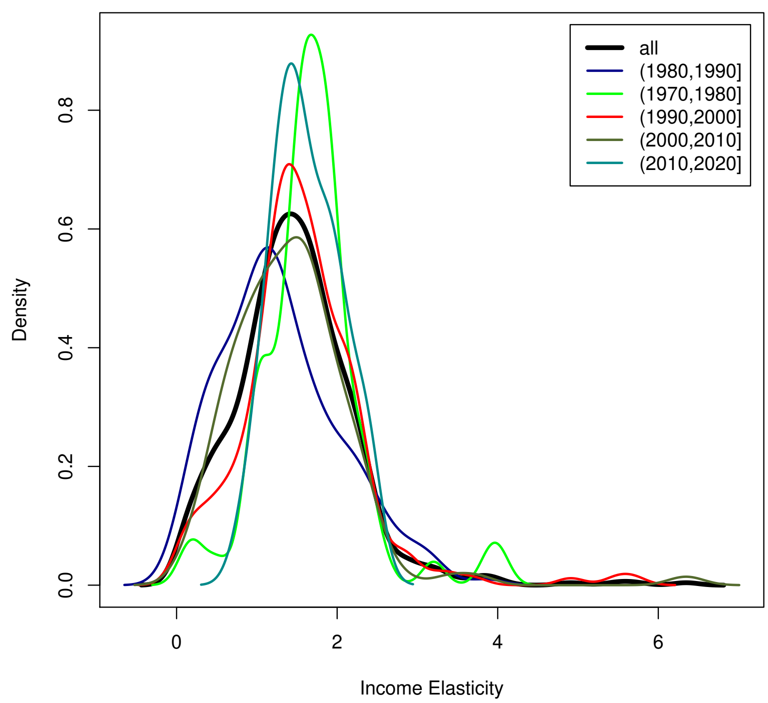
Figure 8: Number of income elasticity estimates by publication year



ward models. By comparison, the distributions from the 1980s and 2000s exhibit a considerably wider mode, likely caused by research focused on both more complex empirical specifications and lagged responses of imports to its determinants.

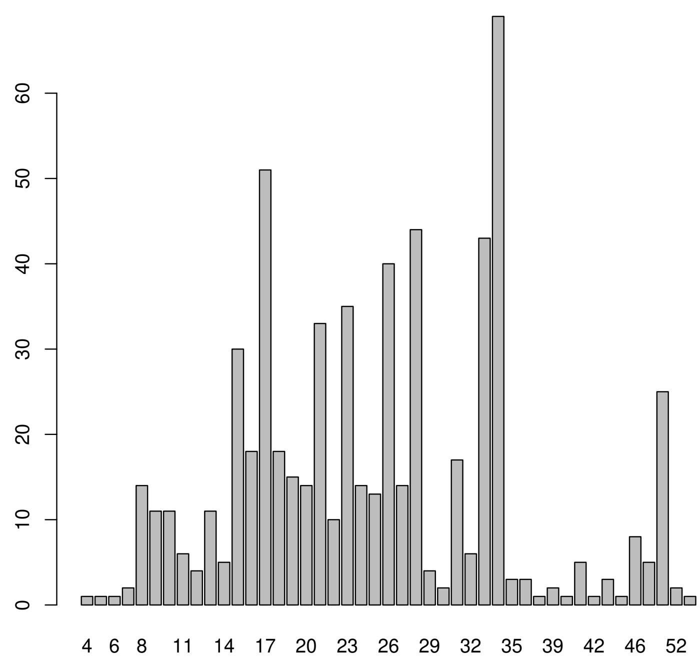
The time dimension of the research on import demand also encompasses the length of the sample periods used in the literature. As can be seen from Fig. 10, most studies cover a range of between 15 and 30 years, although the largest number of estimates comes from a sample containing 33-34 years. While the data seemingly comprise a relatively long time period, the actual number of observations for estimation purposes can be rather small, given that the relevant statistics are reported on a quarterly basis. Accordingly, an average study of import demand elasticities examining a 30-year sample period effectively relies only on 120 observations. Another important aspect of the time dimension is that statistics for many countries are available for years prior to the early 1970s. However, mixing pre-1970 and post-1970 data can be problematic because the estimation of import demand could be affected by the breakup of the Bretton Woods system of fixed exchange rates and the subsequent introduction of floating exchange rates. A similar situation can occur in the cases of developing countries that adopted a floating exchange rate regime at a later date. As a result, researchers often face a tradeoff between the length of the

