UNIVERSITY OF LJUBLJANA
FACULTY OF ECONOMICS

ALEŠ GORIŠEK

RELATIONSHIP BETWEEN NON-TRADABLE AND TRADABLE SECTOR IN SLOVENIA AND OTHER SELECTED EUROPEAN ECONOMIES

DOCTORAL DISSERTATION

Ljubljana, 2017

AUTHORSHIP STATEMENT

The undersigned Aleš Gorišek, a student at the University of Ljubljana, Faculty of Economics, (hereafter: FELU), declare that I am the author of the doctoral dissertation with the title Relationship between non-tradable and tradable sector in Slovenia and other selected European economies, prepared under supervision of prof. Janez Prašnikar, PhD and co-supervision of prof. Polona Domadenik, PhD

DECLARE

1. this doctoral dissertation to be based on the results of my own research;
2. the printed form of this doctoral dissertation to be identical to its electronic form;
3. the text of this doctoral dissertation to be language-edited and technically in adherence with the FELU's Technical Guidelines for Written Works, which means that I cited and / or quoted works and opinions of other authors in this doctoral dissertation in accordance with the FELU's Technical Guidelines for Written Works;
4. to be aware of the fact that plagiarism (in written or graphical form) is a criminal offence and can be prosecuted in accordance with the Criminal Code of the Republic of Slovenia;
5. to be aware of the consequences a proven plagiarism charge based on this doctoral dissertation could have for my status at the FELU in accordance with the relevant FELU Rules;
6. to have obtained all the necessary permissions to use the data and works of other authors which are (in written or graphical form) referred to in this doctoral dissertation and to have clearly marked them;
7. to have acted in accordance with ethical principles during the preparation of this doctoral dissertation and to have, where necessary, obtained permission of the Ethics Committee;
8. my consent to use the electronic form of this doctoral dissertation for the detection of content similarity with other written works, using similarity detection software that is connected with the FELU Study Information System;
9. to transfer to the University of Ljubljana free of charge, non-exclusively, geographically and time-wise unlimited the right of saving this doctoral dissertation in the electronic form, the right of its reproduction, as well as the right of making this doctoral dissertation publicly available on the World Wide Web via the Repository of the University of Ljubljana;
10. my consent to publication of my personal data that are included in this doctoral dissertation and in this declaration, when this doctoral dissertation is published.

Ljubljana, 10 January 2017 Author's signature:

ZAHVALE

Iz srca se zahvaljujem prof. dr. Poloni Domadenik. Ko me je sprejela pod svoje mentorstvo, se sploh nisem zavedal, kako zelo velik strokovni in značajski preskok je potreben, da človek vstopi v prakso znanstvenega raziskovanja. Polona me je učila znanstvene obrti in mi s svojim zgledom in delovno etiko kazala pot. Več let mi je redno posvečala svojo pozornost, delila z mano svoje bogato znanje in čas. Polona, hvala ti.

Zahvaliti se želim prof. dr. Janezu Prašnikarju. Občudujem njegov pogum. Od njega sem se in se še učim senzibilnosti za družbeno okolje in sposobnosti strateškega razmišljanja. Njegova zmožnost povezovanja pravih ljudi in ustvarjanja sinergij je vrhunska. Njegove znanstvene kritike in komentarji temeljijo na veliki zakladnici znanja in izkušenj iz teorije in prakse. Prof. dr. Janez Prašnikar je tej disertaciji podaril vsebino.

Večkrat, ko sem se med izvajanjem empiričnih analiz izgubil, mi je s svojimi mojstrskimi nasveti pomagal prof. dr. Marko Pahor. Marko je soavtor članka o ravnanju z manjkajočimi podatki, ki je sestavni del te doktorske disertacije.

Dr. Marija Drenkovska mi je skozi čas doktorskega študija pomagala z nasveti, pogovori in viri. Bila je moj prvi sogovornik in prvo sito mojih idej. Najprej še kot doktorska študentka in na koncu kot mlada doktorica Ekonomske Fakultete v Ljubljani, mi je pomagala tudi z nepogrešljivimi praktičnimi informacijami, ki jih za uspešen zaključek študija potrebuje vsak doktorand.

K tej disertaciji so z nasveti in različnimi viri prispevali tudi asist. dr. Domen Trobec, asist. dr. Daša Farčnik, dr. Tjaša Bartolj, Miha Valenčič in izr. prof. dr. Jelena Zorić.

Ves čas študija mi je vlivala pogum in me bodrila moja življenjska sopotnica, Maja Kunaver. Njej se želim zahvaliti za prvo branje vsakega sklopa disertacije, odpravo tipkarskih napak in slovnični pregled.

Na koncu se želim zahvaliti tudi tričlanski ocenjevalni komisiji, ki je z nasveti in kritikami aktivno sodelovala v končni verziji te doktorske disertacije. Komisija je svoje delo opravljala zelo marljivo, s poudarkom na metodoloških detajlih. Prof. dr. Jan Švejnar, prof. dr. Lubomir Mirek Lizal in izr. prof. dr. Črt Kostevc so s svojimi nasveti in bogatimi izkušnjami pripomogli, da delo ustreza standardom sodobnega raziskovalnega dela. Niso ubrali za njih najlažje poti takojšnjega strinjanja z izdelkom. Z osebnim angažmajem so me, tudi ko sem bil že na koncu z močmi, motivirali, da sem naredil še nekaj korakov več. Po njihovi zaslugi je moje znanje ekonometrije boljše.

Iskrena hvala vsem.

ODNOS MED NEMENJALNIM IN MENJALNIM SEKTORJEM V SLOVENIJI IN DRUGIH IZBRANIH EVROPSKIH GOSPODARSTVIH

Povzetek

Cilj te disertacije je raziskati medsebojni vpliv netržnih in tržnih sektorjev gospodarstva. Ta odnos je ocenjevan skozi prizmo optimalnih monetranih in fiskalnih politik držav v okviru monetarnih unij. V vsaki posamezni državi v okviru monetarne unije upravljalec fiskalne politike stremi k doseganju ravnovesja med optimalno politiko za celotno skupino držav znotraj in izven monetarne unije, ter lastno optimalno fiskalno politiko. Vsaka država tehta med zagotavljanjem učinkovite količine dobrin na eni strani in stabilizacijo domače inflacije in skupne proizvodne vrzeli na drugi. Uporaba delne proizvodne vrzeli posameznih (zgolj netržnih) sektorjev gospodarstva kot instrumenta fiskalne politike je mogoča zaradi trenj, ki nastanejo kot posledica nominalnih togosti.

Republika Slovenija je država z majhnim odprtim gospodarstvom, ki deluje v okviru monetarne unije. Odločitve in interne politike tako majhnih držav nimajo praktičnih učinkov na parametre celotnih sistemov povezanih držav, kot jih poznamo v sodobnih monetarnih unijah. Klasični modeli, ki analizirajo vplive monetarnih in fisklanih politik med državami so utemeljeni na sistemih dveh držav. Kot osnovni okvir za analizo Gali and Monacelli (2008) predlagata primeren makroekonomski model, kjer je v model vključenih več držav, vse pa so modelirane kot infinitezimalno majhne. V Republiki Sloveniji lahko klasične gospodarske sektorje uvrstimo med tržne sektorje gospodarstva, tako kot drugod po svetu. Specifična je situacija v bančnem, zavarovalniškem, telekomunikacijskem in energetskem sektorju. Ti sektorji se v Republiki Sloveniji nagibajo v netržne sektorje. Tako stanje je moč pripisati nacionalnemu gospodarskemu protekcionizmu. V tem posebnem slovenskem primeru imamo situacijo, ko podjetja iz storitvenih dejavnosti, ki so običajno razvrščena v tržne sektorje, delujejo kot podjetja iz netržnih sektorjev gospodarstva. Ta podjetja imajo previsoko porabo proizvodnih tvorcev (vložkov) glede na količino proizvodov (storitev). Naj bi bila torej neučinkovita.

Učinkovitost je možno izboljšati z ustvarjanjem večje količine izdelkov oziroma storitev (izložkov) z danimi produkcijskimi tvorci (vložki) ali z zmanjšanjem produkcijskih tvorcev pri ustvarjanju enake količine izložkov. Cene izložkov neučinkovitih podjetij so ceteris paribus višje od cen izložkov učinkovitih konkurentov. Neučinkovita podjetja imajo namreč vezanih več produkcijskih tvorcev oziroma potrošijo več dela in kapitala za proizvodnjo enote izložka.

