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Faculty of Social Sciences

Institute of Economic Studies

BACHELOR THESIS

A Meta-Analysis of the Estimates of the Armington Elasticity

Author: **Josef Bajzík**

Supervisor: **doc. PhDr. Tomáš Havránek, Ph.D.**

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Declaration of Authorship

I hereby proclaim I wrote my bachelor thesis on my own under the leadership of my supervisor and that the included references are all the resources I have used.

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Prague, May 14, 2017

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Abstract

We examine determinants of Armington elasticities throughout history and nations employing 3,524 observations from 42 studies. We conduct meta-analysis using Bayesian model averaging approach to test the most influential factors. We explore more than 30 variables and compare our results with previous summarizing articles. In this thesis is, for instance, the first comparison of employment of different type of models in this area. Finally, we find out that the level of aggregation of the data used for estimation matters as well as the power of the currency. On the other hand, we discover that there is no significant distinction between long-run and short-run estimates. Moreover, we test for publication bias and we find evidence for it in this field.

Keywords	Armington elasticity, meta-analysis, Bayesian model averaging, publication bias

Author's e-mail	`bajzik22@seznam.cz`
Supervisor's e-mail	`tomas.havranek@ies-prague.org`

Abstrakt

Na 3 524 pozorováních ze 42 studií zkoumáme určující faktory pro Armingtonovo elasticity napříč historií a národy. Je provedena metaanalýza a pro získání nejvíce ovlivňujících činitelů je použita bayesovská metoda průměrování modelů. Více než 30 proměnných je prozkoumáno a výsledky jsou porovnány se závěry z předchozích souhrnných článků. Tato práce je například první, která porovnává různé modely použité v této oblasti. Nakonec je zjištěno, že důležitá je úroveň agregace dat, stejně tak síla měny. Na druhou stranu, zde není žádný významný rozdíl mezi krátkodobými a dlouhodobými odhady. Publikačním vychýlení je také objektem analýzy a jsou pro něj nalezeny důkazy v této oblasti.

Klíčová slova	Armingtonova elasticita, metaanalýza, bayesovská statistika, publikační vychýlení

E-mail autora	`bajzik22@seznam.cz`
E-mail vedoucího práce	`tomas.havranek@ies-prague.org`

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Acronyms

BMA Bayesian Model Averaging

CORC Cochrane-Orcutt Procedure

ECM Error Correction Model

EU European Union

EMU European Monetary Union

FGLS Feasible Generalized Least Squares

FAT Funnel-Asymmetry Test

MRA Meta-Regression Analysis

OLS Ordinary Least Squares

PET Precision-Effect Test

PIP Posterior Inclusion Probability

PMP Posterior Model Probability

REER Real Effective Exchange Rate

TSLS Two-Stage Least Squares

UIP Uniform Information Prior

US United States of America

WLS Weighted Least Squares

Bachelor's Thesis Proposal

Author	Josef Bajzík
Supervisor	doc. PhDr. Tomáš Havránek, Ph.D.
Proposed topic	A Meta-Analysis of the Estimates of the Armington Elasticity

Research question and motivation The so-called Armington elasticity is elasticity between domestic and foreign goods. It is based on the Paul Armington's assumption that the products are differentiated by country of origin in international trade. It has become a standard assumption of international general equilibrium models. In comparison with models with homogenous products, these models evince more realistic response of trade to price changes. Therefore I found important to conduct meta-analysis in this field. The one of the most remarkable merit of meta-analysis approach is revealing the publication bias of the estimates reported in literature. First estimates of Armington elasticities were conducted in US by Shiells & Stern (1986), or Reinert & Roland-Holst (1992). At these days there are more than fifty articles, working papers and researches subjected to this topic across countries and continents. Some of them (e. g. McDaniel & Balisteri, 2002; Cassoni & Flores, 2010) summarize the results and compare them. They found that long-run elasticities are higher than short-run ones, micro elasticities are higher than macro ones. Another factors, which affect the results are time-frequency and type of data. But no one made an overall meta-analysis of this topic up till now. WI will investigate which variable influence the results the most. I am interested in findings of publication bias in this literature as well. Therefore I will cover in my analysis many other variables like midyear of data, length of time period, model used, estimation method, impact, or citations of the primary article.

Contribution Meta-analysis is modern approach of summarizing and qualifying primary researches. Moreover it can correct potential biases in estimates, explain heterogeneity, or give the direction to future empirical investigation. Surprisingly, there is still no meta-analysis of the estimates of the elasticity between domestic and foreign goods. Therefore, I want to fill-in this niche.

Methodology I will conduct meta-regression analysis (MRA) on this topic. MRA is the statistical analysis of previously reported, or published research findings on a given empirical effect, or phenomenon. It is a systematic review of all relevant researches about a specific topic. The first step will be the collection of primary studies. I will search for them by using Google Scholar and Repec Ideas. For using modern meta-analysis method and correction for publication bias, I will need the standard error of each elasticity (or another statistical tool from which standard error could be computed). After making whole dataset of estimates and their related differences, such as standard error, model used, estimation method, midyear of data, type of data, level of aggregation etc., I will run a linear regression on the data set. Hence, I will interpret what and how influence the estimates. Finally, I will use funnel graphs, chronological ordering of data, or summary statistics to expound the data in more agreeable way to the reader.

Outline

1. Motivation: There is no meta-analysis on the Armington elasticity. There is just few researches summarizing previous results, e.g. McDaniel, Balisteri, 2002. Surprisingly, none of them is comprehensive enough. No one reports publication bias, the impact on the results originated from length of time period of collecting data, midyear of data, model, or estimation technique used.
2. Studies on Armington elasticity: I will delineate the methods people conduct estimates of Armington elasticity.
3. Data: I will clarify the way I will collect estimates from primary studies.
4. Methods: I will explain and use meta-analysis methods, such as funnel graphs, chronological ordering of data, summary statistics, or regressions.
5. Results: I will discuss my robustness checks and regressions.
6. Concluding remarks: I will encapsulate my findings and present their benefits for future researches.

Core bibliography

STANLEY, T. D. & H. DOUCOULIAGOS (2012): Meta-regression analysis in economics and business. New York: Routledge

FEENSTRA, ROBERT C., ET AL. (2014): In search of the Armington elasticity. *NBER Working Paper Series w20063*, National Bureau of Economic Research.

GALLAWAY, M. P., C. A. MCDANIEL, & S. A. Rivera (2003): Short-run and long-run industry-level estimates of US Armington elasticities. *The North American Journal of Economics and Finance* 14.1: pp. 49–68.

McDaniel, C. A. & E. J. Balistreri (2002): A discussion on Armington trade substitution elasticities. *Working Paper No.2002-01-A*, U.S. International Trade Commission, Washington, D.C.

Schürenberg-Frosch, H. (2015): We could not care less about Armington elasticities – but should we? A meta-sensitivity analysis of the influence of Armington elasticity misspecification on simulation results. *Working paper 594*, Ruhr Economic Papers,.

Cassoni, A. & M. Flores (2008): Methodological shortcomings in estimating Armington elasticities. *MPRA Paper 34544*, Facultad de Ciencias Sociales, Universidad de la Republica, Uruguay.

Author

Supervisor

Chapter 1

Introduction

The elasticity of substitution between domestic and foreign good, also known as the Armington elasticity, is the key parameter in trade policy analysis (Gallaway *et al.* 2003). It is based on the Paul Armington's assumption that the products are differentiated by country of origin in international trade. He published his crucial work in 1969. During next five decades the influence and popularity has spread rapidly.

This elasticity measures the degree of similarity between these two sources. The sources are the better substitutes, the higher is the value of the parameter. It means that the products are exactly identical as the parameter is approaching infinity. On the contrary, when the parameter is low, these two products are dissimilar (Warr & Lapiz 1994).

The Armington elasticities play an important role in the international trade literature. The first application is in testing Grossman and Helpman's "Protection for Sale" model. Since the international borders reducing trade flows, the magnitude of the trade substitution elasticity is important when one discusses the "border effect" (McCallum 1995). Here the extent relies on the degree of substitutability between domestic and imported goods. This is the second employment.

Besides it has become a standard assumption of partial- and general-equilibrium models. Trade policies are almost universally sensitive to trade elasticities and the Armington assumption considerably simplifies the parametrizing. Last but not least, Armington elasticities are important for computable-general-equilibrium (CGE) policy modeling (Gallaway *et al.* 2003).

One of first important estimates of Armington elasticities were conducted in US by Shiells *et al.* (1986), or Reinert & Roland-Holst (1992). Currently there are more than fifty articles, working papers and researches subjected to this topic across countries and continents. Most of them are from USA and Europe, but there are several even for South Africa, Latin America, Asia and Australia. Today, there are at least three papers from each continent.

Some of the studies sum up and compare other studies (e. g. McDaniel & Balistreri 2002, or Flores & Cassoni 2008). They conclude, for example, that long-run elasticities are higher than short-run ones, or that micro elasticities are higher than macro ones. Another factors, which affect the results are data-frequency and type of data. It might be surprising that up till now the overall meta-analysis in this field is not accomplished. Therefore, we consider as important to conduct one and fill-in this niche.

The objective of this thesis is to comprehend all written literature about above mentioned topic and to inspect it with meta-regression analysis (MRA). MRA is modern approach of statistical analysis of previously reported, or published research findings on a given empirical effect, or phenomenon. It is a systematic review of all relevant researches about a specific topic. Moreover, it reveals "study-invariant" principles (Stanley & Doucouliagos 2012). The one of the most remarkable merit of meta-analysis approach is revealing the publication bias of the estimates reported in literature. Moreover, MRA can correct potential biases in estimates, explain heterogeneity, or give the direction to future empirical investigation. This technique has been used, for instance, by Card & Krueger (1995) on employment effects of minimum wage.

The first step is the collection of primary studies. We search for them by using Google Scholar and RePEc Ideas. For using modern meta-analysis method and publication bias detection, we need the standard error of each elasticity (or another statistical measurement from which standard error may be computed).

After all the effort, the data set contains 3,524 observations from 42 studies. It ranks this thesis among the largest meta-analysis. When whole data set of estimates and their related differences, such as standard error, model used, estimation method, midyear of data, type of data, level of aggregation etc., is created we investigate it by using Bayesian model averaging (BMA). We search for the most influential variable, or variables. Similar approach in economics has been used, for example, by (Havranek & Irsova 2015) in the area of border effect.

From results obtained from BMA, we interpret what and how influence the estimates. Secondary, we want to confirm or disprove conclusions from previously written summarizing articles. Ultimately, some variables arise as more significant than other ones. This is the case of level of aggregation, real effective exchange rate or if the estimates are from secondary industries or not.

As it is asserted, we compare our findings with the previous ones. For instance, our results support Hummels (1999) in discussion of level of aggregation. Besides our findings often agreed with the ones from Flores & Cassoni (2008) as well. We back up them for example in matter of data frequency.

On the contrary, we cannot silently be in agreement with the results from Welsch

(2008) in matter of "age" of the data set. He claims that newer estimates show higher Armington elasticities, we find the opposite. In addition to, it is concluded that there is no statistical difference between long-run and short-run estimates, which is in sharp disagreement with all previous findings.

Additionally, this study is the first one that compares different models employed across articles and different estimation procedures used in this area. It is found out that the nonlinear models evinces higher estimates (+0.268) than all the other models. On the contrary, this result is considered as insignificant. Results from all other models do not differ at all. This is not startling conclusion, especially when we consider that some papers (Gallaway *et al.* 2003) use three different kinds of models and expect comparable results.

In the case of data structure we cannot agree with Schürenberg-Frosch (2015), since there is discovered no clear-cut in data frequency or in comparison of type of data. More than on the data structure the differences of results stems from the estimation methods. The OLS, FGLS, TSLS and GMM methods do not differ significantly. On the other hand, other techniques typically used for panel data (the ones such as fixed effects and random effects) are recognized lower by -0.429 than the above mentioned procedures. The significance of this conclusion is again not high.

Apart from all interesting findings, we realize that real effective exchange rate is significant tool to measure elasticities. But it exhibits opposite results than it is expected. It is probably caused by former studies from US.