Figure 9: Distribution of income elasticity estimates by publication decade



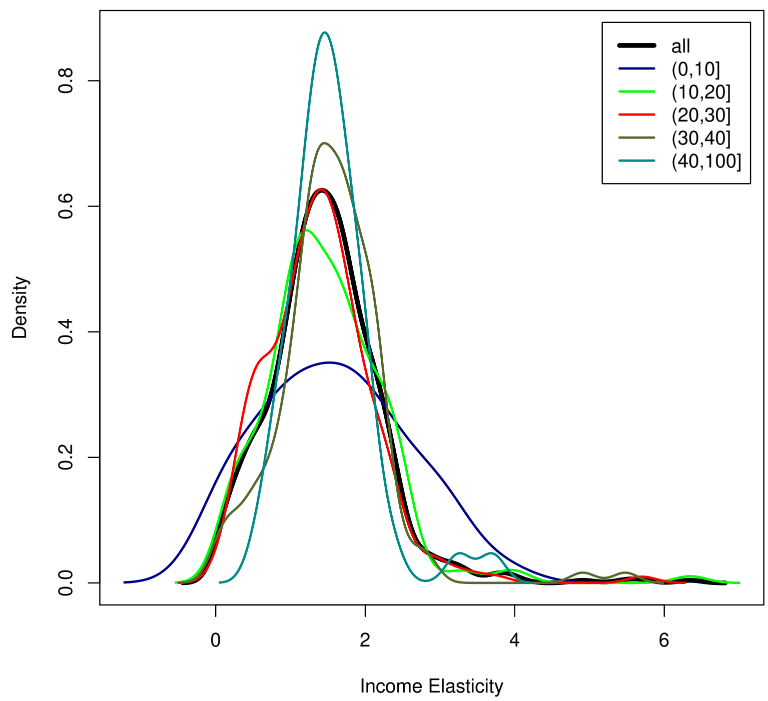
time series and the potential issues a structural break in the data may cause.

Figure 10: Number of years covered by the estimation of income elasticity



Despite these concerns, the length of the sample period is positively correlated with the precision of the estimation. Fig. 11 shows that while the main mode of all distributions of income elasticity estimates is concentrated around the same value of around 1.5, the variance differs based on the number of time observations. As one would expect, the distribution for a sample period of up to 10 years is wide and the extension of the time series drives the probability mass closer to the average value, reducing the variance and improving the accuracy of the estimation.

Figure 11: Distribution of Income elasticity estimates by year ranges



4.2 Quantile regression

The non-parametric approach in the previous section provides key insights into the shape of the distribution of income elasticity estimates and its change across various dimensions. To gain a better understanding of the exact levels of the estimates at individual points along the distribution and the statistical significance of differences across distributions, we employ quantile regressions.

Table 1: Results of the quantile regressions with regional dummies

	0.5		0.1		0.9		Quantile difference
Intercept	1.93	***	1.403	***	2.167	***	(+)***
	(17.05)		(10.14)		(11.53)		
InvPeriod	0		-5.27	***	7.208	***	(+)***
	(0)		(-2.8)		(2.7)		
SSA	-0.79	***	-0.815	***	-0.569	**	(+)
	(-6.23)		(-5.33)		(-2.25)		
MENA	-0.76	***	-0.714	***	-0.84	***	(−)
	(-5.38)		(-4.38)		(-2.75)		
LATAM	-0.64	***	-0.678	***	-0.227		(+)
	(-6.34)		(-4.81)		(-0.94)		
EAP	-0.62	***	-0.446	**	-0.269		(+)
	(-5.79)		(-2.46)		(-1.38)		
SA	-0.62	***	-0.75	***	-0.266		(+)
	(-3.28)		(-4.83)		(-0.36)		
EU	-0.33	***	-0.518	***	-0.285	*	(+)
	(-3.24)		(-3.32)		(-1.78)		