Če imajo netržni sektorji široko proizvodno vrzel, kar pomeni, da proizvajajo količine nižje od teoretičnih zmogljivosti glede na vezan kapital in število zaposlenih delavcev, se ta vrzel manifestira kot nizka učinkovitost. Tako stanje ima dve posledici. Prvič: država, ki nadzira proizvodno vrzel v okviru bruto domačega proizvoda (BDP) kot eno količino, lahko napačno izmeri oziroma spregleda razliko med neproporcionalno učinkovitostjo tržih in neučinkovitostjo netržnih sektorjev gospodarstva, ki sta dve količini. Z eno mero domače proizvodne vrzeli lahko na ta način napačno oceni dejansko situacijo v gospodarstvu in sprejeme neustrezne monetarne in fiskalne politike, ki

zadevajo vse sektorje v državi. Ločeno ugotavljanje proizvodne vrzeli za netržne in tržne sektorje gospodarstva snovalcem fiskalne politike omogoča, da politiko primerno prikroji dejanski situaciji. Drugič: izložki neučinkovitih netržnih sektorjev so običajno potrošeni kot vhodne storitve oziroma proizvodi v praviloma bolj učinkovitih tržnih sektorjih. Podjetja iz tržnih sektorjev, ki te vhodne storitve oziroma proizvode kupujejo v lastni državi, kjer imajo svoje proizvodne zmogljivosti, tako plačujejo nepotrebno premijo. To slabo vpliva na njihovo konkurenčnost na zunanjih trgih.

To doktorsko delo prispeva snov v znanstveno literaturo na dveh področjih. Vsebuje nov pristop k analizi možnih posledic fiskalne politike z ločitvijo nadzora nad proizvodno vrzelijo netržnih in tržnih sektorjev gospodarstva. Drug pomemben prispevek je uporabljen niz metod za obdelavo velikih količin podatkov in ekonometričnih metod vključujoč DEA. Zelo pomemben je prispevek o analizi in vstavljanju majkajočih podatkov, ki je opisan v poglavju 4. Cilj naloge je predstaviti kvantitativno ekonomsko raziskavo, ki dokazuje *vpliv ekonomske politike na povečanje učinkovitosti netržnih sektorjev in s tem na učinkoviost tržnih sektorjev gospodarstva.* Tak vpliv v majhnih odprtih tržnih gospodarstvih v okviru monetarnih unij kakršno je Evrsko območje, kjer klasična orodja nominalnih menjalnih tečajev in nominalnih obrestnih mer niso pod nadzorom državnih inštitucij, lahko vršimo samo s fiskalnimi vplivi na povečanje produktivnosti netržnih sektorjev.

Rezultat raziskave je pozitiven kvantitativen dokaz učinka učinkovitosti netržnih sektorjev na učinkovitost tržnih sektorjev posameznih držav v izmerjenih v globalnem okolju. Z upoštevanjem obstoječe makroekonomske literature na temo monetarne in fiskalne politike v denarnih unijah in obstoječe literature na temo nominalnih togosti cen in plač, rezultati potrjujejo primernost ukrepov domače politike za doseganje večje učinkovitosti netržnih sektorjev gospodarstva. Med različnimi kazalniki, inštrumenti in cilji, ki jih za maksimiziranje družbene blaginje oziroma minimiziranje poslabšanja družbene blaginje uporabljajo snovalci gospodarskih politik, bi bilo smiselno kot cilj postaviti tudi zmanjšanje proizvodne vrzeli netržnih sektorjev gospodarstva. Povečanje učinkovitosti netržnih sektorjev gospodarstva je namreč moč doseči brez hkratnega negativnega vpliva na druge ekonomske entitete znotraj države ali v drugih državah znotraj denarne unije. Vloga fiskalne politike kot inštrumenta za stabilizacijo ni zaželjena le z vidika vsake posamezne države, temveč tudi z vidika denarne unije kot celote, ker jo je moč izvajati na način, ki nima negativnih vplivov na druge države v sistemu.

Majhna država z odprtim tržnim gospodarstvom, kakršna je Republika Slovenija, bi morala izrazito ciljati učinkovitost v netržnih sektorjih lastnega gospodarstva. Ker podjetja iz tržnih sektorjev že poslujejo bolj učinkovito, je ločen pogled na učinkovitost v netržnih sektorjih lastnega gospodarstva možen način, da se popravijo meritve neprimernih signalov in indikatorjev, ki jih za nadzor nad stanjem v posameznih državnih gospodarstvih trenutno uporablja Evropska unija. Lahko se namreč zgodi, da ima centralna evropska oblast, ki določa politiko v celotni uniji in bdi nad posameznimi državnimi gospodarstvi, napačne informacije zaradi napačno zastavljenih meritev. V tem primeru lahko od posamezne države zahteva omejitve, ki bi imele katastrofalne posledice za prihodnost.

Ključne besede: produktivnost, učinkovitost, tržni in netržni sektorji, malo odprto gospodarstvo, metoda podatkovne ovojnice, vstavljanje manjkajočih podatkov, masovni podatki

RELATIONSHIP BETWEEN NON-TRADABLE AND TRADABLE SECTOR IN SLOVENIA AND OTHER SELECTED EUROPEAN ECONOMIES

Summary

The aim of this dissertation is to explore the relationship between non-tradable and tradable sectors of economy. This relationship is evaluated within the frame of optimal monetary and fiscal policy in monetary unions. Each country's fiscal authority is in part striving to achieve it's own optimal policy setting within a monetary union and in part to achieve a common optimal policy setting in cooperation with other countries within and outside of monetary union. Each country has to trade-off between the provision of an efficient level of public goods and, on the other hand, the stabilization of real domestic inflation and the total output gap. Driving the partial output gap of non-tradable sectors as an instrument of fiscal policy implementation is only possible due to frictions that arise from nominal rigidities.

Slovenia is a small open economy, operating in monetary union. The decisions and internal policies of such small countries have practically no effect on the parameters of the whole system of inter-connected countries as can be observed in contemporary monetary unions. As a basic framework for analysis Gali and Monacelli (2008) propose a suitable model, where all countries modeled as infinitesimally small. In Slovenia, industrial companies are part of the tradable sector, as elsewhere in the world. Due to Slovenian specifics, banking, insurance, telecommunications and energy companies classification leans towards non-tradable sector. Such situation could be attributed to national economical protectionism. In this special Slovene scenario we come across a situation, where service companies, that are usually classified into tradable sector, operate as companies from non-tradable sector. Non-trading companies have excessive number of employees, considering sector's productivity. In other terms, non-trading companies have low efficiency.

Efficiency can be increased by producing more output with the given resources or by keeping the same output utilizing less resources. Prices of outputs of the inefficient companies are ceteris paribus higher than those of their efficient counterparts, since more resources are consumed to produce one unit of output. If the non-tradable sectors have high output gap, meaning that they are producing quantities below their production capabilities with a certain amount of capital and labor, this is manifesting as low efficiency. Consequences of such situation are twofold. First, a country that is monitoring its output gap in terms of GDP may not detect the output gaps of inefficient non-tradable sectors and more efficient tradable sectors as two different quantities. Thus it may only detect a certain general domestic output gap and employ inappropriate monetary and fiscal policies in the whole national economy. Monitoring output gaps of non-tradable and tradable sectors separately would allow the policy setting authorities to tailor the policy measures according to the real situation. Second, since the outputs of inefficient non-tradable sectors are usually consumed as inputs in more efficient tradable sectors, the companies buying these products and services are paying an unnecessary premium, which harms their position in competitive global markets.

This dissertation contributes to the literature in two important ways. It features a novel approach to analysis of possible policy implications for controlling the output gap with a separation of control of non-tradable and tradable sectors of economy. Also novel is the stream of data treatment methods and various econometric methods including DEA. A very important digression on data imputation methods is described in Section 4. The aim was to prepare a quantitative microeconomic evidence of *the influence of price targeting of non-tradables*, which can be achieved only through productivity increases in small open economies, where nominal exchange rates and nominal interest rates are fixed by the policy of a central institution within the monetary union, as is the case in the countries with EUR.

The result of the research is a positive quantitative proof of the effect of efficiency of non-tradable sectors on the efficiency of tradable sectors of countries in the global arena. Taking into account the existing macroeconomic literature on the topic of monetary and fiscal policy in monetary unions, and the literature on frictions and nominal rigidities of prices and wages, the results confirm the suitability of controlling the prices of non-tradables as an instrument of each country's fiscal authority to implement the desired policy. To maximize the general welfare or minimize the welfare loss function that policy makers are monitoring using various econometric models, they should among other things focus on decreasing the output gap of non-tradable sectors. Increasing the efficiency of non-tradable sectors does not come at the expense of any other entity inside or outside a particular national economy, operating independently or within a monetary union. A stabilizing role for fiscal policy is desirable not only from the viewpoint of each individual country, but also from that of the union as a whole and does not result in beggar-thy-neighbor policies.

A small open economy like Slovenia should explicitly target the efficiency of its non-tradable sectors. Since the trading companies are already operating at a more efficient level this is a possible way to correct the amplitude of the inappropriate signals or indicators currently used by EU policy authorities to measure the status of national economies. Otherwise, a misinformed policy authority may require fiscal policy restrictions, that can have disastrous effects in the years to come.

Key words: productivity, efficiency, tradable and non-tradable sectors, small open economy, data envelopment analysis, missing value imputation, big data

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

INTRODUCTION

Foreword

The aim of this dissertation is to explore the relationship between non-tradable and tradable sectors of economy. This relationship is evaluated within the frame of optimal monetary and fiscal policy in monetary unions. Each country's fiscal authority is in part striving to achieve it's own optimal policy setting within a monetary union and in part to achieve a common optimal policy setting in cooperation with other countries within and outside of monetary union. Each country has to trade-off between the provision of an efficient level of public goods and, on the other hand, the stabilization of real domestic inflation and the total output gap. Driving the partial output gap of non-tradable sectors as an instrument of fiscal policy implementation is only possible due to frictions that arise from nominal rigidities. These implications are contained in parts of economic models put forward by Calvo (1983), Clarida et al. (1999), Clarida et al. (2001), Gali and Monacelli (2005), Gali and Monacelli (2008), Monacelli and Perotti (2010), Eggertsson et al. (2016b), Hjortsoe (2016), etc.