Besides these facts the results and robustness check are used to suggest design for future researchers. We recommend to use techniques developed by Feenstra (2014). They employ modern approach that uses more disaggregated data at the data collection phase than at the results phase. The level of aggregation is found using our procedure as the most important factor in computing Armington elasticities. This simulated model evinces higher results (2.86 for unpublished and 3.15 for published articles) than the median value (1.03) and even than mean value (1.45) from the collected data. This conclusions point out a little publication bias, which is discovered even in funnel asymmetry test.

The thesis is structured as follows: Chapter 2 summarizes all previous conclusions of Armington elasticities. In addition to in Chapter 3 the attitude to the data collection is covered and variables used are enumerated. Next chapter, Chapter 4 contends with publication bias, e. g. with funnel plots. In Chapter 5 the BMA approach is clarified. Than, in Chapter 6 the obtained results are discussed, robustness check is provided and the summary statistics is used to expound the data in more agreeable way to the reader. The simulated model is computed in this section as well. Finally, Chapter 7 summarizes our findings.

Chapter 2

The Nature of the Data

As it is mentioned above Paul Armington published his breakthrough article in 1969 (Armington 1969). The oldest articles responding to the topic according to my research are Alaouze (1977) and Alaouze *et al.* (1977). Both inquire into elasticity of substitution in Australia.

Most of the articles discuss the issue in US, for example, Reinert & Shiells (1991) or Gallaway *et al.* (2003). In last decades more studies from Europe has emerged (for example, Lundmark & Shahrammehr 2011b). Even several papers written in Spanish, e. g. Hernández (1998) or Lozano K. (2004), and Portuguese (Faria & Haddad 2011), is included.

Because of demanding character of data collection we needed to start with creating data set in spring 2016. Therefore, we collected almost all papers published before the beginning of March 2016. We wanted to update it during April 2017, but no new papers about this topic were found. After all, the newest study contained in my research was published by Aspalter (2016) in February 2016.

Moreover, due to the fact that we want to investigate publication bias, we were pushed to discard all papers that do not have neither t-statistics nor standard errors, which are essential for genuine statistics. It caused removal of 16 papers, even one very cited - Broda & Weinstein (2004).

We had to drop the estimates with confidence interval, which do not include matching estimate as well. They were obviously wrong, or caused by typos. Finally, it was collected 3,524 estimates from 42 studies. This ranks this thesis among the most comprehensive ever written meta-analysis.

2.1 Different Armington Elasticities

The key attribute of Armington (1969) approach to demand is the supposition that consumers are to distinguish products by their source. In this thesis we use this product-differentiation just for distinction between domestic goods and their imported substitute. This is the most common approach.

Some of newer studies called these Armington elasticities as "macro elasticities" (Aspalter 2016). They moreover suggest to estimate "micro" elasticities. These ones differentiate imported goods by the country of origin. From these equations authors usually got higher results. Reader may compare it with Balistreri & Dahl (2010).

Balistreri & Dahl (2010) argues that the studies which use this economic-geography approach (they called the elasticity "import-import", but it is the same as "micro") with gravity equation are nowadays preferred in GTAP[1] default elasticities. Other comprehensive critique of common approach provides Erkel-Rousse & Mirza (2002).

Despite these facts we do not examine these elasticities in this study. There is written about ten to fifteen papers about these elasticities, which is not sufficient for conducting meta-analysis. Moreover, we are not interested in comparing two different sources of imported goods. We aim at investigation of relations between domestic goods and imported ones.
But if the reader is interested more in these elasticities, besides the critical papers mentioned above we may recommend Hertel *et al.* (2007) or Hillberry *et al.* (2005).

2.2 From Utility Function to Base Equation

Now we shortly describe, how the authors usually derive the elasticity of substitution between domestic goods and imports. Reader may appreciate more information about it. It might be found, for example, in Lundmark & Shahrammehr (2011a).

The elasticity can be derived from a familiar two-stage budgeting process (Galloway *et al.* 2003).

At first, we define utility function over composite goods C for a well-behaved representative consumer. The composite goods C contains amount of domestic goods D and quantity of imported goods M. In the first stage our consumer allocates his (her) total expenditures to miscellaneous product categories. Then, in the second stage, he (she) allocates expenditures within each group between M and D taking relative prices into consideration as proposed. Finally, following CES functional form for the composite good can represent Armington specification:

$$C = \alpha[\beta M^{((\sigma\ \ 1)/\sigma)} + (1-\beta) D^{((\sigma\ \ 1)/\sigma)}]^{\sigma/(\sigma\ \ 1)}, \tag{2.1}$$

where σ stands for the constant elasticity of substitution between domestic and

[1] The Global Trade Analysis Project (GTAP) is a global network of policy makers and researchers conducting quantitative analysis of international policy matters. For more information: https://www.gtap.agecon.purdue.edu/

import goods. α and β are then calibrated parameters in the demand function (Gibson 2003).

In addition to, we follow the standard assumptions of continuous substitution between M and D and a well-behaved utility function. Moreover, the assumption of weak separability of product categories within the utility function indicates that the allocation of expenditures to goods within an industry group is conditional on the level of spending in this group (Gallaway *et al.* 2003).

Then, a ratio of imports to domestic goods is yielded from an optimization of the second-stage. This sub-utility function is a function of the ratio of domestic prices to import prices:

$$\frac{M}{D} = \left[\frac{\beta}{1-\beta}\frac{p_d}{p_m}\right]^{\sigma}, \tag{2.2}$$

where prices are multiplicative and p_d and p_m represents domestic and import prices respectively. Here the first-order condition is got, in which rate of substitution equates the rate of relative prices. Furthermore, the Armington elasticities can be now easily estimated for disaggregated commodity categories Winters (1984). It is useful to rewrite this condition into base equation:

$$y = a_0 + a_1 x, \tag{2.3}$$

where $y = log(M/D)$, $x = log(p_d/p_m)$, $a_0 = \sigma log[\beta/(1-\beta)]$ and a_1 is the elasticity of substitution between imports and domestic sales. From this equation almost all other equations used to estimate Armington elasticities are derived.

2.3 Previous Findings

Conclusions from previously written papers are summarized in this section in order to compare them with our results in Chapter 6. Not surprisingly, the correct size of Armington elasticities is disputed since they have entered CGE*Computable General Equilibrium.* modelling as an important parameter. Some of the authors simply adopt them from other studies with roughly comparable characteristics. On the other hand, there exists a broad literature about this topic (Schürenberg-Frosch 2015).

Since the 1970s more than 50 studies with estimated Armington elasticities have been published. First studies have come with comparable results. At least at the first glance it looks like it, these estimates are slightly smaller than unity. As it is mentioned in Chapter 1 majority of older studies are from US. The latter ones, which are from other countries have come with higher estimates (Welsch 2008).

Gallaway *et al.* (2003) claims that long-run estimates are approximately two times higher than the short-run estimates. Similar conclusion provides, for example, Schürenberg-Frosch (2015). This is very important note, because long-run estimates are more appropriate for most trade-policy analysis.

Besides this they use three-digit SIC[2] classification and they get statistically different results, which indicate importance of estimations on disaggregated data. From different point of view, Hummels (1999) is engaged in discussion of this issue, which is well-known as "aggregation bias". He provides robust evidence on the existence of a negative bias. He employs in his paper gravity models. In conclusion, he claims that the bias originates in heterogeneity of goods included in aggregated categories.

It is plausible, because more aggregated data includes sectors that are more heterogenous in the produced goods and thus also smaller in their international substitutability.

For example, Shiells *et al.* (1986) find out that estimates differ across industries. They use three-digit ISIC[3] level and divide them into three groups. In the first group aree "extremely import sensitive" industries as wearing apparel, rubber products, transport equipment". Secondly, industries as "food", "beverages", "tobacco", "textiles" or "metal including electrical machinery" were classified as "moderately import sensitive" and "wood" and "paper" industries were found as "import inelastic".

The argument that estimates differ across the history devises Schürenberg-Frosch (2015) as well. She even writes that the recent estimates are higher than those from 1980s and 1990s. The sole fact is that during globalization the varieties from different countries have got more similar and have reduced market power. Thus, it might increase Armington elasticities (Hübler & Pothen 2016).

For instance, McDaniel & Balistreri (2002) compare two articles on different level of aggregation of US goods, namely the ones written by Gallaway *et al.* (2003) and Reinert & Roland-Holst (1992), but they completely have forgotten about different time periods of the data sets (Flores & Cassoni 2008). Thereby, we want to capture level of aggregation and time periods of data set of study in this research as well. For that reason, we use midyear of the data from each study.

Furthermore, Schürenberg-Frosch (2015) claims that the estimations varies more substantially across countries than have been expected. Because of that the dummy for level of development of the country (division on development and developed) is employed and variable for market size is used as well. The second reason for including variable *Market size* is that Flores & Cassoni (2008) asserts that even small economies has market power, which is necessary for setting international prices.

[2]Standard Industrial Classification.

[3]The International Standard Industrial Classification.

This variable measures the GDP in the midyear of the data set for specified country (countries). This factor should distinguish between small, middle-sized and huge economies.

Other ideas in discussion why some estimates are lower provide Flores & Cassoni (2008). They suggest that low Armington elasticities may arise in case of ignoring some important components in equations. Thus we create several model groups (namely seven) to compare the different approaches.

Moreover, Hertel *et al.* (1997) contend that the lower the frequency of the data the more inelastic elasticities. Others, e. g. Flores & Cassoni (2008), find no clear-cut results in matter of data frequency.

Besides the facts mentioned above, Flores & Cassoni (2008) asserts that cross sectional estimates, for instance, Hummels (1999), are generally higher than time series ones (e. g. Gallaway *et al.* (2003)). It might be the case that time series studies use reduced-form equations, but these with cross-sectional data take into consideration a supply condition (McDaniel & Balistreri (2002)). In contrast is that panel data provide even smaller estimates (Schürenberg-Frosch 2015). Panel data are used for example by Saito (2004), or Németh *et al.* (2011).

Last emerging problem according to Flores & Cassoni (2008) is econometric methodology, which is very hard to compare reversely. Despite this fact the division according to estimation methods employed in each study is included.

2.4 Review of Used Articles

In the following table an overview of all articles used for this meta-analysis is situated. It includes the number of observations (n), its means, standard deviations and medians as well.