Note: Dependent variable is the income elasticity estimate. Independent variables are regional dummies. EAP=East Asia and Pacific; EU=Europe and Central Asia; LATAM = Latin America and Caribbean; MENA = Middle East and North Africa; NAM = North America; SA = South Asia; SSA = Sub-Saharan Africa. Control group is NAM. InvPeriod = inverse of the sample length. *** p<.01; ** p<.05; * p<.10.

The results for the regional dimension are presented in Table 1 with the median in the first column followed by the 1^{st} and 9^{th} deciles in the second and third columns, respectively. The intercept denotes the average level of income elasticity for the control group, which is North America. As the negative signs of the remaining dummies suggest, all other regions have significantly lower estimates, whereby Europe is the closest in magnitude and SSA the farthest. These differences from the benchmark are statistically significant for the median and the 1^{st} decile, but not for the 9^{th} decile.[8]

[8] The only exceptions are SSA and MENA with a significant coefficient in the 9^{th}-decile regression. The reason, as seen in Fig. 5, is the lack of an extended right tail for these two regions.

These results support the evidence provided in Fig. 3, where the main mode of the distribution for North America is farther to the right than for the rest of the world. This, in turn, concurs with Houthakker and Magee's (1969) observation that the US income elasticity is higher on average than for other developed countries, which was confirmed in later studies.

Table 2: Results of the quantile regressions with income dummies

	0.5		0.1		0.9		Quantile difference
Intercept	1.565	***	0.973	***	1.896	***	(+)***
	(18.02)		(6.9)		(17.51)		
InvPeriod	0.474		-6.053	***	8.16	***	(+)***
	(0.24)		(-2.74)		(3.16)		
LI	-0.436	***	-0.338	***	-0.059		(+)
	(-4.67)		(-2.88)		(-0.18)		
LMI	-0.281	***	-0.125		0.039		(+)
	(-5.18)		(-1.04)		(0.31)		
UMI	-0.23	***	-0.208		-0.019		(+)
	(-3.1)		(-1.61)		(-0.1)		

Note: Dependent variable is the income elasticity estimate. Independent variables are dummy variables based on the World Bank's 1987 classification: LI = low income; LMI = low middle income; UMI = upper middle income; HI = high income. Control group is HI. InvPeriod = inverse of the sample length. *** p<.01; ** p<.05; * p<.10.

The coefficients for Europe and EAP, although significantly different from the benchmark, are still the closest to the level for North America. It is compelling to conclude that higher stages of economic development might be a factor, especially given the evidence in Fig. 6. The results from the regression by income group in Table 2 corroborate this conclusion by showing that high-income countries, the control group, with a coefficient of 1.57 have significantly higher income elasticity at the median than the rest of the world. As expected, poor countries have the lowest elasticity and the difference to the rich group is statistically significant both at the median as well as at the 1^{st} decile.

Table 3: Results of the quantile regressions with specification dummies

	0.5		0.1		0.9		Quantile difference
Intercept	1.433	***	0.744	***	1.979	***	(+)***
	(19.86)		(5.76)		(16.68)		
InvPeriod	0.567		-2.532		6.037	**	(+)**
	(0.34)		(-0.79)		(2.16)		
Model (2)	-0.187		-0.241	**	0.105		(+)
	(-1.49)		(-2.38)		(0.58)		
Model (3)	0.091		-0.36		0.308		(+)
	(0.33)		(-1.36)		(0.91)		
Model (4)	-0.159		-0.213		-0.053		(+)
	(-0.57)		(-0.69)		(-0.07)		
Model (5)	-0.669		-0.528		-0.153		(–)
	(-0.92)		(-0.84)		(-0.21)		

Note: Dependent variable is the income elasticity estimate. Independent variables are dummy variables for model specifications: Model (1) = price ratio; Model (2) = domestic price + foreign price; Model (3) = price ratio + exchange rate; Model (4) = domestic price + foreign price + exchange rate; Model (5) = only exchange rate. All models include income as an independent variable. Control group is Model (1). InvPeriod = inverse of the sample length. *** p<.01; ** p<.05; * p<.10.