National economies can be divided into two complementary parts: tradable and non-tradable sectors. The classification of companies into these sectors is based on the markets the companies operate in. Many different methods exist, that test to which of these groups particular company belongs. Still, the division between sectors is not clear. The indicator of tradability can be constructed using data in Jensen et al. (2005), who calculate the Gini coefficient for geographical dispersion of each activity and use it to identify trading and non-trading companies. The idea is that when something is traded the production of the activity is concentrated in a particular region to take advantage of some economies in production. As a result, not all regions will support local production of the good, and some regions will devote a disproportionate share of productive activity to it and then trade it. Jensen et al. (2005) observe that goods, that are traded, tend to be geographically concentrated in order to capitalize on increasing returns to scale, access to inputs such as natural resources, etc. Goods, that are not traded, tend to be more ubiquitously distributed. Same economic intuition is extended to classification of services. It is expected, that non-traded services do not exhibit geographic concentration in production. This intuition is revealed more descriptively by Paul Krugman, who notes: "In the late twentieth century the great bulk of our labor force makes services rather than goods. Many of these services are non-tradable and simply follow the geographical distribution of the goods producing population – fast-food outlets, day-care providers, divorce lawyers - surely have "location Gini" pretty close to zero. Some services, however, especially in the financial sector, can be traded. Hartford is an insurance city; Chicago the center of futures trading; Los Angeles the entertainment capital; and so on. ... The most spectacular examples of localization in today's world are, in fact, services rather than manufacturing. ... Transportation of goods has not gotten much cheaper in the past eighty years. ... But the ability to transmit information has grown spectacularly, with telecommunications, computers, fiber optics, ..." (Krugman, 1991). Beside "location Gini", other empirical approaches to measure geographic concentration and agglomeration exist. Some are explained in Duranton and Overman (2005).

Because of globalization, service industries are becoming more and more tradable (Chen et al., 2005). FMCG[1], tourism, transport and IT companies are between pure tradable and pure non-tradable sectors. Non-tradable are public utility companies, real-estate companies, education and healthcare (Clarida et al., 1999; Gali and Monacelli, 2005).

Many methods exist to classify the companies into tradable and non-tradable sectors (Jensen et al., 2005; Krugman, 1991; Duranton and Overman, 2005). Delving deeper into these methodologies would open another, totally different field of research. Another approach would be to classify the companies into two groups: exporters and companies, that sell only on domestic markets. A lot of research already exists in this area. Damijan et al. (2004) report that in Slovenia the productivity difference between future export starters and non-exporters is higher for firms that start to export to more advanced markets. In 54 microeconometric studies with data from 34 countries that were published between 1995 and 2006, exporters are found to be more productive than non-exporters, and the more productive firms self-select into export markets, while exporting does not necessarily improve productivity (Wagner, 2007). The focus of this thesis is comparison of the sectors, not individual companies. Sectors will be evaluated using SORS[2] data on ratios of exporters and importers for sectors of Slovene economy. These ratios will be used to classify a sector as tradable or non-tradable. Companies will be assigned to a trading or non-trading group according to their sector affiliation.

Hjortsoe (2016) shows that cooperative fiscal policy makers may face a trade-off between stabilizing output gaps and reducing intra-union imbalances. Analyses show that this trade-off is sensitive to the degree of substitutability of traded goods (the trade elasticity). The less substitutable are the traded goods, the more is this trade-off leans towards improving intra-union risk sharing rather than reducing output gaps. This is because the lower the trade elasticity, the larger are intra-union imbalances relative to output gaps, the higher is the relative weight policy makers attach to reducing these imbalances and the more effective is fiscal policy in reducing them relative to reducing output gaps. As a consequence, if traded goods are little substitutable, it is optimal from a cooperative perspective to set fiscal policy such as to reduce intra-union imbalances. Goods and services provided by the companies from non-tradable sectors are perfect candidates to control and drive such effects. Optimal fiscal policy plays a risk sharing role which clearly overshadows its output stabilization role when prices are flexible: it improves intra-union risk sharing at the expense of lower output gap stabilization. Most importantly, when prices are sticky, or when the re-allocation of labor across sectors within countries is inefficient, reducing the inefficiencies from imperfect risk sharing does not come at the expense of greater output gaps. It still remains true, that optimal fiscal policies consist in reducing intra-union imbalances.

In Slovenia, industrial companies are part of the tradable sector, as elsewhere in the world. Due to Slovenian specifics, banking, insurance, telecommunications and energy companies classification leans towards non-tradable sector (Prašnikar, 2011). Such situation could be attributed to national

[1]FMCG – fast moving consumer goods

[2]SORS - Statistical office of the Republic of Slovenia, exports and imports by 8-digit code of the Combined Nomenclature and by countries, Slovenia, cumulative data

economical protectionism. In this special Slovene scenario we come across a situation, where service companies, that are usually classified into tradable sector, operate as companies from non-tradable sector. A study by Domadenik et al. (2003) points out that non-trading companies have excessive number of employees, considering sector's productivity. In other terms, non-trading companies have low efficiency.

Efficiency can be increased by producing more output with the given resources or by keeping the same output utilizing less resources. Prices of outputs of the inefficient companies are ceteris paribus higher than those of their efficient counterparts, since more resources are consumed to produce one unit of output. If the non-tradable sectors have high output gap, meaning that they are producing quantities below their production capabilities with a certain amount of capital and labor, this is manifesting as low efficiency. Consequences of such situation are twofold. First, a country that is monitoring its output gap in terms of GDP may not detect the output gaps of inefficient non-tradable sectors and more efficient tradable sectors as two different quantities. Thus it may only detect a certain general domestic output gap and employ inappropriate monetary and fiscal policies in the whole national economy. Monitoring output gaps of non-tradable and tradable sectors separately would allow the policy setting authorities to tailor the policy measures according to the real situation. Second, since the outputs of inefficient non-tradable sectors are usually consumed as inputs in more efficient tradable sectors, the companies buying these products and services are paying an unnecessary premium, which harms their position in competitive global markets.

To maximize the general welfare or minimize the welfare loss function that policy makers are monitoring using various econometric models, they should also focus on decreasing the output gap of non-tradable sectors. Increasing the efficiency of non-tradable sectors does not come at the expense of any other entity inside or outside a particular national economy, operating independently or within a monetary union.

This dissertation contributes to the literature in two important ways. It features a novel approach to analysis of possible policy implications for controlling the output gap with a separation of control of non-tradable and tradable sectors of economy. Also novel is the stream of data treatment methods and various econometric methods including DEA. The aim was to prepare a quantitative microeconomic evidence of *the influence of price targeting of non-tradables*, which can be achieved only through productivity increases in small open economies, where nominal exchange rates and nominal interest rates are fixed by the policy of a central institution within the monetary union, as is the case in the countries with EUR.

The result of the research is a positive quantitative proof of the effect of efficiency of non-tradable sectors on the efficiency of tradable sectors of countries in the global arena. Taking into account the existing macroeconomic literature on the topic of monetary and fiscal policy in monetary unions, and the literature on frictions and nominal rigidities of prices and wages, the results confirm the suitability of controlling the prices of non-tradables as an instrument of each country's fiscal authority to implement the desired policy. It is expected that the influence of non-tradable sectors on tradable sectors is going to be different in different countries. To deepen the understanding of the results, the topic is also investigated on the case of Slovenia, which is a specimen of a small open economy operating in monetary union[3].

Methodologically, DEA analysis[4] provides efficiency scores for companies, that are stripped of current state of technology and total factor productivity's "manna from heaven" (Hulten, 2001) influences. The only thing that is left is the relative efficiency of companies within sectors, aggregated on country level, competing in global arena. These DEA scores are fed to a regression model in order to determine the amount of the influence. The aim is to investigate how much of the effect of increase in efficiency of companies operating in non-tradable sectors translates to increase in efficiency of companies of tradable sectors in any national economy, within global markets.

I hope that readers will find the contents of this work and its complexity challenging. Research process is following the idea of reproducible research. All 4077 lines of computer code for analysis was written in programming language R (R Core Team, 2016), using the "Benchmarking" package (Bogetoft and Otto, 2015), package "gvlma" (Pena and Slate, 2014). Visualizations have been produced with the use of "ggplot2" package (Wickham, 2009) and "gridExtra" package (Auguie, 2016). Research is conducted on a huge dataset containing yearly financial reports of over two hundred thousand (217194) companies from fifteen (15) countries for a period of nine (9) years. At this size it is impossible to manually check every individual observation for missing values and possible deviations from expected behavior. Special care was taken to properly treat outliers and missing values. All the results are reported as calculated from the initial dataset. Data was not preselected on any dimension in order to accommodate expected findings or provide a misleadingly clear picture. The clean results, that were obtained despite this fact, suggest that the findings are robust. The analysis in this work is a step off the beaten path of "use a well tested procedure to reconfirm or disprove a well known theory on some new dataset". One of the peripheral aims of this dissertation is to explore the interoperability of the available methods and procedures that can be applied with the help of modern IT technology, not to exhaust the intricacies of each individual one. The rich set of methods is applied to a real dataset and is used to provide empirical evidence of effects of efficiency of non-tradable sectors on efficiency in tradable sectors. Effects shown are as expected according to existing economic theory.