Table 2.1: Review of Used Articles

Authors	*Country*	*n*	*Mean*	*SD*	*Med*
Alaouze (1977)	Australia	68	0.96	0.93	0.96
Alaouze *et al.* (1977)	Australia	184	0.86	0.95	0.90
Corado & de Melo (1983)	Portugal	24	0.79	0.67	0.71
Lächler (1985)	Germany	92	0.69	0.97	0.80
Shiells *et al.* (1986)	US	122	2.32	9.96	2.34
Reinert & Shiells (1991)	US	16	0.76	0.40	0.89
Reinert & Roland-Holst (1992)	US	127	0.91	0.64	0.85

Continuation of Table 2.1					
Authors	*Country*	n	*Mean*	*SD*	*Med*
Reinert & Shiells (1993)	US	106	0.71	0.39	0.80
Warr & Lapiz (1994)	Thailand	135	1.11	0.91	1.00
Hernández (1998)	Columbia	16	0.16	0.55	0.22
Hummels (1999)	US, New Zealand, Brazil, Argentina, Chile, Paraguay	118	7.04	9.37	5.61
Gallaway *et al.* (2003)	US	408	0.99	0.77	0.94
Gibson (2003)	South Africa	46	0.98	0.56	0.90
Lozano K. (2004)	Columbia	28	0.57	0.57	0.48
Saito (2004)	14 OECD	10	1.91	0.88	2.04
Ivanova (2005)	Russia	81	1.15	2.42	0.93
Nganou (2005)	Lesotho	25	2.10	3.00	1.28
Gan (2006)	US	67	0.66	0.79	0.46
Welsch (2006)	France	143	0.61	1.39	0.52
Bilgic *et al.* (2008)	US	21	1.06	0.59	0.93
Welsch (2008)	France, Germany, Italy, United Kingdom	53	0.67	1.09	0.66
Flores & Cassoni (2008)	Uruguay	53	1.11	0.55	0.98
Huchet Bourdon & Pishbahar (2009)	15 EU	8	1.24	0.51	1.10
Imbs & Méjean (2009)	US	8	5.42	1.47	5.38
Kawashima & Sari (2010)	Japan	2	1.11	0.42	1.11
Tourinho *et al.* (2010)	Brazil	28	1.16	1.07	1.09
Flores & Cassoni (2010)	Uruguay	64	1.30	0.74	1.08
Ogundeji *et al.* (2010)	South Africa	13	2.32	1.03	2.03
Németh *et al.* (2011)	25 EU	18	1.54	0.85	1.35
Sauquet (2011)	France	20	0.58	0.3	0.55
Faria & Haddad (2011)	Brazil	110	1.78	0.56	1.94
Lundmark & Shahrammehr (2011b)	Sweden	10	0.67	2.29	-0.10
Lundmark & Shahrammehr (2011a)	19 EU	37	0.53	1.1	0.33
Lundmark & Shahrammehr (2012)	8 EU	76	0.45	0.9	0.16
Turner *et al.* (2012)	US	26	0.94	0.47	0.93
Mohler & Seitz (2012)	27 EU	27	26.06	55.32	13.02

Continuation of Table 2.1

Authors	*Country*	*n*	*Mean*	*SD*	*Med*
Corbo & Osbat (2013)	Germany	105	5.37	5.78	3.60
Feenstra (2014)	US	33	1.52	1.33	1.39
Tourinho *et al.* (2015)	Brazil	28	1.34	1.43	1.15
Saikkonen (2015)	South Africa	111	1.07	0.67	0.94
Schürenberg-Frosch & Olekseyuk (2016)	8 EU	41	0.91	0.56	1.01
Aspalter (2016)	15 EMU countries	816	1.31	2.82	1.31

Chapter 3

Data Collection

During the data collection we proceed according to Stanley & Doucouliagos (2012). On the basis of their classification, we collect essential, typical and value-added data.

3.1 Essential Variables

The essential variables are effect size (usually Armington elasticity, or Elasticity of Substitution), standard error and sample size. For the time series data, if the number of observation is not mentioned, we simply use duration of author's observation. When author uses panel data and does not mention total number of observations we multiply number of cross-sectional units with numbers of the time series units. If we contend with one or two sided t-statistics, confidence intervals or p-values instead of standard error, it is recalculated[1] because of need of unification of the variables.

3.2 Typical Variables

The typical data for our paper are mostly mention in the Section 2.3 - level of data aggregation, level of results aggregation, sector of industry, type of data, data frequency and whether the data are classified as short-run or long-run. These variables serves to correct the original econometric research.

The divisions of industries we adopts from paper written by Saikkonen (2015) - see Appendix A. If the paper used more precise division of products, the SIC[2] (Standard Industry Classification) is used on its level of aggregation up to the eight

[1]Stat Trek: T Distribution Calculator: Online Statistical Table [online]. Infogram: ©2016 [cit. 10. 10. 2016]. Dostupné z: http://stattrek.com/online-calculator/t-distribution.aspx.

[2]Scientific Telephone Samples: SIC Code List [online]. Infogram: ©2013 [cit. 10. 10. 2016]. Dostupné z: http://www.stssamples.com/sic-code.asp.

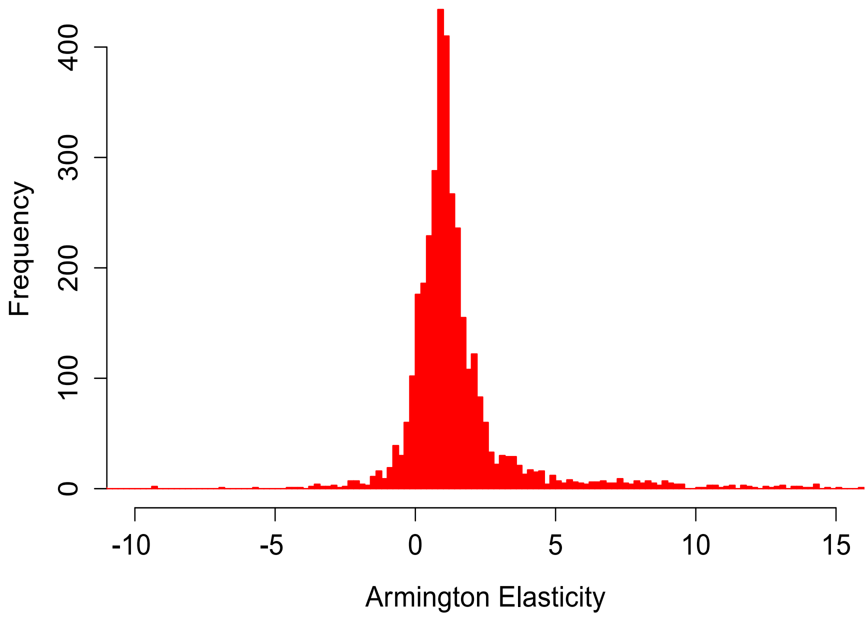

Figure 3.1: Histogram of Armington Elasticities

digit classification. This division use, for example, Gallaway *et al.* (2003). They also published the second largest sample of estimates. Otherwise, researchers usually classify the variables using ISIC (Shiells *et al.* 1986), NACE[3] (Aspalter 2016) or TSUSA[4] (see Reinert & Roland-Holst 1992, or Reinert & Shiells 1993).

As it is mentioned above, at least several papers (e. g. Aspalter 2016, Mohler & Seitz 2012) use different classification for aggregating data and the final results. Thus, we want to capture both of these phenomena. Moreover, except the linear terms, we want to add squares for the case the relationships between the values of estimations the levels of aggregation are not linear. In the end, we have to cease from this idea because of strong correlations between linear and squared terms.

Furthermore, at the beginning of the research it was planned to create two data sets. These two should differ in level of aggregation of estimates. First one should use just division on primary, secondary and tertiary sectors. The second one then should use more precise division - nine sub sectors altogether. In the end, we realize that there are just about eight observations of finance & insurance sub sector, or 16 observations of transportation sub sector. Altogether five of the nine sub sectors have less than 35 observations (less than 1% of total number of observations). This is extremely low occurrence for more than half sectors. This is the reason why only first option with division on three sectors is used.

[3]The Statistical classification of economic activities in the European Community.
[4]Tariff Schedule for The United States.

The classification according to types of data is simply on cross-sectional data, time series data and panel data. Data frequency is then distinguished by monthly, quarterly and annually gathering.

Gallaway *et al.* (2003) was the first one, who used distinction on short-run and long-run estimates. Thereafter, this aspect is usually included in the studies. Thus, our meta-analysis use these specifications as well. Non-specified estimates are included into "long-run" subgroup, despite the fact that the former studies "did not consider explicitly the long-run aspect of applied partial- and general-equilibrium modeling" (Gallaway *et al.* 2003, p. 3).

Furthermore, we gather data about length of the time period, midyear of data, publication year, examined countries, estimation methods and type of model used in studies.

Midyear and publication year are adjusted by subtracting the year of the oldest observation (1968 and 1977 respectively). Due to this fact we observe whether newer data or publication shows different results than former or not. We thought about adding squares of these variables, but they are strongly correlated (correlation more than 0.9) with its linear terms. As in the case of data aggregation we abandon this idea at the end. Despite this fact it should be sufficient to use them just in linear terms. This assertion is based on findings from Schürenberg-Frosch (2015). She proposes recent estimates are higher than the older, so one can say she finds roughly linear relationship among them. Moreover, midyear of data and publication year are strongly correlated as well (correlation is slightly below 0.88), thus just midyear of the data is held. This figure is more important for results than the year of publication.

Examined countries are after all divided just into developing and developed, while we classify developed as those from Central and Western Europe, North America. In addition to them Australia, New Zealand and Japan are added. On the contrary other Asian countries, those from Latin America and Africa are classified as developing.

Despite the fact that more than ten studies use panel data, surprisingly just two of them employ fixed effects. Thus, we divide estimation methods only into five groups: first is OLS, in second are Cochrane-Orcutt (or FGLS), third one includes TSLS and IV, in fourth group is GMM (for more check, for instance, Aspalter 2016) and the last group contains all other estimation method.

3.2.1 Model's Overview

The division of the model follows the Section 2.2, models are split into seven groups. As a base is used the group with the most observations, which is called *Static*

Armington[5]. These models are employed on stationary data with log-level structure. In literature these models are often called "Static Armington" and hence originates my label as well. The structure of the first group's models is easily the base equation - Equation 2.3:

$$y = a_0 + a_1 x_t + e, e \sim N(0, \sigma^2), \tag{3.1}$$

where y and x are defined in addition to Equation 2.3. The elasticity of substitution between imports and domestic sales is then given by term a_1. The same definitions have these coefficients in the other equations as well.

Second group of models is defined identically, only time trend is added because of achieving stationarity of data (Lundmark & Shahrammehr 2012). Moreover, we put the same ones with one lag of explanatory variables to this group of models. The models of this extension has just few observations (Tourinho *et al.* 2015). In this study just final elasticities of substitution are reported, so the adjustments are not needed:

$$y = a_0 + a_1 x_t + (a_2 x_{t\ 1}) + a_3 t + e, e \sim N(0, \sigma^2). \tag{3.2}$$

The distinction of the next group stems from lag term of explained variable. This basis of model apply, for instance, Ogundeji *et al.* (2010):

$$y = a_0 + a_1 x_t + a_2 y_{t\ 1} + e, e \sim N(0, \sigma^2). \tag{3.3}$$

The further group of model is used typically, when data do not have log-level form and are not cointegrated. For these reasons, both series (for prices and quantities) are first-differenced. The structure of these models were similar to Equation 3.1, but the differences are used, therefore we classify these model as Error-Correction Models (ECM) (Gibson 2003). The extension of the equation as in Equation 3.2 is used as well:

$$\Delta y = a_0 + a_1 \Delta x + (a_2 x_{t\ 1}) + e, e \sim N(0, \sigma^2). \tag{3.4}$$

When the time series of the logarithms are both integrated of order one, I(1), and cointegrated of order (1,1), CI(1,1), then another form of ECM model is used to avoid spurious regression (Gan 2006):

$$\Delta y = a_0 + a_1 \Delta x + a_2 y_{t\ 1} + a_3 x_{t\ 1} + e, e \sim N(0, \sigma^2). \tag{3.5}$$

Several articles (e. g. Corado & de Melo 1983 and Saikkonen 2015) employ nonlinear models, especially Feenstra (2014) does great development within these

[5] The own name of the variable is always written with capital letter and it is in italics.

models. Their structures are more complicated and differ slightly, thus we do not mention them here. They form another group of models, besides their structures are quite similar to those, by which authors estimates the "micro" elasticities" (e. g. Aspalter 2016 reports both "micro" and "macro"). Thus we might expect higher estimates of elasticities as it is mentioned in Section 2.1.

In the last group of models are gathered all observations originated from different models than above mentioned ones. In addition to this classification, we include dummies for seasonality and import constraint. They determine whether the study considers these phenomenons in estimation or not.

3.3 Value-added Variables

The value-added variables are usually such that are unavailable during conducting the primary study. These relevant pieces of information are typically "study-invariant". On the other hand, they have power to explain variation from different researches. The value-added variables in this case are if the paper is *Published* or not, discounted recursive *Impact*[6] factor from RePEc Ideas[7], and number of *Citations* from Google Scholar[8]. These variables are useful in identification of potential publication bias.

Besides these variables related to publication bias the real effective exchange rate (*REER*) in midyear of data is collected. Moreover, data for above mentioned *Market size* of examined country are gathered in terms of GDP in midyear of data. The information about GDP is downloaded from the World Bank[9] and those for *REER* from Federal Reserve Bank[10].

The base for *REER* is set to year 2010 and this parameter measures the value in percents of a specific currency in relation to an an average group of major currencies. It is important measure when assessing country's trade capabilities and current both import and export situations. Similarly to midyear of data, this variable is adjusted by the lowest entry, in this case it is by subtracting 38. Since this variable is originally stated in percents, there is no reason to transform it by logarithms.