In Fig. 7, we determined that the empirical specification matters mostly with regard to the variance of the estimates distribution. The findings of the corresponding quantile regressions in Table 3 reveal that the only deviations from the standard model to attain statistical significance are for Model (2). Decomposing the price ratio leads to considerably lower estimates than the benchmark at the median and the 1^{st} decile.

Table 4: Results of the quantile regressions with regional, income, and model dummies

	0.5		0.1		0.9		Quantile difference
Intercept	1.94	***	1.34	***	2.299	***	(+)***
	(16.91)		(5.77)		(8.97)		
InvPeriod	0.566		-3.375		3.929		(+)**
	(0.34)		(-1.23)		(1.2)		
MENA	-0.792	***	-0.768	***	-0.944	***	(–)
	(-5.52)		(-3.43)		(-3.19)		
SSA	-0.768	***	-0.605	**	-1.033	***	(–)
	(-4.28)		(-2.28)		(-2.7)		
LATAM	-0.735	***	-0.692	***	-0.256		(+)
	(-5)		(-2.8)		(-0.76)		
EAP	-0.633	***	-0.425	*	-0.609	**	(–)
	(-5.6)		(-1.89)		(-2.29)		
SA	-0.511	**	-0.383		-0.608		(–)
	(-1.98)		(-1.17)		(-0.58)		
EU	-0.365	***	-0.515	**	-0.284		(+)
	(-3.39)		(-2.32)		(-1.25)		
LI	-0.14		-0.268		0.428		(+)
	(-0.81)		(-1.18)		(1.02)		
UMI	-0.013		-0.002		0.068		(–)
	(-0.16)		(-0.01)		(0.39)		
LMI	0.087		0.035		0.319		(+)
	(0.76)		(0.26)		(1.49)		
Model (2)	-0.133		-0.234		0.037		(+)
	(-0.71)		(-1.55)		(0.16)		
Model (3)	0.142		-0.118		0.634	*	(+)
	(0.54)		(-0.44)		(1.8)		
Model (4)	-0.217		-0.303		0.499		(+)
	(-0.85)		(-0.86)		(0.78)		
Model (5)	-0.543		-0.223		-0.341		(–)
	(-1.14)		(-0.63)		(-0.62)		

Note: Dependent variable is the income elasticity estimate. Control groups are North America (NAM), high-income countries (HI), and Model (1). InvPeriod = inverse of the sample length. *** p<.01; ** p<.05; * p<.10.

After examining the regional, income-level, and model dimensions separately, we also run quantile regressions including all three groups of dummy variables and present the results in Table 4. The regional dummies largely retain their signs and significance from Table 1, while the magnitudes of the coefficients shift slightly at both ends of the distribution, albeit without causing major changes in our previous conclusions. In contrast to the findings in Tables 2 and 3, income categories and model specifications do not seem to matter anymore. As we suspect collinearity between regional and income dummies, the quantile regressions are estimated again after excluding the former from the model. The estimates in Table 5 confirm our conjecture by showing that the coefficients of the income dummies are very similar to the ones in Table 2. However, the finding that regional dummies rather than income group dummies retain their significance when tested jointly suggests that other shared characteristics besides income drive the importance of regions, such as membership in customs unions, harmonization of trade legislation, and other institutional similarities.