First section of this thesis describes the existing landscape of mostly macro-economic concepts and existing literature which provides the source of ideas and the matter for the narrative of this thesis. Second section narrows the scope to productivity analysis and describes the methodological techniques applied in the research. Third section describes the data, the scales and descriptive statistics of the observed variables. Section four is a digression on missing value imputation methods,

[3]Extensive body of literature (see Betts and Devereux (2001), Benigno and Benigno (2003), Bacchetta and Van Wincoop (2000), Justiniano and Preston (2010), Corsetti et al. (2010),...) modeling open economies in two-country setting. Although such approach is offering some insight into possible relations of systems at work in small open economies also, two-country models do not adequately represent the reality of small open economies like Slovenia. The decisions and internal policies of such countries have practically no effect on the parameters of the whole system of interconnected countries as can be observed in contemporary monetary unions. Gali and Monacelli (2008) propose a much more suitable model, where all countries modeled as infinitesimally small.

[4]DEA - data envelopment analysis

which can have important influence on the results of the research[5]. Section five describes the empirical model and research results. Section six concludes and provides suggestions for future research.

[5]Most part of the section on missing values is also prepared to be published as a separate paper with co-author, prof. Marko Pahor, PhD.

1 MOTIVATION AND MACROECONOMIC CONTEXT

1.1 Basis for economic policy research

People in early 19th century were very poor by today's standards. GDP per capita in Europe was roughly 1,000 EUR (Maddison, 2007). Industrial Revolution caused a sharp rise in productivity over the next two hundred years. By the start of new millennium, GDP per capita had grown way over 20,000 EUR in developed countries. This growth was not always smooth, but it has been persistent. In USA, GDP was rising at an average annual growth rate of 1.7 percent. Another change that was happening was the transformation of working tasks due to automation and other technical innovations brought about by the industrial revolution. Jobs moved people off the farms to jobs in the manufacturing and in later periods increasingly to the service sectors of the economy (Hulten, 2001; Chen et al., 2005). Economists who have found the explanation of aforementioned phenomena one of the main goals of their research, responded with two classes of models. Marxian and neoclassical theories of growth assign the greatest weight to productivity improvements driven by advances in the technology and the organization of production. The second class consists of the New Growth Theory and another branch of neoclassical economics, the theory of capital and investment. Scientists belonging to this class have put the increase in investments in human capital, knowledge, and fixed capital in the main focus of their research. The division between research based on technology and organization of production on one hand and capital formation on other hand, carries over to empirical growth analysis. Empirical growth economists are faced with two practical tasks:

- acquisition and treatment of historical data on inputs and outputs,
- measurement of the degree to which output growth is due to technological factors ("productivity") vs. capital formation.

The second task may be referred to as *sources of growth analysis* and is the intellectual framework of the Total Factor Productivity (TFP) residual. However, focus on GDP in current prices as the the only metric of economic progress is not sufficient. Economic wellbeing is based on the quantity and quality of goods and services consumed, while preserving the natural and cultural resources (Hulten, 2001). In past decades economists developed several complex models in order to control and predict the effects of various policies on national and general welfare. These models incorporate a number of economical concepts: household behavior, firms behavior, trade conditions, substitution elasticities, international risk sharing, exchange rate, inflation, output gap, GDP, various nominal rigidities, cooperation between policy makers, etc.

Total factor productivity (TFP), i.e. output per unit input, is a very simple productivity measure. However its determination is somewhat elusive. It is possible to augment it with constructs such as constant monetary value which is closely related to consumer price index (CPI), alternating between analysis from producer and consumer side, accounting for deterioration of environment, increase in quality, etc. This makes the analysis of productivity much more complicated. Building on Tinbergen (1942), Solow (1957) developed a link between the production function and the index number approach to productivity analysis. Earlier index number studies had interpreted the results in light of a production function. Solow started with the production function and deduced the consequences and restrictions on the productivity index. Solow measured the TFP using a nonparametric index number approach. He developed a measure called Solow residual, which measures the residual growth rate of output not explained by the growth in inputs. It is a true index number in the sense that it can be computed directly from prices and quantities. As noted by Abramovitz (1956), Solow residual is a"measure of our ignorance", because is a residual. This ignorance covers many components. Some of them such as the effects of technical and organizational innovation we want to measure. Others are unwanted, but still contained in the residual: measurement error, omitted variables, aggregation bias, and model misspecification (Hulten, 2001).

In principal a TFP residual can be computed for every level of economic activity, from individual production unit to the aggregate economy. However, these residuals are not independent of each other. The productivity of a firm as a whole reflects the productivity of its component plants. Similarly, industry residuals are related to those of the constituent firms, and productivity in the aggregate economy is determined at the industry level. As a result, productivity at the aggregate level will increase if productivity in each constituent industry rises, or if the market share of the high productivity industry increases. A complete picture of the network dynamics of an economy would include a mutually consistent measure of the TFP residuals at each level in the web of links used to connect the levels. Construction of such graph of residuals can be approached from the top down or bottom up. Domar (1961) was the first to approach the problem from top to bottom and identified the complication introduced by the presence of intermediate goods. This complication arises because plants and firms in each sublayer produce goods and services that are used as inputs in the production processes of the plants and firms. The magnitude of these intermediate deliveries grows in each subsequent layer when progressing from top to bottom. The bottom-up approach to productivity measurement takes the complete set of production units or firms as the basic frame of reference and does not impose any restrictive aggregation assumptions needed to achieve a consistent measure of overall productivity. Instead, it stresses the basic heterogeneity of the microproduction units. An important goal of this approach is to explain the observed heterogeneity of plant productivity in terms of factors such as R&D spending or patenting, or in terms of the differences in the financial or industrial structure (Hulten, 2001). Some contributions using bottom-up approach were developed by Davis and Haltiwanger (1991), Hall et al. (1993) and Griliches (1994).

Analysis of the productivity on the macro level can provide important information for the policy maker. How national economic resources are allocated across establishments that differ in productivity can be an important factor in the research of cross-country differences in output per capita. Restuccia and Rogerson (2008) show that policies which create heterogeneity in the prices faced by individual producers can lead to considerable decreases in output and measured total factor productivity (TFP). Competitiveness of the sector often depends on its firms meeting their production potential (Kapelko and Lansink, 2015). Baily et al. (1992) document that about half of overall productivity growth in US manufacturing in the 1980's can be attributed to factor reallocation from low productivity to high productivity industrial units. This and other evidence shows the importance of capital and labor allocation across establishments as a determinant of aggregate productivity. Most models assume that in the competitive equilibrium without distortions all producers face the same prices. However, it is possible to construct a model, that can account for policy distortions whose direct effect is to create heterogeneity in the prices faced by individual companies. These idiosyncratic distortions can be different for each producer and can lead to a reallocation of resources across companies. Even if the policies considered do not rely on changes in aggregate capital accumulation and in aggregate relative prices, Restuccia and Rogerson (2008) find substantial effects of these policies on aggregate output and measured TFP.

Pressing problems of modern governments and central financial institutions as policy makers are revolving around optimal monetary and fiscal policies. A lot of attention in latest years is dedicated to optimal policies in monetary unions. Monetary policy coordination may be desirable, but it is complicated (Claessens et al., 2015). The theoretical New Keynesian literature has been identifying the role of real factors in driving monetary policy spillovers for some time. Distortions typically included in New-Keynesian models are price stickiness, monopolistic competition, and pricing to market (Corsetti et al., 2010; Engel, 2011). However, when one calibrates these types of models to real world circumstances, spillovers from countries pursuing national macroeconomic stability tend to be small, suggesting limited scope for international cooperation. Earlier papers on monetary policy spillovers largely assumed complete and perfect international financial markets. Further, these models assume that increased financial integration improves market completeness and risk-sharing. If that enables greater diversification and insurance opportunities, adverse spillovers from monetary policy are less likely and the need for international coordination is correspondingly smaller. Theory also shows that in the presence of imperfections there can be offsetting effects of increased financial globalization. It is evident that countries that are financially self-sufficient are less impacted by foreign monetary policy changes through direct financial channels, while financially open countries are more exposed (Claessens et al., 2015). Many models of monetary policy spillovers, as well as other broader models of monetary and fiscal policies address large, two-country cases. However, small countries may be subject to strongest effects from lack of coordination. They are arguably more exposed to capital flow volatility induced by changes in large countries' monetary policy and have low influence and bargaining power when deciding various policy parameters in monetary and other unions. Small open economies are not well covered in most existing models. This gap is somewhat filled with Gali and Monacelli (2008). It is not always clear that a coordinated solution would be Pareto improving for all participating countries even if global welfare is increased. Fratzscher et al. (2013) argue that quantitative easing policies increased the pro-cyclicality of portfolio flows to emerging markets. Therefore, this literature suggests that spillovers related in part to monetary policy can adversely affect recipient countries. There are other points, where there is no consensus among economists: which are more relevant demand or supply shocks, what is the degree of price and wage rigidities, slope of the Phillips curve and presence and relevance of balance sheet effects. There seems to be a wide agreement that the limits regarding stronger international monetary policy coordination should lead one to encourage countries to strengthen the resilience of their own economy, and thereby the global economy, via other means. Enhanced macro-prudential and capital flow management could be a way forward, and indeed countries are exploring new ways to find protection from the booms and busts cycles in capital flows (Bole et al., 2014b; Claessens et al., 2015).