[6]This variable does not have unit.

[7]RePEc IDEAS: Recursive Discounted Impact Factors for Series and Journals [online]. Infogram: ©1997 [cit. 20. 4. 2017]. Dostupné z: https://ideas.repec.org/top/top.series.rdiscount.html.

[8]Google Scholar [online]. Infogram: ©2004 [cit. 20. 4. 2017]. Dostupné z: https://scholar.google.cz/.

[9]The World Bank: GDP [online]. Infogram: ©2016 [cit. 23. 9. 2016]. Dostupné z: http://data.worldbank.org/indicator/NY.GDP.MKTP.CD?locations=US.

[10]Federal Reserve Bank: Real Effective Exchange Rates [online]. Infogram: ©2016 [cit. 23. 9. 2016]. Dostupné z: https://fred.stlouisfed.org/series/CCRETT02USQ661N.

3.4 Final Adjustments

After the collection of the data some adjustments are needed. Firstly, we get rid of one dummy variable from each group of dummies (e. g. one of panel, time series, cross-sectional data) to avoid dummy variable trap (multicollinearity).

Besides four variables are transformed into logarithms - *Total* number of observations, number of *Citations*, *Market size* and *REER*.

Last but not least, winsorizing is used to contend with outliers in explained variable and in collected standard errors in some legal way. The winsorizing is a method, which takes the lowest and the highest estimates and sets their values to the desired percentiles. It is difference against trimming, which just easily drops the lowest and highest estimates. We employ 2,5% and 97,5% percentiles as it is proposed in Lusk *et al.* (2011).

Finally, the number of estimates differ from study to study significantly. From only two estimates in Kawashima & Sari (2010) to more than 800 in Aspalter (2016). Therefore, the multiplication by inverse of the number of estimates per study is used to guarantee that each paper has the same weight.

3.5 Variables in Use

In following table reader may find final overview of variables used in this thesis. The variables that are dropped because of dummy variable trap are not included.

At *Armington elasticity* and *Standard errors* reader may find two results. The results in brackets are those before winsorizing. The huge differences between winsorized and non-winsorized standard deviations indicates presence of outliers. This fact allows me to use winsorized estimates of Armington elasticities and its standard errors, as it is mentioned in Section 3.4. Median values remain naturally the same. Moreover, the difference between mean and median observation of the elasticity detects possible publication bias. We refer to this more in Chapter 4. Reader may keep in mind that *Total* number of observations, *Citations* and *Market size* are in logarithms[11] and *midyear* and *REER* are adjusted (-1968 and -38 respectively).

[11] All means of variables in logarithms were computed by average partial effect method (Wooldridge 2015).

Table 3.1: Variables in Use

Label	*Description*	*Mean*	*SD*	*Med*
Armington elasticity	Winsorized estimates of Armington elasticity (explained variable)	1.45 (1.63)	1.78 (6.23)	1.03 (1.03)
SE	Winsorized estimates of standard errors of Armington elasticity	0.72 (2.26)	1.18 (30.58)	0.31 (0.31)
Long-run	=1 if the estimated long-run Armington elasticity	0.84	0.36	1
SIC level of data	Level of data aggregation (=1 whole economy, 2,..., =8 disag.)	6.49	1.58	7
SIC level of results	Level of results aggregation (=1, 2,...8)	5.06	1.21	5
Secondary ind.	=1 if the estimate is for secondary sector	0.86	0.34	1
Tertiary ind.	=1 if the estimate is for tertiary sector	0.02	0.14	0
Length	Length of time period	14.24	9.76	16
Total	Total of observation (in logarithms)	4.64	1.93	4.22
Midyear	Adjusted midyear of data	23.45	12	24
Developed	=1 if the estimate is for developed country	0.76	0	1
Monthly	=1 if the data were collected monthly	0.14	0	0
Annually	=1 if the data were collected annually	0.65	0	1
Time series	=1 if the time series data were used	0.58	0	1
Cross-sectional	=1 if the cross-sectional data were used	0.08	0	0
Dynamic Armington	=1 if Equation 3.2 was used	0.10	0	0
Arm. model with lag	=1 if Equation 3.3 was used	0.15	0	0
ECM	=1 if Equation 3.4 was used	0.09	0	0
ECM with lags	=1 if Equation 3.5 was used	0.04	0	0
Nonlinear	=1 if nonlinear model was used	0.28	0	0
Other models	=1 if another model was used	0.11	0	0
Import constraint	=1 if import constraint was took into consideration	0.03	0	0

Continuation of Table 3.1				
Label	*Description*	*Mean*	*SD*	*Med*
Seasonality	=1 if seasonality was took into consideration	0.20	0	0
OLS	=1 if OLS or GLS estimation method was used	0.48	1	0
CORC	=1 if Cochrane-Orcutt or FGLS estimation method was used	0.16	0.37	0
TSLS	=1 if 2SLS or IV estimation method was used	0.09	0.28	0
Other estimation methods	=1 if other types of estimation were used	0.03	0.17	0
Impact	Discounted recursive impact factor from RePEc IDEAS	0.12	0.24	0.07
Citations	Number of citations (in logarithms)	2.80	1.96	2.64
Published	=1 if the article was published	0.39	0.49	0
Market size	Market size in terms of GDP (billions of dolars) in midyear of data (in logarithms)	6.45	1.86	6.42
REER	Adjusted real effective exchange rate in the midyear of data (in logarithms)	66.39	18.71	62.9

Chapter 4

Publication Bias

The MRA is a very feasible tool for detecting one well-known phenomenon. The publication bias, or publication selection bias arises when estimates have a different probability of being reported based on statistical significance or their magnitude. Researchers may hide estimates that are insignificant or have unintuitive signs. Moreover, they can search for estimates that are easier to publish (Havranek & Irsova 2015).

For instance, Doucouliagos & Stanley (2013) study the problem and found out in their survey of publication bias that most fields of empirical economics are seriously affected by this problem. From this point of view, publication bias can be potentially present even among estimates in our study. Similarly as Havranek & Irsova (2015) we test for publication bias before we proceed to the analysis of heterogeneity.

For instance, in medical science this problem scales up. Therefore, the best medical journals now require registration of clinical trials before publication, so that researchers may find results of all trials (Havranek & Irsova 2015).

The easiest way to detect the publication bias is visually by using so-called funnel plots. This is proposed by Egger *et al.* (1997). This scatter plot shows on horizontal axis the magnitude of the estimated effects and the precision by the inverse of the estimated standard error on the vertical axis.

The most precise estimates of the effect are close to the mean underlying effect, if it is the case that the research is not influenced by publication bias. If the estimates get more spread forming a symmetrical reversed tunnel it means that the precision decreases. When the publication bias is present, the funnel plot becomes hollow (in case that researchers rejected statistically insignificant estimates), or asymmetrical (researchers rejected estimates of a particular sign or magnitude), or both Havranek & Irsova (2015).

4.1 Funnel plot

Funnel plot for all estimates of Armington elasticities is reported in Figure 4.1.

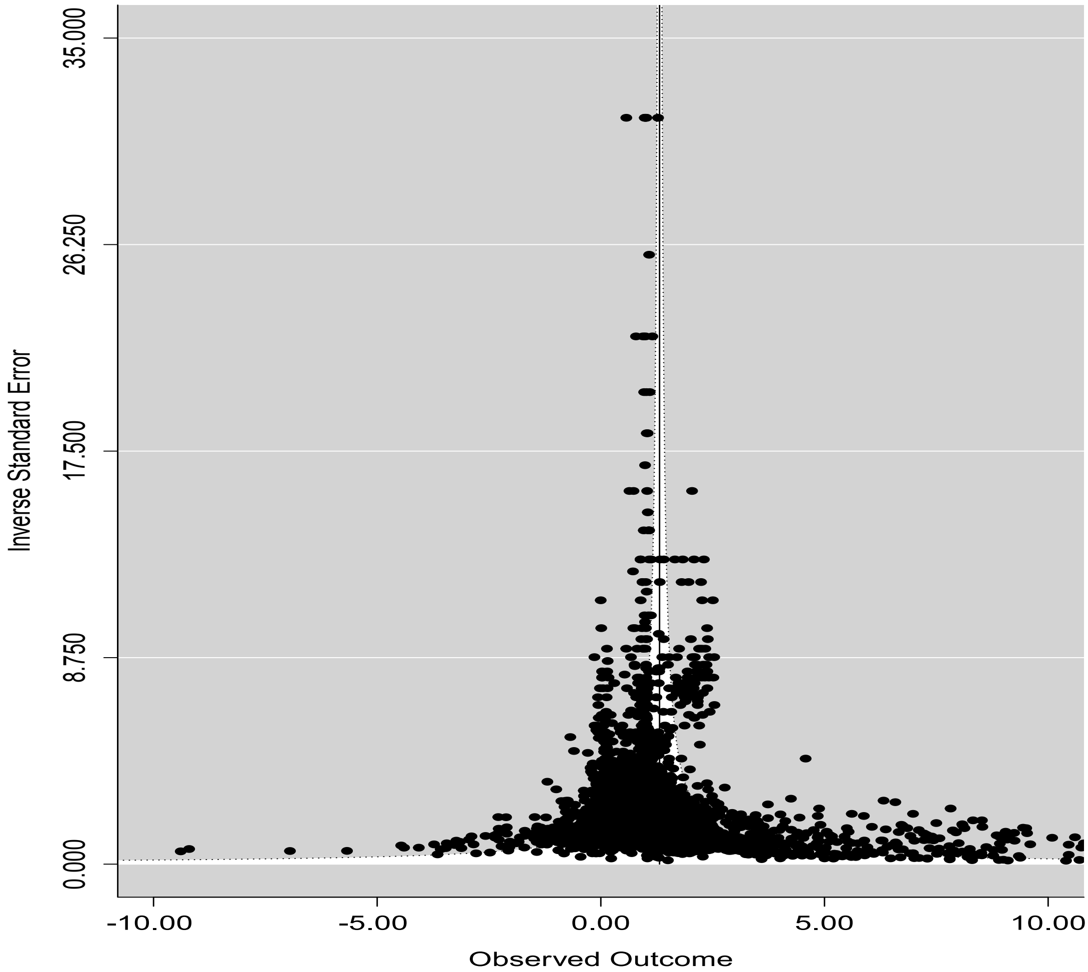

Figure 4.1: Histogram of Inverse Standard Errors

The funnel plot is relatively symmetrical. The most precise estimates are close to the average reported elasticity. Obviously, the funnel plot is not hollow and even estimates with very little precision are reported. Moreover, the plot does not have multiple peaks. It indicates that there is no heterogeneity in the estimated Armington elasticities. When we consider typical funnel plots with publication bias reported, we find visible differences (compare with Stanley & Doucouliagos 2012). At the first glance, the publication bias is not so convincing, but it is better to rely on formal tests than on feelings.

4.2 Formal tests

Since the funnel plot is just a simple visual tool for the evaluation of publication bias, we test the presence of publication bias more formally. The example of Stanley & Doucouliagos (2012) is followed as they explore relationship between estimated effect (Armingiton elasticity) and its standard error (SE_i). They prefer the regression with standard error against the one with variance.

$$Armel_i = \beta_0 + \beta_1 SE_i + e_i, e_i \sim N(0, \sigma^2). \tag{4.1}$$

Results for our observations are summarized in following table.

Table 4.1: Test of Publication Bias according to Equation 4.1

Variables	*Estimate*	*t-value*	*p-value*
β_0	0.873	29.39	$< 2 * 10^{16}$
β_1	0.808	37.70	$< 2 * 10^{16}$
n	3524	NA	NA

These results propose underlying effect (β_0) and publication bias skewed to the right (positive sign at β_1). One can realize that these are the same conclusion as for difference between mean and median of Armington elasticities in Table 3.1. To confirm these inferences we employ another modification for this test used by Stanley & Doucouliagos (2012). They simply apply weighted least squares (WLS) to adjust the Equation 4.1, the SE_i is the weight.

$$t_i = \beta_1 + \beta_0 \frac{1}{SE_i} + v_i, \tag{4.2}$$

where t_i is t-statistics of observed effect (it emerged by definition from division the observed effect by its standard error) and the v_i is defined as e_i/SE_i. The next table summarizes this estimation.