In the last column of Tables 1-5, we also test the difference between the 1^{st} and 9^{th} decile for the dummy variable coefficients but do not detect statistical significance. The exception is the inverse sample length, which deviates significantly between the lower and upper deciles in all regressions. Given that we include this variable to control for uncertainty, our findings suggest that the small samples used in the estimation of income elasticities are the main source of uncertainty rather than the variation in imports across countries.[9]

[9]To test the robustness of our coefficients, we estimate the same specifications using weighted quantile regressions with the inverse sample size as weight. The results are broadly consistent with

Table 5: Results of the quantile regressions with income and model dummies

	0.5		0.1		0.9		Quantile difference
Intercept	1.571	***	0.882	***	2.002	***	(+)***
	(20.59)		(5.44)		(14.03)		
InvPeriod	0.367		-1.743		5.905	*	(+)*
	(0.24)		(-0.54)		(1.73)		
LI	-0.412	***	-0.389	***	-0.016		(+)
	(-3.76)		(-2.66)		(-0.04)		
LMI	-0.282	***	-0.16		-0.066		(+)
	(-4.87)		(-1.3)		(-0.45)		
UMI	-0.223	***	-0.298	**	0		(+)
	(-3.02)		(-2.01)		(0)		
Model (2)	-0.105		-0.256		0.088		(+)
	(-0.71)		(-1.63)		(0.48)		
Model (3)	0.204		-0.189		0.298		(+)
	(0.8)		(-0.61)		(0.86)		
Model (4)	-0.284		-0.439		-0.06		(+)
	(-0.97)		(-1.51)		(-0.1)		
Model (5)	-0.794		-0.303		-0.168		(–)
	(-1.13)		(-0.55)		(-0.24)		

Note: Dependent variable is the income elasticity estimate. Control groups are high-income countries (HI) and Model (1). InvPeriod = inverse of the sample length. *** $p<.01$; ** $p<.05$; * $p<.10$.

5 Conclusions

As a key determinant of the trade balance, import demand has attracted the attention of researchers in international economics for almost 80 years. The income elasticity of import demand has featured prominently in the empirical literature on the subject because of its relevance for assessing the impact of various trade measures and policies. However, existing studies have employed different countries, models, sample periods, and estimation techniques to produce estimates for the income elas-

our findings in Tables 1-5 and are available from the authors upon request.

ticity that vary in magnitude. Some results have suggested that rich, industrialized countries, and the US in particular, exhibit a demand for imported goods that is considerably more sensitive to changes in income than poorer parts of the world.

The goal of this paper is to survey the literature and conduct a meta-analysis of empirical studies on import demand with the intention of clarifying the effect of economic development represented by changes in income on the willingness and ability of a country to import goods from the rest of the world. In other words, we would like to test the hypothesis that as countries grow richer, their income elasticity of import demand increases. Our results, based on a sample of 152 papers published between 1975 and 2014, support this notion and indicate that the relationship is robust.

First, we use a non-parametric approach to show that the kernel densities of income elasticity estimates deviate from the average for various geographic regions and income groups. Specifically, North America and Europe display larger income elasticities than South Asia or SSA. The same pattern is detected when countries are classified by income categories with high-income countries recording a higher sensitivity of import demand to changes in income than their low-income counterparts. Furthermore, we establish that model specification, year of publication, and length of the sample period have an impact on the distribution of income elasticity estimates. We find that publications in the 1970s and 2010s, which use the longest possible sample period (40-50 years) to estimate a standard model of import demand that includes price ratio and income as determinants, produce the most precise income elasticity estimates.

Next, we test our outcomes by applying quantile regressions to estimate the conditional median and the 1^{st} and 9^{th} decile of the distributions. The results of this parametric approach provide more detailed insights but largely confirm the earlier conclusions. Regional and income-level differences in income elasticity of import demand are significant at the median and the 1^{st} decile, but they are much less pronounced at the top of the distribution. Most importantly, the outcome that high-income countries in North America and Europe have significantly higher income elasticities remains robust after controlling for the effect of model specifications.

In conclusion, we show that existing studies establish a statistically significant link between economic development and the income elasticity of import demand. Rich countries increase their imports by between \$1.60 and \$1.90 for every additional dollar in income, while the corresponding rise for low-income states is on average less than \$1.20. One likely explanation for this pattern is that in the course of economic development the share of manufactured goods imports increases. Given that these goods have generally a higher income elasticity of import demand, the overall sensitivity of imports to income growth increases accordingly (Lo et al., 2007).

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