1.2 Monetary policy

Monetary policy is executed through actions of modifying the interest rate, buying or selling government bonds, and changing the required amount of bank reserves. All these influence the rates at which companies and households save, borrow, invest and spend money. It also affects the productivity of firms and financial flows between countries.

Beside the role of the non-monetary factors in the business cycle, it became apparent in the empirical economic research that monetary policy has a significant impact on the short-term activities in the real economy. Despite the latest fall in popularity of DSGE[6] models (Buiter, 2009; Krugman et al., 2011; Fagiolo and Roventini, 2016), with the inclusion of techniques introduced through DSGE theory, tools and theoretical frameworks used for policy analysis have been substantially improved. An important point of distinction from the real business cycle theory was the explicit incorporation of new variables into the models, such as nominal price rigidities or frictions in money demand (Clarida et al., 1999). One of the most important price variables used to be the real exchange rate, since it had substantial consequences on external competitiveness and terms of trade, as well as internal sectoral resource allocation (Gali and Monacelli, 2005). However, with membership of many open economies in monetary unions, exchange rate control was lost as an instrument of monetary policy control for many countries. This is especially true for small open economies like Slovenia, that do not have neither the size, neither the bargaining power to affect exchange rates of the currency their economy is operating in.

It is important that the results that models provide are robust over a wide variety of macroeconomic frameworks (Ouyang and Rajan, 2013). Proven results, that depend on highly specific models and datasets, are of limited use. A useful model capable of serving as an analytical framework for small open economy operating in monetary union has to satisfy a number of expectations. First, it has to incorporate some of the main features characterizing the optimizing models with nominal rigidities that have been developed and used for monetary policy analysis in recent years. Secondly, it should contain a fiscal policy sector, with a purposeful fiscal authority. Thirdly, the framework should comprise many open economies, linked by trade and financial flows (Gali and Monacelli, 2008).

Taking into account the nominal rigidities, central banks were historically able to change the short-term real interest rate with changing the nominal rate through monetary policy. It is evident, that the countries accepting a common currency like EUR, loose their ability to individually control their monetary policy and need to drive their economy using available fiscal policy instruments.

[6] DSGE - Dynamic Stochastic General Equilibrium

1.3 Fiscal policy

Fiscal policy is the only set of tools left to countries taking part in a monetary union. Indeed, in the absence of national monetary policy instruments, fiscal policies play a key role in accommodating country-specific shocks. Therefore fiscal policies are at the center of the theory on optimal currency areas (Kenen, 1969) and played a central role in discussions leading up to the creation of the European Economic and Monetary Union (EMU). The debate on the role of fiscal policies was then largely based on a framework in which current account movements resulting from country-specific shocks only had limited effects on welfare. Meanwhile, the euro area crisis has pointed out that sub-optimal current account imbalances can arise within monetary unions in which risk sharing is imperfect, and that reversing these imbalances can prove painful. A paper by Hjortsoe (2016) investigates whether optimal cooperative fiscal policies prevent such intra-union imbalances from arising by leaning against them.

With modification of taxation policies being largely unpopular, the only instrument that is left to be controlled are the prices, that, due to some frictions, are not subject to immediate free market economy rules. Since products and services of non-tradable sectors are little (if at all) substitutable, it is possible to make an assumption, that the best way of fiscal policy control can be executed through the prices of outputs of non-tradable sectors. Such control could be carried out with the increase of productivity of companies in non-tradable sectors. In this thesis, we are empirically confirming a link between the productivities of non-tradable and tradable sectors of economy. Thus, control of productivity of non-tradables could be used to control the output gap, which is positively related to the inflation via the Phillips curve. Having the output gap as a target, policy needs to push the companies from non-tradable sectors towards elimination of wage / labor frictions, which would result in increased productivity of these sectors and drive down the output gap. Clarida et al. (1999) state: "To the extent cost push inflation is present, there exists a short run trade-off between inflation and output variability". This, again, points in the direction of controlling the prices of goods and services obtained from non-tradable sectors in order to keep cost-push inflation in check.

1.4 Modeling economy to optimize policy, a DSGE approach

Throughout modern history, sovereign countries have been manipulating macroeconomic instruments in order to maximize some perceived implicitly or explicitly defined welfare function that maximizes utility U, broadly defined as:

$$E_0 \sum_{t=0}^{\infty} \beta^t U(C_t^i N_t^i G_t^i) \tag{1.1}$$

where E_0 represents expectation at time 0, C_t^i represents private consumption, N_t^i hours of work and G_t^i index of public consumption.

Instruments, that were contained in the traditional tool set of policy drivers in most countries were:

- Interest rate;
- Exchange rate;
- Price control; and
- Duties and taxes.

First two belong to the class of monetary policy and the latter two to the class of fiscal policy levers.

With the aim of achieving maximal utility of available resources for the society in general, countries are monitoring various indicators like GDP, inflation and output gap. Output gap is a less well known concept in the general public and represents a difference between the actual and the potential output. In the literature it is commonly defined as $x_t \equiv y_t - z_t$. π_t usually represents the inflation rate in period t and is defined as the percent change in prices from $t-1$ to t.

Various authors have recommended several DSGE and VAR[7] models and approaches to measure, monitor and manage multiple rather similar sets of macroeconomic indicators and instruments (Taylor, 1993; Bernanke and Mishkin, 1997; Clarida et al., 1999, 2001; Gali and Monacelli, 2005, 2008; Monacelli and Perotti, 2010; Claessens et al., 2015; Eggertsson et al., 2016b; Hjortsoe, 2016).

Basic framework for this thesis stems from the model presented by Gali and Monacelli (2008). This model is special since it models small open economies in monetary union like a set of infinitesimally small countries, subject to imperfectly correlated productivity shocks. In contrast with models featuring two large economies, the majority of the countries in European monetary union are small relative to the union as a whole. As a result, their policy decisions, taken in isolation, do not have a lot of impact on other countries. By looking at the limiting case of a continuum of economies, with each economy of negligible size relative to the rest of the world, authors overcome the tractability problems associated with "large N". Their analysis focuses on the optimal fiscal and monetary policies from the view-point of the currency union as a whole. They determine the monetary and fiscal policy rules that maximize a second-order approximation to the integral of utilities of the representative households inhabiting the different countries in the union.

To start building a model, we define household consumption c_t as constant elasticity of substitution composite of domestic and foreign products and services, expressed in log-linear form by:

$$c_t = (1-\gamma)c_t^h + \gamma c_t^f \tag{1.2}$$

Superscripts h stands for home, f for foreign and $h*$ for home products consumed in foreign countries. γ is a parameter which is measuring openness. Next, we define domestic output y_t classified to a part of products and services sold to domestic consumers c_t^h and products and services sold to foreign

[7] VAR - Vector Auto Regression

consumers $c_t^{h^*}$:

$$y_t = (1-\gamma)c_t^h + \gamma c_t^{h^*} \tag{1.3}$$

Households are maximizing their utility, taking into account the discounted value of future consumption index, leisure and real money. In order to maximize their utility they are managing current levels of consumption, work (i.e. labor supply) and savings. The first order conditions expressed in log-linear form are:

$$c_t^h - c_t^f = \eta s_t \tag{1.4}$$

$$w_t - p_t - \gamma s_t = (\phi n_t + \sigma c_t) + \mu_t^w \tag{1.5}$$

$$c_t = E_t c_{t+1} - \frac{1}{\sigma}[r_t - E_t(\pi_{t+1} + \gamma E_t \Delta s_{t+1})] \tag{1.6}$$

$$E_t \Delta s_{t+1} + r_t^* - E_t \pi_{t+1}^* = r_t - E_t \pi_{t+1} \tag{1.7}$$

The first Equation 1.4 introduces terms of trade s_t, where η represents elasticity of substitution between domestic and foreign products and services. *Law of one price* is assumed, stating that $s_t = e_t + p_t^* - p_t$, e_t representing the nominal exchange rate, p_t^* the foreign price level and p_t the price of domestic output. Labor supply is addressed in the Equation 1.5. $p_t + \gamma s_t$ represents the consumer price level, which combined with the nominal wage w_t forms the real wage. The first term on the right is the marginal rate of substitution between leisure and consumption. n_t represents employment, ϕ is the inverse of labor supply elasticity and σ is the coefficient of relative risk aversion. The last term μ_t^w represents the "wage markup" and reflects frictions in the wage setting that may distort the real wage from its competitive equilibrium value $(\phi n_t + \sigma c_t)$. In general, these frictions may stem from either real rigidities (e.g. efficiency wages) or nominal rigidities (e.g. long term nominal contracts). For simplicity, μ_t^w is assumed to be an exogenous stationary first order stochastic process. Propensity to consume is related to saving in the Equation 1.6. Saving in domestic bonds is assumed, where the expected return is the difference between the nominal interest rate r_t and the expected rate of consumer price inflation $E_t(\pi_{t+1} + \gamma \Delta s_{t+1})$. Domestic inflation is calculated as $\pi_{t+1} = p_{t+1} - p_t$. Terms of trade are depreciating at the rate of $\Delta s_{t+1} = s_{t+1} - s_t$. Equation 1.7 links the foreign real interest rate to the growth of foreign output, assumed to be an exogenous stationary process.