Table 4.2: Test of Publication Bias according to Equation 4.2

Variables	*Estimate*	*t-value*	*p-value*
β_1	0.761	66.871	$< 2 * 10^{16}$
β_0	1.558	5.771	$8.56 * 10^{9}$
n	3524	NA	NA

This results just confirms my previous findings. There are two points of view to test. First is so-called funnel-asymmetry test (FAT). It may be considered that this test shows whether funnel graph is asymmetric or not. The null hypothesis is of no publication selection. It is given by $H_0 : \beta_1 = 0$. Apparently, we do reject H_0 (t-value is high - 66.871). The positive sign of t-statistics means that the funnel plot is skewed to the right. Hence, we can see that Figure 4.1 is not considered as symmetric in formal approach.

The second test is so-called precision-effect test (PET). The null hypothesis is $H_0 : \beta_0 = 0$ in this case. It tests whether or not there is genuine empirical effect beyond the potential distortion due to publication selection. As reader can see, the H_0 is strictly rejected at the 1% level, so there is underlying empirical effect beyond the potential distortion. This conclusion supports the presumption about publication bias in this field.

Chapter 5

Bayesian Model Averaging

Besides investigation of publication bias we resolved to determine, which factor influences the Armington elasticity the most. Since the data set is already completed it is feasible to proceed to own estimation procedure. Rather than model selection approach we employ classical method of meta-analysis - the Bayesian model averaging. This method of estimation is not based on finding the best model, but it uses weighted average of all (or all important) linear models (without squares of variables, or interaction terms). The whole estimation procedure is here shortly described. If it is not be stated differently, it is proceeded according to Zeugner (2011). During own estimation we use well-known statistical software *R* and its package *bms*.

5.1 Foundation

At the beginning, we easily assume a linear model structure, with dependent variable y, coefficients i and with vector of independent variables X, where e is normal iid[1] error term, with variance σ^2.

$$y = \alpha_i + \beta_i X_i + e, e \sim N(0, \sigma^2), \tag{5.1}$$

Since we have many potential explanatory variables in the matrix X it yields further questions. Some examples would be "Which of the variables $X_i \in X$ should be included?" or "How important the variables are?" The straightforward approach of conducting inference on single linear model that includes all variables is not efficient. It is better to say that it is infeasible.

BMA contends with this problem by estimating all (in case of less than fifteen variables, with more variables we need to select the "best" models) possible combinations of sets of explanatory variables. During the estimation BMA constructs

[1] Independent and Identically Distributed.

weighted average over all of them. If the matrix X provides k explanatory variables, there 2^k possible models arise. Because of the k power we need to select "best" models in case of more than fifteen explanatory variables. The models weights emerge from posterior probabilities from Bayes' theorem:

$$\begin{aligned} p(M_i|y,X) &= \frac{p(y|M_i,X)p(M_i)}{p(y|X)} \\ &= \frac{p(y|M_i,X)p(M_i)}{\sum_{s=1}^{2^k} p(y|M_s,X)p(M_s)}. \end{aligned} \tag{5.2}$$

The p(y|X) is integrated likelihood which is constant over all models and therefore it is simply interpreted as a multiplicative term. Thus, the posterior model probability (PMP), p(M_i|y,X) is proportional to the marginal likelihood of the model, p(y|M_i, X) times a prior model probability, p(M_i). The marginal likelihood of the model is the probability of the data given by the model M_i. The prior model probability indicates, how probable the researcher estimates the model M_i before looking at the data.

Very popular choice is to set a uniform prior probability $p(M_i) \propto 1$ for each model. It may be seen, for example, in Havranek & Irsova (2015). It expresses the lack of prior knowledge. In addition to this approach, we select a second way because of the necessity for a robustness verification. We follow Ley & Steel (2009). They suggest a binomial-beta hyperprior on the prior inclusion probability.

Moreover, we get the model weighted posterior distribution for any statistic θ (e. g. β in our case - Equation 5.1).

$$p(\beta|y,X) = \sum_{i=1}^{2^k} p(\beta|y,X,M_i)p(M_i|y,X). \tag{5.3}$$

From PMP it is only one step to get the posterior inclusion probability (PIP), which is reported as standard in BMA framework. PIP is simply the sum of PMPs of the models including the particular variable k. It reflects the probability a certain regressor is included in the particular model. The PIP may be expressed by following equation (Horvath *et al.* 2017).

$$PIP = p(\beta_k \neq 0|y,X) = \sum_{i=1}^{2^k} p(M_i|\beta_k \neq 0,y,X). \tag{5.4}$$

5.2 Other Important Settings

Another important step is the choice of hyperparamter g we again proceed according to Havranek & Irsova (2015). We use Zellner's g and choose "uniform information prior" - UIP. It set $g = N$. It means that for all models there is attributed the same information as it is contained in one single observation.

In robustness check other Zellner's g, so called "BRIC", is employed. It combines above mentioned Bayesian information criterion ($g = N$) with risk inflation criterion ($g = K^2$). Its final set up is then $g = max(N, K^2)$. Read Ley & Steel (2009) for more comprehensive information .

5.3 MCMC Sampling

As it is mentioned in Section 5.1 with a small number of covariates, it is feasible to enumerate all potential variable combinations to gain posterior results. In case of more variables it is very time consuming. And it is obviously our case.

Since we have altogether 31 variables in use (after dropping several because of dummy variables traps) it means that there is 2^{31} possible models to be estimated. For gaining an idea, it is more than $2 * 10^9$ models. Therefore, Markov Chain Monte Carlo (MCMC) sampling technique (Raftery *et al.* 1997) is employed to gather results from the most important part of the posterior model distribution. It approximates the models as closely as possible.

This chain in BMA relies on the Metropolis-Hastings algorithm. It walks through the model space consequently:

Suppose that at step i, the sampler stand at some specific model M_i with posterior model probabilities p(M_i|y,X). In the next step *i+1* another model M_j is suggested. From the current model to the suggested one the sampler switches with probability $p_{i,j}$, which is defined as follows:

$$p_{i,j} = min\left(1, \frac{p(M_j|y,X)}{p(M_i|y,X)}\right) \tag{5.5}$$

If the model M_j is rejected, the MCMC sampler proceeds to the next step, say *i+2* and suggests a new model M_k. But if the model M_j is accepted, it becomes the current model and has to hold out against further new models. The probability by which each model is kept is derived from this manner. It converges to the PMP p(M_i|y,X).

For estimation we use R with package "bms". It has already inbuilt some simple algorithm for choosing "good" starting model. Moreover, as it is proposed in

Havranek & Irsova (2015) we use birth-death sampler with 1000000 burn-ins and 2000000 iterations.

It means that one of variables K is chosen randomly. If this chosen variable is contained of the current model M_i, then the suggested model in step *i+1* has the same set of variables as the model M_i from the step i. Just it is for the chosen variable. Another situation appears, when the chosen variable is not part of M_i. In this case the suggested model includes all the variables from current model and it adds the chosen covariate.

It may happen that the start model does not be a "good" one, therefore, several first models is removed (so-called burn-ins). Then the MCMC sampler computes the posterior model probabilities based on number of iterations.

Chapter 6

Results of BMA

After describing the theoretical background of the estimation procedure and its own realization, it is possible to interpret the results in proper way. The results of the variables that were identified as most important are in the following table - Table 6.1. During classification of the variables, it is proceeded according to Eicher *et al.* (2011). His division is based on posterior inclusion probability and the classification is following. We consider the variable as weak if the PIP is 0.5 - 0.75, substantial if it is 0.75 - 0.95, strong if the PIP is 0.95 - 0.99 and decisive if this value exceeds 0.99. For the reader it might be surprising that there are not many variables, which are characterized at least as substantial. Namely, we classify just one variable as decisive, two as substantial and two as weak. Thus, the results exhibit that the choice of level of aggregation creates the most usual difference among results. The comprehensive model distribution can be found in Figure 6.1.

On the contrary, we observe high stability of the variables. It is visible from conditional positive signs. This indicates how probably the variable has positive sign, when it appears in model. The result "1" implies "in all cases", oppositely "0" means that the variable is always negative.

Table 6.1: Results of Bayesian Model Averaging

Label	*Pos. Mean*	*Pos. SD*	*PIP*	*Cond. Pos. Sign*
SIC level of data	0.875	0.189	1.000	1.000
SIC level of results	-0.601	0.185	0.936	0.000
REER	-0.012	0.008	0.776	0.000
SE	0.144	0.102	0.731	1.000
Secondary ind.	0.129	0.142	0.507	1.000
Total	0.046	0.075	0.319	0.999
Citations	0.067	0.111	0.312	0.997
Other estimation methods	-0.443	0.773	0.287	0.001

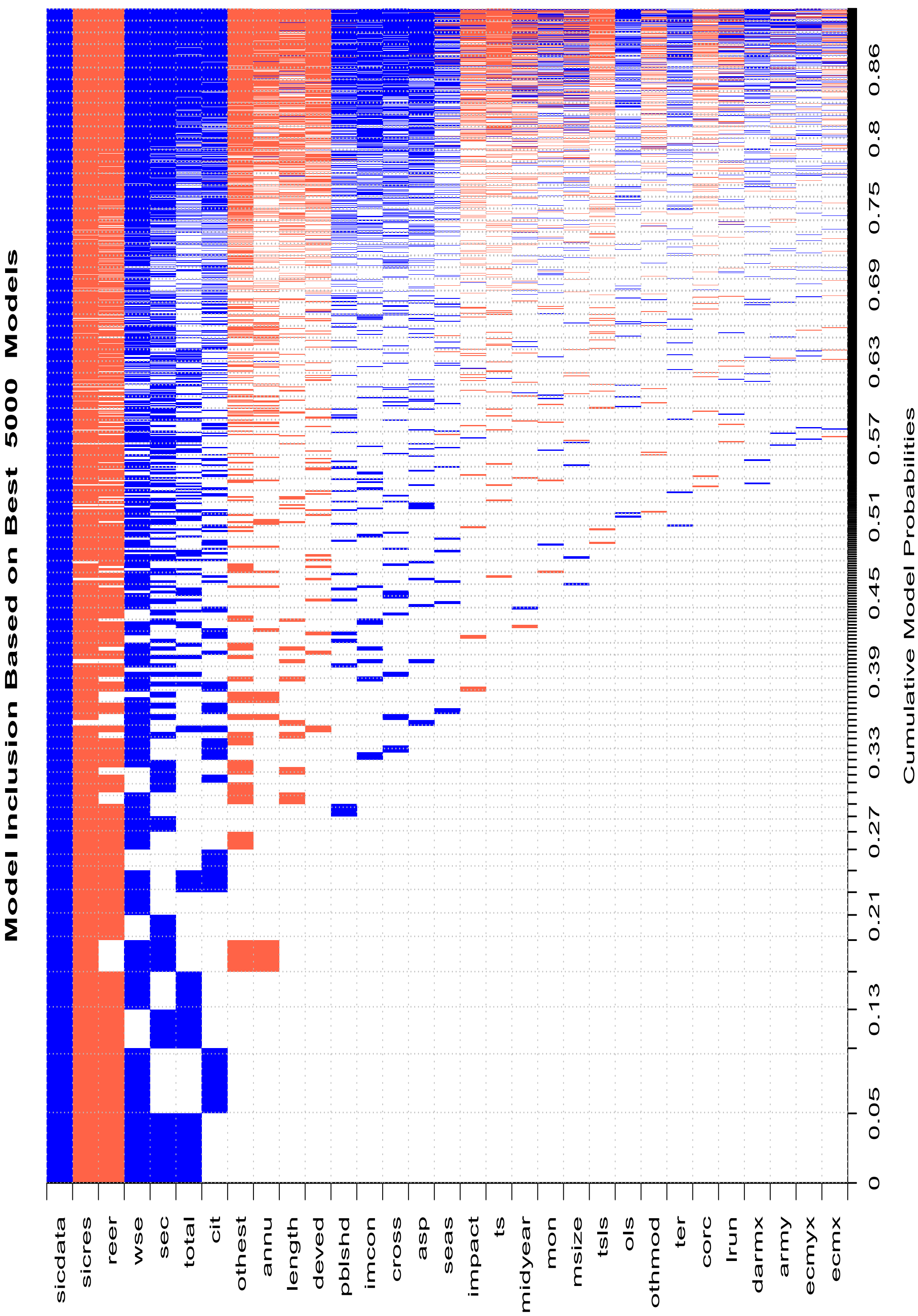

Figure 6.1: Bayesian Model Averaging

6.1 Comparison with Previous Findings

These results can be easily compared to those mentioned in Section 2.3. At first glance, one can see that the intercept is even slightly negative (-0.002, check Table 6.2). This is obviously even smaller estimate than Flores & Cassoni (2008) find between the first papers written by American authors. It is misleading to some extent, because the magnitude of the Armington elasticity may be affected by other factors, e. g. by level of aggregation of the data.