A composite consumption index C_t^i can be defined as:

$$C_t^i \equiv \frac{(C_{i,t}^i)^{1-\alpha}(C_{F,t}^i)^\alpha}{(1-\alpha)^{(1-\alpha)}\alpha^\alpha} \tag{1.8}$$

where $C_{i,t}^i$ is an index of country i's consumption of domestic goods, the goods that are produced in country i itself and $C_{F,t}^i$ is an index of country i's consumption of imported goods.

Maximization of Equation 1.1 is subject to a sequence of budget constraints of the form:

$$\int_0^1 P_t^i(j) C_{i,t}^i(j) dj + \int_0^1 \int_0^1 P_t^f(j) C_{f,t}^i(j) dj df + E\{Q_{t,t+1} D_{t+1}^1\} \leq D_t^i + W_t^i N_t^i - T_t^i \tag{1.9}$$

for $t = 0, 1, 2, ...$, where $P_t^f(j)$ is the price of good j produced in country f (expressed in units of the single currency). D^i_{t+1} is the nominal payoff in period $t+1$ of the portfolio held at the end of period t (and which may include shares in firms, local and foreign), W^i_t is the nominal wage, and T^i_t denotes lump-sum taxes.

Using i_t as representation for interest rate, a simple macroeconomic framework can be described with two equations:

$$x_t = -\Phi[i_t - G_t\pi_{t+1}] + G_t x_{t+1} + v_t \tag{1.10}$$

$$\pi_t = \lambda x_t + \beta G_t \pi_{t+1} + u_t \tag{1.11}$$

Equation 1.10 is an IS[8] curve that relates the output gap inversely to the real interest rate. G_t represents government consumption. Equation 1.11 is a Phillips curve that relates inflation to the output gap. v_t and u_t are disturbance terms:

$$v_t = \mu v_{t-1} + \hat{v}_t \tag{1.12}$$

$$u_t = \rho u_{t-1} + \hat{u}_t \tag{1.13}$$

where $0 \leq \mu$ and $\rho \leq 1$. Both $\hat{g}_t$ and $\hat{u}_t$ are independent and identically distributed random variables with $E[\hat{g}_t] = 0$ and $E[\hat{u}_t] = 0$ and variances σ^2_g and σ^2_u (Clarida et al., 1999).

However, in a multi country setting, equations are more complex. The clearing of market for good j produced in country i requires:

$$\begin{aligned}
Y^i_t(j) &= \int_0^1 C^i_{i,t}(j)df + G^i_t(j) \\
&= \left(\frac{P^i_t(j)}{P^i_t}\right)^{-\epsilon}\left[(1-\alpha)\left(\frac{P^i_{C,t}}{P^i_t}\right)C^i_t + \alpha\int_0^1\left(\frac{P^f_{C,t}}{P^i_t}\right)C^f_t\,df + G^i_t\right] \\
&= \left(\frac{P^i_t(j)}{P^i_t}\right)^{-\epsilon}\left[(1-\alpha)(S^i_t)^\alpha C^i_t + \alpha(S^i_t)^\alpha\int_0^1 (S^i_t)^{1-\alpha}C^f_t\,df + G^i_t\right] \\
&= \left(\frac{P^i_t(j)}{P^i_t}\right)^{-\epsilon}\left[C^i_t(S^i_t)^\alpha + G^i_t\right]
\end{aligned} \tag{1.14}$$

Plugging the previous condition into the definition of country i's aggregate output $Y^i_t \equiv \left(\int_0^1 Y^i_t(j)^{1-\frac{1}{\epsilon}}\right)^{\frac{\epsilon}{\epsilon-1}}$ we obtain the following aggregate goods market clearing condition for country i:

$$Y^i_t = C^i_t(S^i_t)^\alpha + G^i_t \tag{1.15}$$

On the supply side, a new Keynesian Phillips curve for an open economy constructed by Gali and Monacelli (2008) that incorporates rigidities, purposeful fiscal policy sector and assumes small open economy operating in a framework of countries, linked by trade and financial flows is constructed as:

$$\pi^i_t = \beta E_t\left\{\pi^i_{t+1}\right\} + \lambda\left(\frac{1}{1-\gamma} + \phi\right)\hat{y}^i_t - \frac{\lambda\gamma}{1-\gamma}\hat{g}^i_t - \lambda(1+\phi)a^i_t \tag{1.16}$$

[8] IS stands for investment-saving in the IS/LM macroeconomic model.

Since Gali and Monacelli (2008) model the currency union as a closed system, made up of a continuum of small open economies, represented by the unit interval. Each economy is indexed by $i \in [0, 1]$ and is of measure zero. E_t is expectation at time t, ϕ is the inverse of labor supply elasticity, $\hat{y}_t^i$ is a log-linear approximation of GDP, $\hat{g}_t^i$ is log-linear approximation of government spending, γ is the government's share of purchases in economy and a_t^i is a country-specific productivity shifter.

As can be seen, DSGE modeling is a huge undertaking and detailed mathematical model analysis is not the aim of this literature review. Interested reader can find further mathematical derivations in original articles.

In their model, under the optimal policy setting, Gali and Monacelli (2008) find that each country's fiscal authority plays a dual role, trading-off between the provision of an efficient level of public goods and the stabilization of domestic inflation and output gap. They further show that the existence of such a stabilizing role for fiscal policy is desirable not only from the viewpoint of each individual country, but also from that of the union as a whole. Their simulations under the optimal policy mix of a representative economy's response to an idiosyncratic productivity shock show that the strength of the countercyclical fiscal response increases with the importance of nominal rigidities. Such finding may call into question the desirability of imposing external constraints on a currency union's members ability to conduct countercyclical fiscal policies, when the latter seek to limit the size of the domestic output gap and inflation differentials resulting from idiosyncratic shocks. To the extent that price stickiness is present, there are welfare losses associated with departures from price stability, in addition to those stemming from nonzero output and fiscal gaps. They find that the flexible price/efficient allocation is not feasible under the currency union regime. In particular, the rise in productivity must be absorbed only via a gradual and persistent fall in the price level, with the consequent relative price distortions. As a result, the optimal policy mix requires expanding the fiscal gap to bring about the rise in demand necessary to accommodate the desired expansion in output, thus smoothing the adjustment of prices over time (Gali and Monacelli, 2008). This issue is developed even further by Hjortsoe (2016), who finds that risk sharing role of optimal fiscal policy clearly overshadows its output stabilization role when prices are flexible. It improves intra-union risk sharing at the expense of lower output gap stabilization. However, reducing the inefficiencies from imperfect risk sharing does not come at the expense of output gap when prices are sticky, or when the re-allocation of labor across sectors within countries is inefficient. This finding is not in contrast with the fact that optimal fiscal policies consist in reducing intra-union imbalances. The finding that optimal fiscal policy consists in reducing intra-union imbalances does not hinge on there being no frictions associated with re-allocating resources within each country. Indeed, the results go through in a two-sector two-country model in which wages are sticky and thus labor cannot immediately be efficiently allocated across sectors in response to shocks. Details of the model show that also when there are frictions associated with re-allocating labor across sectors, the optimal fiscal policy consists in reducing the demand gap. As under sticky prices, this policy simultaneously reduces inflation in the traded sector. However, it is noteworthy that the optimal policy also reduces aggregate output gaps in Hjortsoe (2016) model.

1.5 Closed economy vs. small open economy

When modeling small open economy, certain assumptions have to be made. When Clarida et al. (2001) define a small open economy framework, they assume money, imperfect competition, nominal price rigidities and friction in the labor market. Size of an economy can be assumed as small, when it does not influence the foreign output, price level or interest rate. One thing that is dependent on both, home and foreign disturbances, are the equilibrium *terms of trade*. Gali and Monacelli (2008) define the bilateral terms of trade between countries i and f as $S^i_{f,t} \equiv \frac{P^f_t}{P^i_t}$. The price of country f's domestically produced goods are expressed in terms of country i's. From this definition it follows, that the effective terms of trade for country i are given by:

$$S^i_t = P^*_t P^i_t = \exp \int_0^1 \left(p^f_t - p^i_t\right) df = \exp \int_0^1 s^i_{f,t} df \tag{1.17}$$

where $s^i_{f,t} \equiv \log S^i_{f,t}$. $P^*_t \equiv \exp \int_0^1 p^f_t df$ is the union-wide price index, which is, from the viewpoint of individual country, also a price index for imported goods. Prices in logs for domestic goods and for foreign goods are denoted by p^i_t and p^f_t, respectively.