The level of aggregation of the data (*Sicdata*) and the level of aggregation of the results (*Sicres*) are two of most influential variables in our research. It may be quite surprising that these variables have opposite sign. It is caused probably by the fact that the second one counterbalances the first one. During data exploration, these two variables have in one half of the cases the same value, but some of the articles gather more disaggregated data than for which they finally published elasticities' results (it is not possible to do it reversely). When the average value of *Sicdata* (6.49) and *Sicres* (5.06) is taken into account and we add up them together related to unity (0.875 +(-0.601) = 0.274), it is found that the intercept is increased for average observation (2.638). This exceeds highly the verdict proposed by Flores & Cassoni (2008).

As it is said the opposite sign of the variables *Sicdata* and *Sicres* is quite surprising, but their overall effect is always positive, which is not startling at all. The results propose that the more disaggregated the data are the higher the estimates. This conclusion is in link with previous findings - Section 2.3.

On the contrary, it is found out that the newer estimates, specifically those with the newer data sets does not show higher elasticities than the older one. It is in contrast with results from Welsch (2008). The higher size of newer estimates is thus likely influenced by other factors. It is most likely affected by level of aggregation as it is mentioned above.

The next result is as expected - developed countries have smaller Armington elasticities than developing ones, but with negligible significance. On the other hand, the projection that the market size affects the final elasticities significantly is not confirmed as well as the proposition that long-run estimates are larger than short-run ones.

In investigation of data structure all of the previous findings cannot be supported. And it applies even in the case that these variables are insignificant is passed over. The results for time series are found lower than the ones for cross-sectional data as it is proposed by e. g. Flores & Cassoni (2008). On the contrary, panel data results are located between time series and cross-sectional. It implies that results from panel data sets are generally higher than those from time series ones. It is in sharp contrast with findings from Schürenberg-Frosch (2015). One cannot cast doubt upon it arguing that "other factors fixed" every additional year of observation decreased the elasticity by 0.003 (check variable *Length*), because it declines the estimation of both panel and time series data, so they on average do not change "their order".

Moreover, we may endorse at least partially the findings from Flores & Cassoni (2008) once more. They claim that there is no clear-cut how results differ in matter of data frequency. We expose that the difference between monthly and quarterly data is not so important. Furthermore, because of insignificance of the *Annually* variable, the unimportance of data frequency in this field is only highlighted. So we cannot agree with findings of Hertel *et al.* (1997) who claim that the lower the frequency of the data the more inelastic elasticities.

Because of lack of materials on different sub industries we estimate differences among industries only for aggregated level. Our ability to describe differences among different industries is very constrained. We can just claim that the secondary industries are more elastic than the primary and tertiary ones. But such a comprehensive analysis as Shiells *et al.* (1986) cannot be provided by MRA tools.

6.2 New Relations and Outcomes

In this thesis the first comparison of the models and different estimation procedures employed in this area takes place. The following results are distinguished. The differences arising from groups using Equation 3.1. Equation 3.2, Equation 3.3, Equation 3.4, Equation 3.5 and the group of other models seem not to be important in overall analysis. Their PIPs are among the smallest and posterior means do not differ from zero significantly. On the other hand, the prognosis from Subsection 3.2.1 about nonlinear models is partially fulfilled. The estimates from these models are even about 0.277 higher (and even by 0.440 according to Section 6.3) than those for other models. But in this case as well, the PIP is not considered even as weak.

The difference between results from nonlinear models and those for all other models is not balanced out by the estimation procedure. The nonlinear models use typically GMM estimation procedure, which is set as base. The results for OLS, CORC do not differ from GMM at all and TSLS differs just a little (-0.033). Interesting here is that other estimation methods are found lower than others (-0.429, but only -0.179 in robustness check). The importance of this variable is not significant again. Under other estimation procedures are hidden those, which are not covered frequently in the papers. These techniques are usually those for panel data, typically techniques such as fixed effects and random effects. It may clarify, why we do not find posterior mean for panel data lower than the one for time series. The difference between time series and panel data does not depend on the data structure directly, but it depends on the estimation procedure connected to the structure.

Other additional results spring from ”Value-added” variables, which indicate following. Curiously, the higher the real effective exchange rate the smaller the Armington elasticity. It is completely opposite to what is supposed. Furthermore, this variable has third largest PIP. At the first glance, the posterior mean of this variable looks negligible, but if we take into account that this variable is standardized on 100 and the baseline is set on 38 (according to lowest value in all observations), then for its average value (66.39), the value of the elasticity is lowered by 0.797. The simple intuition is that the stronger the currency the cheaper the imports. Thus, the imports are better interchanged with domestic goods. The Armington elasticity is then higher, this unexpected finding might be caused by the fact that the older studies were usually conducted on US goods. The former elasticities (especially from the eighties) for US are lower as mentioned in Section 2.3. On the contrary, the US *REER* was quite high[1] in those times. The latter findings are higher in general (Flores & Cassoni 2008), but the *REER* is generally lower than those for US in the eighties. From this point of view, the new elasticities are higher regardless of lower *REER*. This conclusion may clarify, why the higher *REER* decreases the Armington elasticity.

We have just one small notion for import constraints. There is almost no evidence that any import constraints influenced the estimated elasticities. Or if yes, the authors do not take it into consideration and thus we cannot recognize it.

Our last notes are on account of published and unpublished articles. The variable *Published*, which distinguish the published and unpublished articles and the variable *Citations*, which counts the total number of citations might be balanced out by the variable *Impact*. The first one suggests that the published articles provide higher estimates and thus results are higher than those for the unpublished ones. On the other hand, the impact factor lower the estimates for the most influencing articles. Unexpectedly, during deeper investigation is discovered, that unpublished articles have higher impact (0.13) than the published ones (0.12). Therefore, impact factor does not balance out anything in the end. Moreover, these variables have high posterior standard deviations, so they are overall insignificant. When only this point of view is considered, some signs of publication bias are recognized in this field. On the other hand, publication bias might be discerned by observation of *SE*. The variable for standard error has positive sign and it is significant according to its PIP.

[1]The World Bank: Real effective exchange rates [online]. Infogram: ©2017 [cit. 12. 5. 2017]. Dostupné z: http://data.worldbank.org/indicator/PX.REX.REER?locations=US.

6.3 Robustness Check

The robustness check is grounded in different choice of prior probability. The prior probability is set in robustness check to a binomial-beta hyperprior on the prior inclusion probability instead of to uniform prior probability. Moreover, different Zellner's g is chosen. In the first case "UIP" is employed, in the robustness check "BRIC" takes place. It is discussed in Section 5.1 and Section 5.2.

The robustness check in most cases confirms my previous findings. Larger differences are noticed only between estimations of *Nonlinear models* (0.277 and 0.440 respectively) and between those of *Other estimation methods* (-0.443 and -0.160). Only significant difference is a substantial decrease in PIPs, which suggest that the differences in data structures, models and estimation methods are even more insignificant.

Table 6.2: Robustness Check

	Bayesian Model Averaging			*Atlernative Priors*		
Label	*Pos. Mean*	*Pos. SD*	*PIP*	*Pos. Mean*	*Pos. SD*	*PIP*
SE	0.144	0.102	0.731	0.083	0.106	0.414
Long-run	0.000	0.054	0.022	-0.001	0.038	0.008
SIC level of data	0.875	0.189	1.000	0.861	0.225	0.999
SIC level of results	-0.601	0.185	0.936	-0.569	0.219	0.884
Secondary ind.	0.129	0.142	0.507	0.074	0.125	0.283
Tertiary ind.	0.008	0.109	0.022	0.002	0.049	0.004
Length	-0.003	0.009	0.105	-0.002	0.008	0.086
Total	0.046	0.075	0.319	0.016	0.048	0.118
Midyear	0.000	0.004	0.044	0.000	0.001	0.007
Developed	-0.083	0.279	0.112	-0.022	0.122	0.038
Monthly	-0.006	0.104	0.037	0.000	0.032	0.006
Annually	-0.080	0.220	0.144	-0.018	0.103	0.033
Time series	-0.017	0.096	0.051	-0.009	0.070	0.021
Cross-sectional	0.085	0.309	0.092	0.017	0.141	0.019
Dynamic Armington	0.000	0.021	0.021	0.000	0.007	0.004
Arm. model with lag	0.000	0.060	0.019	0.000	0.024	0.004
ECM	-0.001	0.093	0.017	0.000	0.040	0.003
ECM with lags	0.000	0.082	0.016	0.000	0.036	0.003
Nonlinear	0.277	0.950	0.098	0.440	1.188	0.126
Other models	-0.004	0.073	0.023	-0.001	0.035	0.005
Import constraint	0.064	0.228	0.097	0.014	0.109	0.022

Continuation of Table 6.2

Label	*Bayesian Model Averaging*			*Atlernative Priors*		
	Pos. Mean	*Pos. SD*	*PIP*	*Pos. Mean*	*Pos. SD*	*PIP*
Seasonality	0.015	0.100	0.051	0.002	0.037	0.009
OLS	0.002	0.034	0.026	0.000	0.010	0.004
CORC	0.000	0.030	0.025	0.000	0.011	0.004
TSLS	-0.037	0.262	0.036	-0.009	0.132	0.008
Other est. methods	-0.443	0.773	0.287	-0.160	0.500	0.106
Impact	-0.023	0.130	0.049	-0.004	0.057	0.010
Citations	0.067	0.111	0.312	0.044	0.093	0.209
Published	0.081	0.284	0.106	0.020	0.125	0.032
Market size	-0.001	0.022	0.038	0.000	0.010	0.011
REER	-0.012	0.008	0.776	-0.011	0.007	0.842
(Intercept)	-0.002	NA	1.000	-0.002	NA	1.000

6.4 Suggested Approach

Besides the investigation of publication bias and conducting meta-analysis, we want to suggest design for future researchers. Our intention is to propose the best approach for computing Armington elasticities, or at least provide short guidance based on above computed final findings from this area.

During the data collection and working on the thesis we have gained considerable experience in area of Armington elasticity. According to the newest knowledge from this field obtained during research, the recommended procedure of estimating Armington elasticity is as follows.

The researcher may use disaggregated panel data from any period and any developing country. It would be recommended to employ the sophisticated method proposed by Feenstra (2014) with nonlinear model and GMM estimation procedure. The gathered data are more disaggregated than the figures for published Armington elasticities. It appears to be sufficient to use annual data and estimate long-run estimates. Seemingly, no one should be concerned by any import constraint. They have just negligible value to Armington elasticities.

During simulating such a model all values of the variables was set on their mean[2]. We predict this model on secondary industries. In Table 6.3 reader can see simulated

[2]The average value of number of observations and *Length* (approximated from 14.83 to 15) were calculated just among studies with panel data
impact was divided into published (0.12) and unpublished (0.13) studies;
Citations were approximated from 2.8 to 3;
The median values were used for *SIC level of data* and *SIC level of results.*

model according to our BMA results and robustness check, both in published and unpublished versions. Finally, the *SE* is set to zero to minimize the bias.