Domestic inflation is defined as the rate of change in the price index for domestically produced goods: $\pi^i_t \equiv p^i_t - p^i_{t-1}$. It is linked to the *CPI inflation* with the equation:

$$\pi^i_{c,t} = \pi^i_t + \alpha \Delta s^i_t \tag{1.18}$$

With some other assumptions that are beyond the scope of this text Clarida et al. (2001) show that the optimal policy problem for the small open economy is isomorphic to the closed economy case described in Clarida et al. (1999). They further state that the optimal policy should be constructed in a way, that the change in the output gap adjusts to deviations of inflations from target:

$$x_t - x_{t+1} = -\frac{\lambda_w}{\alpha_w}\pi_t \tag{1.19}$$

where λ represents gain in reduced inflation per unit of output loss and α represents relative weight placed on output losses. Subscript w denotes $w = \gamma(\sigma\eta - 1)(2 - \gamma)$, where η represents elasticity of substitution, σ is the coefficient of relative risk aversion and γ measures openness for foreign goods.

Since current behavior depends on expectations of future policy, Equation 1.19 implies the following optimality condition:

$$x_t = -\frac{\lambda_w}{\alpha_w} p_t \tag{1.20}$$

Thus, the optimal policy is interpretable as domestic price level targeting. In economies, that are not members of monetary unions and can adjust their exchange rate, it remains optimal, to accommodate movements in the terms of trade. Even with commitment as explained in Clarida et al. (1999), accordingly, pegging the nominal exchange rate does not produce the best policy (Clarida et al., 2001).

When analyzing optimal monetary policy scenarios for small open economies, Gali and Monacelli (2005) stress the fact that "As discussed in Rotemberg and Woodford (1999), under the assumption of a constant employment subsidy τ that neutralizes the distortion associated fifth firms' market power, it can be shown that the optimal monetary policy is the one that replicates the price equilibrium allocation." Such policy commands the real marginal costs and mark-ups to be stabilized at their steady level, which in turn implies that domestic prices must be fully stabilized also. "The intuition for that result is straightforward: with the subsidy in place, there is only one effective distortion left in the economy, namely, sticky prices. By stabilizing mark-ups at their frictionless level, nominal rigidities cease to be binding, since firms do not feel any desire to adjust prices. By construction, the resulting equilibrium allocation is efficient, and the price level remains constant (Gali and Monacelli, 2005)." This is a very important idea, that motivates the research of this thesis: by manipulating productivity of the non-tradable sectors, the "frictionless level" changes. They further state that "domestic output always increases in response to a positive technology shock at home". Improving the productivity of non-tradable sector is exactly that. Further support for focusing fiscal policy on no-tradable sector is provided by Hjortsoe (2016), who proves that when prices are sticky, or when the re-allocation of labor across sectors within countries is inefficient, reducing the inefficiencies from imperfect risk sharing does not come at the expense of greater output gaps.

To address the complementary issue of the increase in of domestic output in response to positive technology shock at home, an increase in world output always generates improvement in the terms of trade (i.e. a real appreciation). Combination of expenditure-switching effect, together with the effect of the real appreciation on domestic consumption through the risk sharing transfer of resources[9], tends to reduce aggregate demand and domestic economic activity. Any change in terms of trade is balanced to some degree with a positive direct demand effect resulting from higher exports, as well as by a positive effect on domestic consumption associated with international risk sharing (and given the implied higher world consumption).

1.6 Exchange rate volatility in sovereign countries

Predating the model of small open economies operating in monetary unions put forward by Gali and Monacelli (2008), to extend the basic monetary policy frameworks used to model closed economy, Gali and Monacelli (2005) introduced a two country small open economy model, that controlled for the impact of exchange rate regime and monetary policy coordination, taking into account the shocks coming from a foreign market.

Various alternative rule based policy regimes exist that small open economies with their own currency can employ (e.g. domestic inflation, CPI-based Taylor rules, exchange rate peg). These regimes differ in the amount of relative exchange rate volatility that they can trigger (Gali and Monacelli, 2005).

[9]International risk sharing has important consequences for economic policy. Risk sharing prevents individuals in participating (risk sharing) countries from experiencing unnecessary fluctuations in their consumption levels that are undesirable.

Real exchange rate can be analyzed:

- in terms of exchange rate regimes (i.e. fixed vs. flexible)(Clarida and Gali, 1994; Lastrapes, 1992; Enders and Lee, 1997; Rogers, 1999);
- with the use of vector autoregression models (VAR) and variance decomposition techniques that estimate the relative contributions of real and nominal shocks to real exchange rate fluctuations (MacDonald, 2000; Ricci et al., 2008)));
- long-run equilibrium real exchange rate determinants, which include productivity, governments spending, etc.;
- deviations from purchasing power parity (PPP) with the focus on the so called "PPP puzzle"[10] (Froot and Rogoff, 1995; Rogoff, 1996);
- by decomposing it into external prices (deviation from PPP) and internal prices (relative prices of tradables and non-tradables) (Engel, 1999; Betts and Kehoe, 2008).

Ouyang and Rajan (2013) suggest, that internal relative prices between tradables and non-tradables are the most important part of the real exchange rate volatility. They expect a positive relationship between government spending and the size of the influence of relative prices on real exchange rate. According to Mendoza (2000), economies with more flexible real exchange rate regimes are more likely to experience deviations from PPP. That means that increased flexibility would result in a smaller influence of internal prices on real exchange rate volatility. Ouyang and Rajan (2013) further hypothesize, that the more open an economy is to capital flows the larger is the influence of internal relative prices between tradables and non-tradables on the real exchange rate volatility. They provide a somewhat questionable empirical model[11], claiming that in line with the size difference between two economies, internal prices have stronger effect on the bilateral exchange rate variability if the size difference, growth differences and inflation rate differences are larger. The effect of internal prices on bilateral exchange rate variability is also increasing with the average trade and financial openness of both countries. However, in the same paper they provide another econometrically valid model, which is suggesting that if the trading relationship between two countries includes at least one high income partner, the relative importance of non-tradables in bilateral exchange rate volatility diminishes. This result is particularly strong in relationships with both trading countries being high-income. Contrary to prior expectations, this suggests that PPP does not necessarily hold between high-income trading countries.

Absence of exchange rate flexibility increases the relative importance of non-tradable prices in bilateral real exchange rate volatility. Another factor that is increasing the importance of non-tradable prices in bilateral real exchange rate volatility is intensity of bilateral trade (Ouyang and Rajan, 2013). The same conclusion is offered by Gali and Monacelli (2005) who state that a high positive

[10]Purchasing Power Parity is the idea that, once converted to a common currency, national price levels should be equal. However, it has been shown, that while real exchange rates are very volatile short-term, the shocks are damping extremely slow at a rate of roughly 15 percent per year

[11]Model contains statistically insignificant factors and is strictly econometrically invalid

correlation between domestic productivity and world output will tend to decrease the volatility of the nominal and real exchange rates.

As Corsetti and Pesenti (2001) suggest, central banks in open economies have another factor, that they may want to manipulate in a way that benefits the domestic consumers: the possibility of influencing the terms of trade. This possibility is a consequence of two factors: sticky prices, which render monetary policy non-neutral and, secondly, the imperfect substitutability between domestic and foreign products and services.

1.7 The role of frictions in designing optimal policy

In the literature, frictions are classified into three broad groups:

- financial market frictions,
- labor market frictions,
- sticky prices of goods and services.

Financial frictions in the accumulation and management of capital have been researched by Bernanke et al. (1999), Christiano et al. (2004) and Christiano et al. (2011). The financial frictions describe the reality that borrowers and lenders are different entities with asymmetric information. Entrepreneurs who usually represent the borrowers, are agents who have a special skill in the operation and management of capital. They posses their own financial resources, but their skill in operating capital is such that it is optimal for them to operate more capital than their own resources can support. To achieve that state, they borrow additional funds. There is a financial friction, because the management of capital is risky. Individual entrepreneurs are subject to idiosyncratic shocks which are observed only by them. Banks, who usually represent the lenders, are agents, who can only observe the idiosyncratic shocks by paying a monitoring cost. To hedge their interests they usually require some guarantee in form of collateral (Christiano et al., 2011). Financial frictions give rise to potentially interesting wealth effects of the sort emphasized by Fisher (1933). For example, when a shock occurs which drives the price level down, households receive a wealth transfer. Because this transfer is taken from entrepreneurs, their net worth is reduced. With the tightening in their balance sheets, their ability to invest is reduced, and this produces an economic slowdown. Also, their ability to acquire loans is diminished, due to bank's requirements for collateral coverage (Bole et al., 2012). Frictions in financial markets lead to functioning of the markets which is different from the one expected in standard macroeconomic models (Stiglitz, 2011).