Table 6.3: Predictions Table

Label	*Value*	*BMA*	*BMA Pub.*	*Rob.*	*Rob. Pub.*
Long-run	1	0.000	0.000	-0.001	-0.001
SIC level of data	7	0.875	0.875	0.861	0.861
SIC level of results	5	-0.601	-0.601	-0.569	-0.569
Secondary ind.	1	0.129	0.129	0.074	0.074
Length	15	-0.003	-0.003	-0.002	-0.002
Total	5.87	0.046	0.046	0.016	0.016
Annualy	1	-0.080	-0.080	-0.018	-0.018
Nonlinear	1	0.277	0.277	0.440	0.440
Impact	0.13/0.12	-0.023	-0.023	-0.004	-0.004
Citations	3	-	0.067	-	0.044
Published	1	-	0.081	-	0.020
Market size	6.45	-0.001	-0.001	0.000	0.000
REER	66.39	-0.012	-0.012	-0.011	-0.011
Intercept	1	-0.002	-0.002	-0.002	-0.002
Results	-	2.863	3.145	2.993	3.145

One can see from the results that the simulated model has higher elasticities than average. The simulated elasticities fluctuate around 3, by contrast mean Armington elasticity across the studies is 1.45 and the median estimate is 1.03 (see Table 3.1). In link with findings from Chapter 4 and Section 6.2 is following detection. The estimates simulated to be published in economic journal tend to be higher (3.145) than the unpublished ones (2.863, or 2.993 for robustness check). Despite the fact that the variables are not significant at all, the previous conclusions are supported slightly.

In spite of the approaches from Feenstra (2014) and Aspalter (2016) are followed mostly in simulating the model, the results differ from theirs significantly - see Table 2.1. The closest estimates of Armington elasticities to the simulated ones are those obtained by Ogundeji *et al.* (2010) and Shiells *et al.* (1986), but they use completely different approaches. This just indicates, why we find many variables insignificant in Table 6.2.

Chapter 7

Conclusions

We conduct a meta-analysis of the estimates of Armington elasticities using 3,524 estimates from 42 studies. Because of this fact this meta-analysis belongs to the largest ones. We controll for many differences (namely 31) such as type of industry, level of aggregation, midyear of data, data frequency, type of data or estimation method used.

Finally, some variables arise as more significant than others. This is the case of level of aggregation, real effective exchange rate or if the estimates are from secondary or not.

The results often support the ones from Flores & Cassoni (2008). In agreement is, for example, in matter of data frequency. Besides the findings back up Hummels (1999) in discussion of level of aggregation as well. On the other hand, we cannot support the results, for example, from Welsch (2008) in question "How the age of the data set influences the results". He claims that newer findings show higher elasticities, we find the opposite.

Moreover, we find no statistical difference between long-run and short-run estimates, which is in sharp disagreement with all previous findings.

Additionally, this work is the first one, which compares different models used in articles and different estimation procedures employed in this field. We conclude that nonlinear models exhibits higher estimates (+0.268) than other ones. On the contrary, this result has just minor significance. Results from all other models do not differ significantly. This is not surprising conclusion, especially when we consider that some papers (e.g. Gallaway *et al.* 2003) use three different kinds of models and expect comparable results. On the other hand, it is proposed in Subsection 3.2.1 that nonlinear models evince higher results.

In the case of data structure we cannot concur with Schürenberg-Frosch (2015), since there is not found any clear-cut in data frequency or in comparison of panel, time series and cross-sectional data. More than on the data structure the results depend on the estimation method. Not surprisingly, the OLS, FGLS, TSLS and

GMM do not differ significantly. On the contrary, other techniques typically used for panel data (the ones such as fixed effects and random effects) are found somehow lower (-0.429) than the above mentioned ones, but again importance is not the highest.

Besides all interesting findings, we find that real effective exchange rate is significant tool to measure elasticities. But it evinces opposite results than it is expected. It might be caused by the former studies from US.

In Section 6.3 the results are just confirmed, because there are no inconsistencies. Furthermore, the similar results for BMA and its robustness check spring from the suggested model simulation. Moreover, this prediction supports the conclusions about many insignificant differences and point out publication bias.

This result is ascertained by Chapter 4. This section reveals suspicion of publication bias in this field. It is not obvious at the first glance, but at the second, data are skewed to the right. It is confirmed by Section 4.2 and even by Section 6.4 as it is mentioned in previous paragraph. Furthermore, the same conclusion is proposed by significance of *Standard Error* variable.

Besides based on all gained knowledge about Armington elasticities the suggested approach is designed. For future research, we recommend the use techniques developed by Feenstra (2014), who employs by modern approach more disaggregated data at the data collection phase than at the results phase. As it is mentioned several times, the level of aggregation is the most influential factor for computing Armington elasticities. This simulated model exhibits higher elasitcities (2.86 for unpublished and 3.15 for published articles) than the median value (1.03) and even than mean value (1.45) from the collected data.

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Appendix A

Data

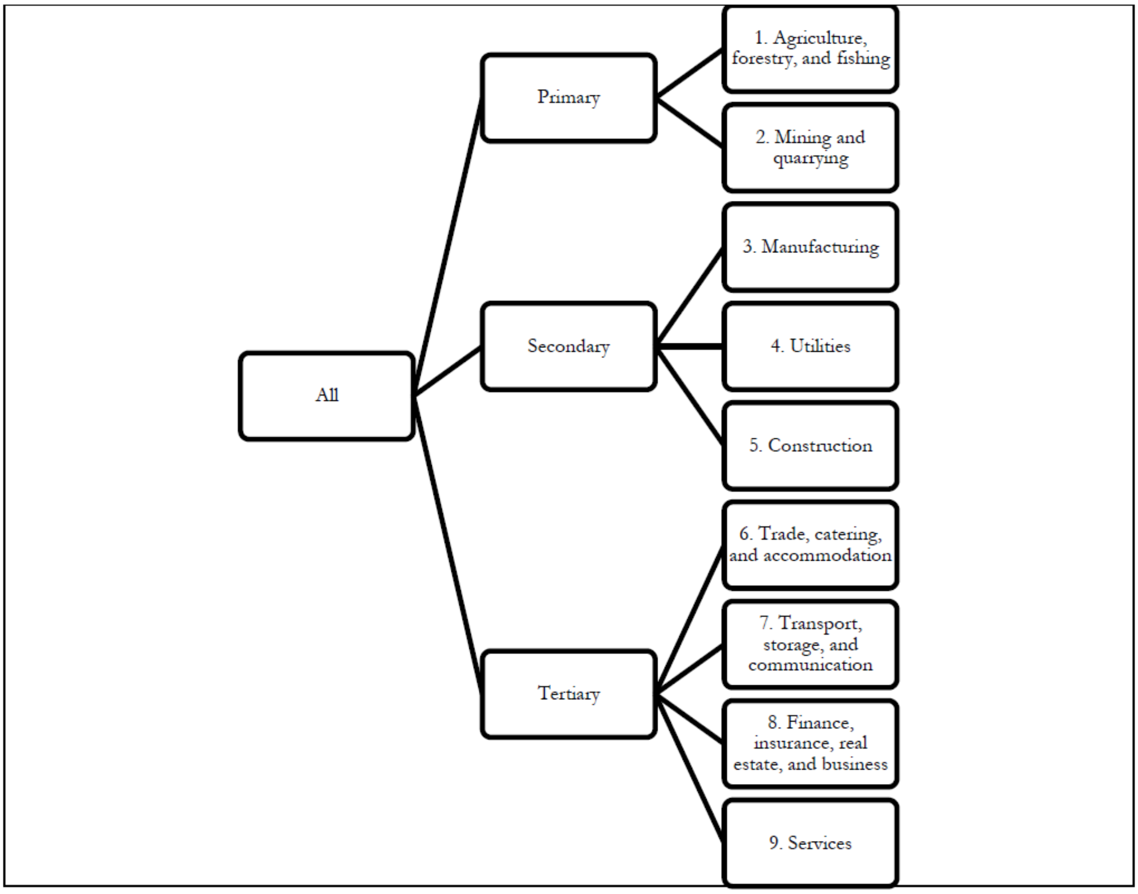

Figure A.1: Aggregated industries

Source: Saikkonen (2015)

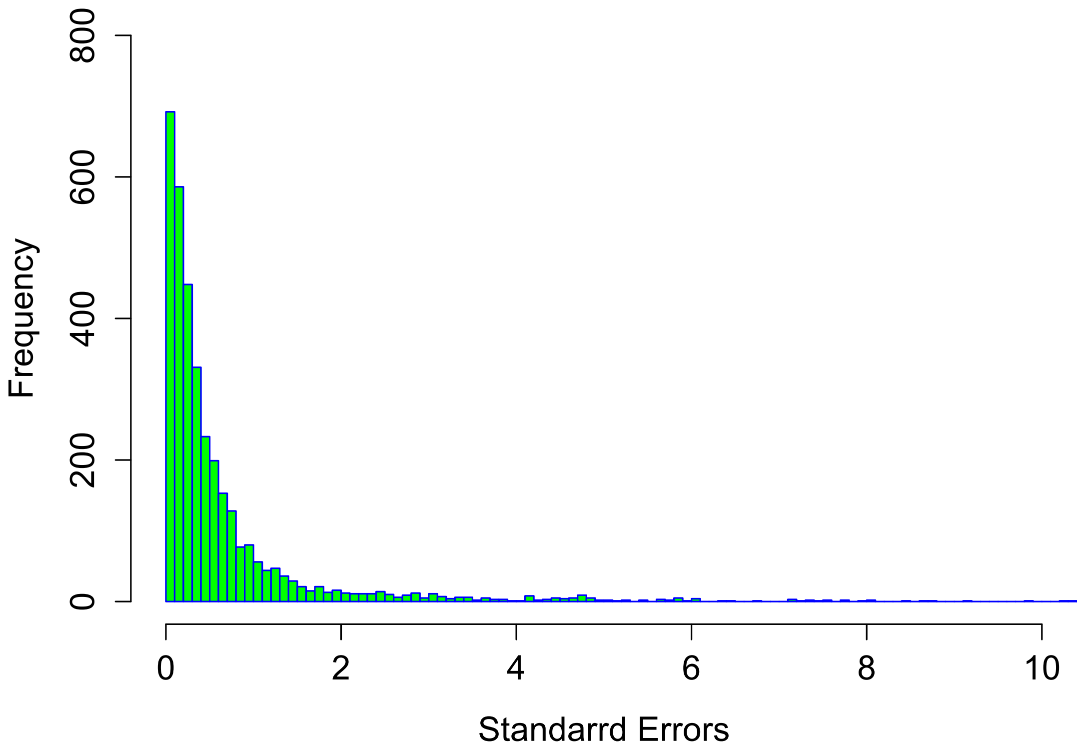

Figure A.2: Histogram of Standard Errors

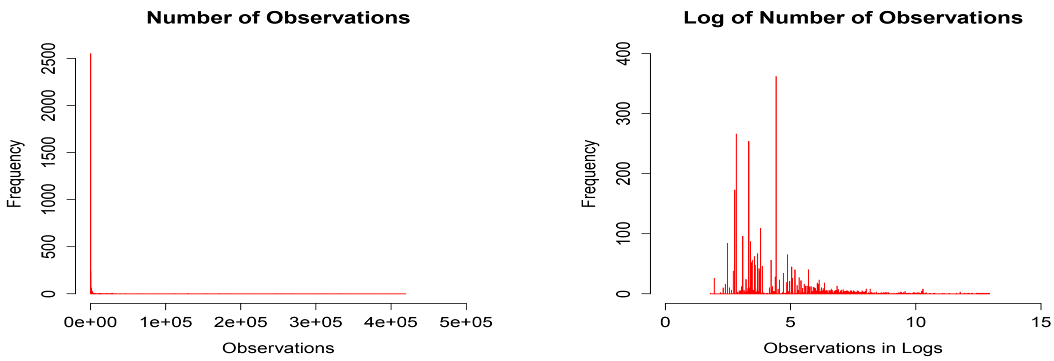

Figure A.3: Difference between distribution between total number of observations and their values in logs

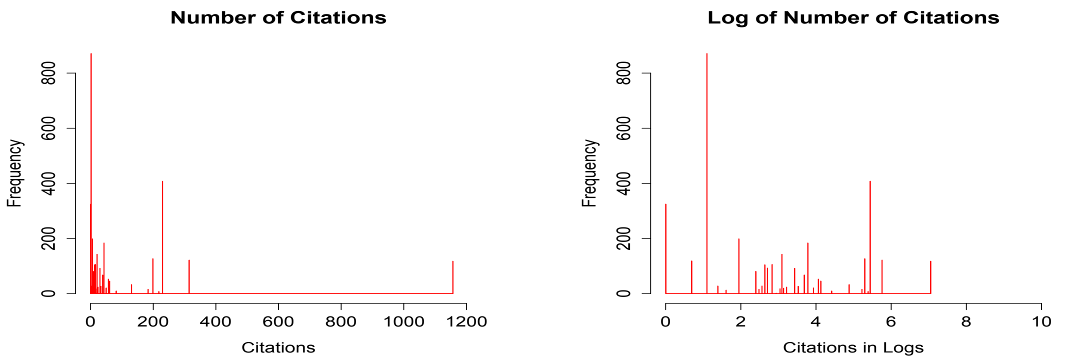

Figure A.4: Difference between distribution between number of citations and their values in logs

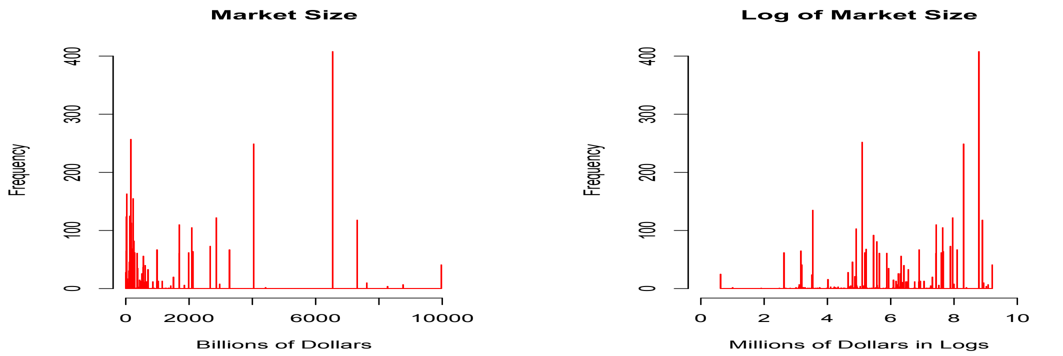

Figure A.5: Difference between distribution between Market sizes and their values in logs

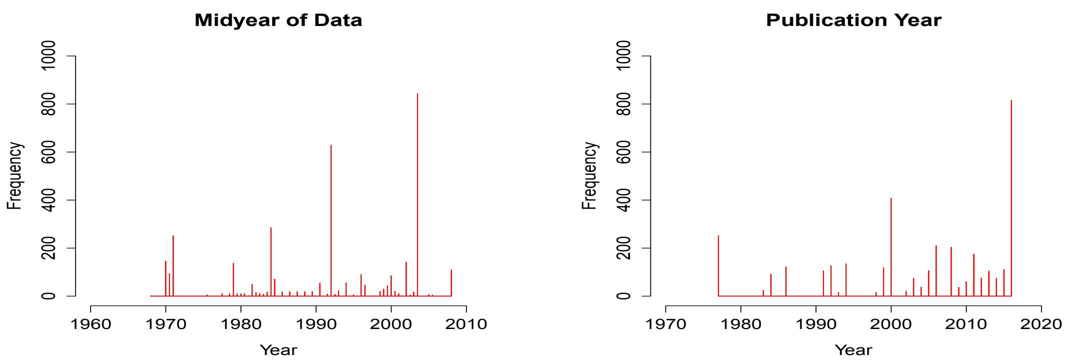

Figure A.6: Distribution of midyears of data and publication years

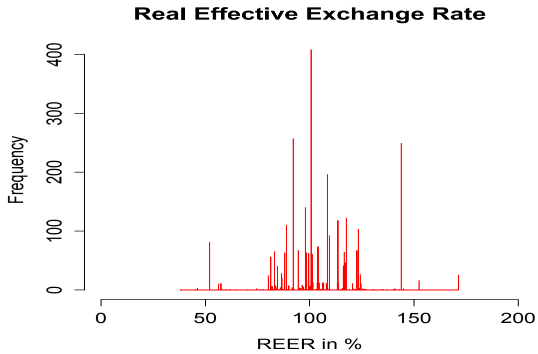

Figure A.7: Distribution of real effective exchange rate

Appendix B

Results

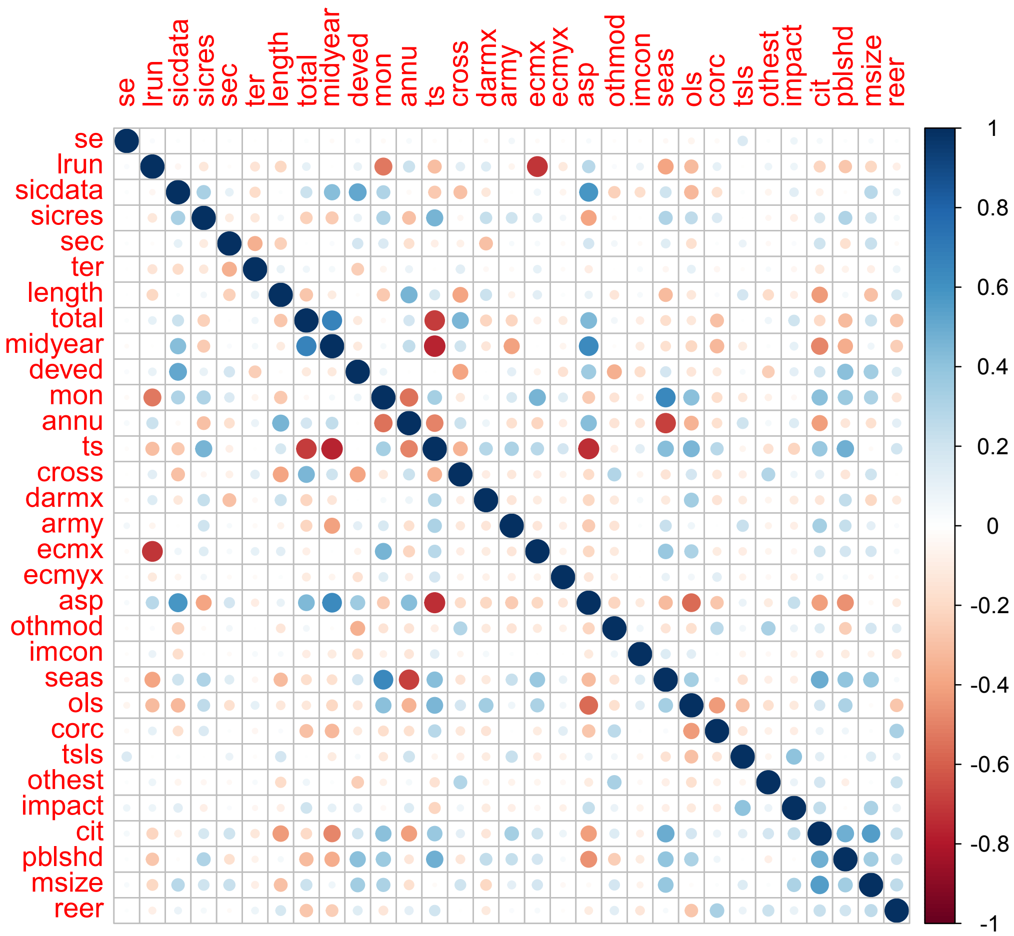

Figure B.1: Correlation Matrix

Variable 1	*Variable 2*	*Correlation*
Midyear	Time Series	-0.765
Time Series	Nonlinear	-0.732
Long-run	ECM	-0.716
Total	Time Series	-0.693
Annualy	Seasonality	-0.682
Total	Midyear	0.665

Table B.1: Correlation Matrix

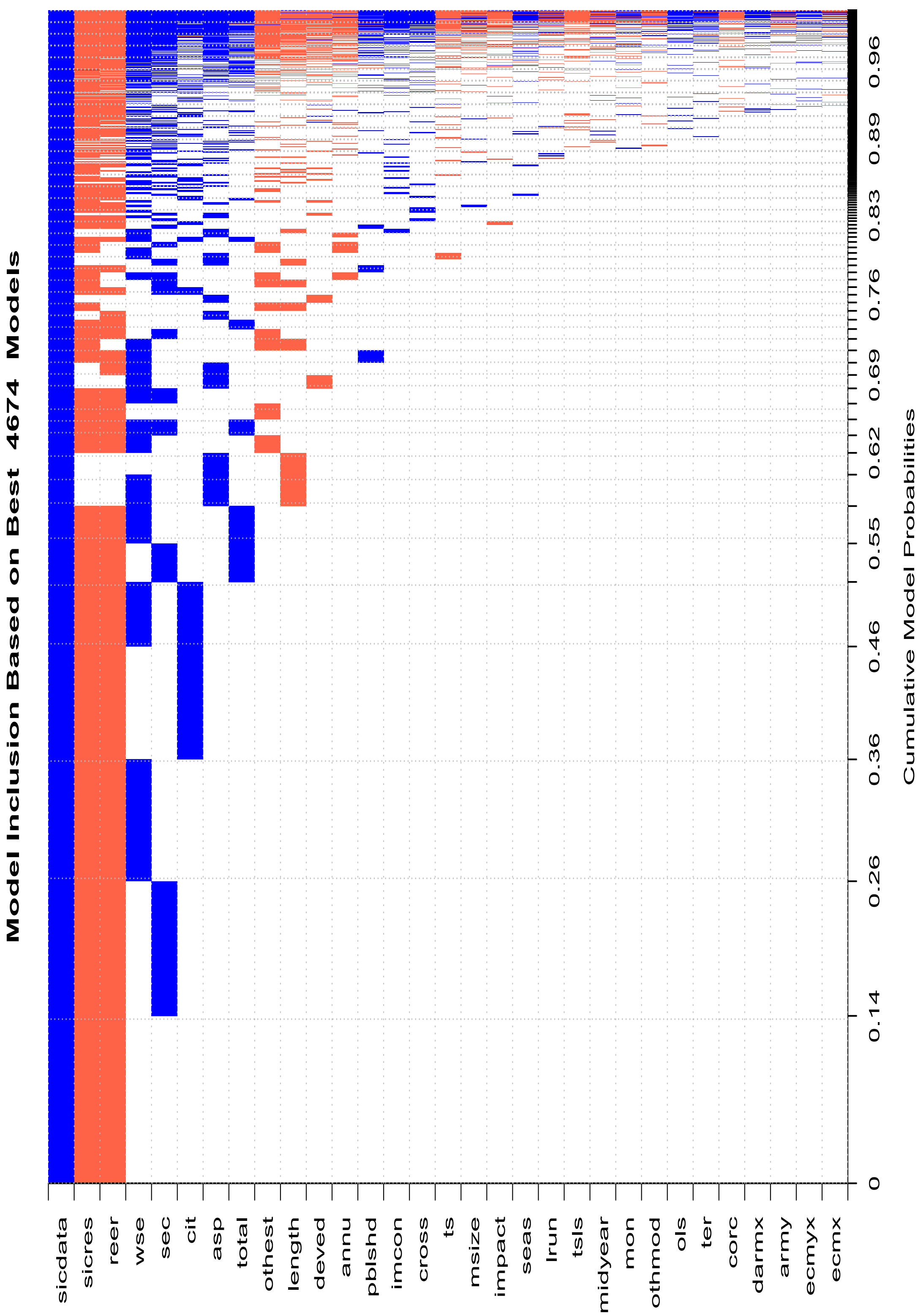

Figure B.2: Bayesian Model Averaging - Robustness Check