Standard models often overlook labor market frictions. Boeri and Garibaldi (2012) identified two transmission channels for the financial crisis to reach the labor markets. First mechanism is in effect when banks increase their demand for collateral for the outstanding loans or require advance repayment, a consequence may lead to a sale or a shut down of parts of company activities and subsequent destruction of jobs. Another mechanism is the mobility of workers. When people loose their jobs, they sometimes adapt to a new situation by moving to another region or country and wish to sell existing real estate. With a crisis in effect, the non-functioning real estate market and financial market significantly decrease labor mobility. This raises unemployment in regions impacted by the crisis even more. Christoffel and Linzert (2005) incorporated a labor market with matching frictions and wage rigidities into the New Keynesian business cycle model. Labor market institutions (including employment protection legislation, unemployment benefits and active labor market policies) and recent labor market trends such as the unemployment rate, have played a key role in absorbing and accommodating the effects of the crisis (Eichhorst et al., 2010). In addition, many European countries owe their increased labor market flexibility to the creation of a dual labor market with two different groups of workers: first, the highly protected group with permanent contracts and second, the group of workers with fixed term contracts. Even in situations of liberal labor legislation, as in some of the Western Balkan countries, it is difficult to lay off workers due to too many informal barriers, especially where very high unemployment exists (Prašnikar et al., 2012). An example of inclusion of labor market frictions to an econometric model are shown in Equation 1.5.

Price setting frictions are widely described using the staggered sticky prices model put forward by Calvo (1983). It serves as a basis for many optimizing models with nominal rigidities that have been developed and used for monetary and fiscal policy analysis.

When preparing various economic models for policy analysis, accounting for all kinds of frictions may be of crucial importance. For the present research, the most important finding is reported by Hjortsoe (2016). She shows in her DSGE model that when prices are sticky, or when the reallocation of labor across sectors within countries is inefficient, reducing the inefficiencies from imperfect risk sharing does not come at the expense of greater output gaps. This is an instrumental finding, which coupled with the research results put forward in this thesis, provides important information for fiscal policy implementation.

1.8 Slovenia - small open economy in monetary union

With 37.3 billion EUR of GDP in year 2014 as reported by Statistical office of Republic of Slovenia (2014), average share of foreign trade is as high as 73% of GDP as reported by Institute of macroeconomic analysis and development of Republic of Slovenia (2013). This classifies the Republic of Slovenia as a small open economy. In the years before the global financial crisis Slovenia experienced GDP growth of 5.8 percent in 2006, 6.0 in 2007 and 3.6 percent in 2008. Prices, in spite of almost constant exchange rate, grew by 3% annually. However the growth built up internal and external imbalances (current account deficit peaked at 7 percent of GDP in 2008) and fiscal deficit (with exception in 2008) throughout the period 1995–2011 (Domadenik et al., 2012). The financial accelerator mechanism endogenously drove the amplification and propagation of the process of a company's debt accumulation, which was triggered by external shock of the abundant financial in-flow. The financial accelerator was an important but overlooked segment of the debt amplification and propagation mechanism. Expected discounted capital returns were the main determinant of its power. The stock market has been inflating through the whole boom period and the real property market peaked just before the global crisis erupted. With real estate and stock prices rising, the size of collateral and therefore accessible size of loanable funds was also increasing through the whole boom period, without interruption (Bole et al., 2012). European Commission autumn report in 2006 predicted that in 2007 Slovenia's economy will not be overheated. Despite the obvious acceleration of economic activities in 2006, it predicted some small and manageable cyclically adjusted deficits. The general belief within the professional community in Slovenia was, that the economy only grew lively. Such assumptions supported a large reduction in the tax burden. Tax on wage bill and the income tax were planned to be reduced with total cut of around 2% of GDP, without contraction of the government spending. Tax cutting measures were scheduled for the end of 2006. The reform course was met by acclamation by all interest groups of the economy. The report of the European Commission was a certificate to the claims of the Slovenian professional public that things in the economy are normal and that in 2007 there is no risk of overheating or deteriorating in the fiscal balance. European Commission did not suggest even any precautionary measures for the case if the activity and the deficit in any way escaped out of the economic policy frameworks. Warnings about the potential catastrophic consequences of reducing taxes for the budget balance and the overheating of the economy were few and were not taken seriously due to general optimism (Bole, 2006). A warning on the possible effects of tax cuts on the government structural balance and overheating in the economy was also stated by Mrs. Sorsa, who was then the head of the IMF mission. She published a warning in the Slovenian daily newspapers, that the economy is clearly overheated, and that it would be necessary to increase and not reduce taxes (Bole, 2016). Following was Slovenia experiencing one of the sharpest GDP declines in the euro area during the crisis, standing at -8.0 percent in 2009. This was at least partly due to inappropriate policy of deleveraging. Reductions in bank's credits to non-financial sectors were driven by requests for collateralization, credit rationing and inappropriate assessment of cash flow performance of client companies. Policy measures imposed by European Commission were, again, counterproductive. The appropriate policy measures in 2009 and 2010 would have to stimulate the provision of additional liquidity to companies if they already have positive cash flow and not push them into deleveraging. Focus on the stability of the financial system is one of the cornerstones of optimal deleveraging process. As such, it should be a constitutional part of macroprudential policy, which is suggested as third macro policy pillar (Bole et al., 2014b). In 2012, the crisis in Slovenia was still deepening. Public deficits highlighted the need for a fiscal consolidation plan for the social, pension and health sectors. It was in urgent need of capital injections for the banking sector and firms in which the state retained a controlling stake. Its recovery was constrained by the continued weakness in final demand, the deleveraging by firms and a credit crunch. Macroeconomic recovery was practically inexistent and vulnerable to external shocks due to overindebted private sector and undercapitalized banks (Domadenik et al., 2012). According to estimates of the Commission in 2016, Slovenian economy was strongly overheated already in 2006. The output gap is estimated to have been already at 3.7% of the potential output. Thus, the tax reform in 2006 in Slovenia was a wrong pro-cyclical stimulus. Looking at the European fiscal framework crucial indicators, policy makers were not able to detect any dangerous situation in the EU and euro area economies. Sizable and systematic errors in output gap and structural deficit estimates, prepared by European Commission, were typical for all years in the period 2006-2008. From the autumn of 2005 till the end of 2008 output gap estimates from European fiscal framework have been systematically too low (Bole, 2016).

Conditions for development of special situation in Slovenia have roots in the year 1991. Slovenia proclaimed independency and began with transition to free market economy. Companies from different industries and sectors of economy were operating under different conditions. For companies from industrial sector, known markets of former Yugoslavia were gone. New competitors, some of them world leaders in certain product categories, were introduced to the market in Slovenia. Industrial companies were forced to adapt to new conditions. They invested in R&D and other tangible and intangible capital, built new sales channels, changed corporate governance and business processes (Prašnikar, 2011). Companies from non-tradable sector, on the other hand, were under some kind of state sponsorship, operating under special conditions with high entry barriers for foreign competitors, in monopolistic conditions or some other form of market anomaly. Management lacked incentives to restructure these companies due to virtually non-existent managerial labor market. Restructuring could call for unpopular measures, which could result in change of managers. Thus, managers preferred the status quo at the expense of efficiency of company operations (Prašnikar, 2011). As a result, companies from non-tradable sector did not adapt to new market conditions in Slovenia. Since these companies are serving the tradable sector, protectionistic national policy is coming back as a boomerang, eroding the competitive position of companies from tradable sector on international markets.

As Slovenia was the most developed country in the South East Europe, it served as a benchmark country for all other transition economies in the past two decades. It was the first post-transition country to become a member of the EMU - European Economic and Monetary Union. Slovenian economy is highly dependent on the external demand. In the years before global financial crisis in 2008 it enjoyed relatively easy access to external financing. The expansionary fiscal policy and flood of cheap loans before the crisis in 2008 led to a credit boom, rising financial debt in the corporate sector, foreign debt in the banking sector and increasing wages. Following the global economic crisis in 2008 Slovenia faced a decline of external demand which resulted in decreased GDP, vulnerable financial institutions and banks, increased governmental debt, higher unemployment and an overindebted corporate sector (Domadenik et al., 2012). Thus, during the last crisis, systemic inefficiencies present in suboptimal policies governing the non-tradable sectors of Slovenian economy became more pronounced and deepened the adverse circumstances.

Frictions in the labor and financial markets affected firms in the Western Balkan countries including Slovenia before and after the crisis. The net worth of entrepreneurs is calculated from profits (including capital gains) accumulated from previous capital investment and income from supplying labor. With the presence of capital market frictions, net worth matters because a borrower's financial position is a key determinant of his cost of external finance. When researching the effects of financial accelerator on pre and post crisis period in Slovenia, Prašnikar et al. (2012) found out that higher levels of net worth allow increased self-financing, mitigate the agency problems associated with external finance and reduce the external finance premium. An unanticipated rise in asset prices was raising net worth more than proportionately during the boom period, which stimulated investment and was raising prices even further. Actual returns of indebted firms were higher than expected, which lead to a bubble that resulted in a balance sheet crisis after the crisis evolved (Bernanke et al., 1999; Miller and Stiglitz, 2010; Bole et al., 2012). Diminishing value of collaterals and contagion of adverse effects become an important factor for the crisis amplification. To offset reductions in information capital banks considerably increased the necessary collateral coverage of their client companies and enhanced credit rationing. Banks completely switched their credit policies from a mark-to-market approach to a mark-to-risk approach. Evidence has shown, that the mechanism of the financial accelerator endogenously drove the amplification and propagation of the process of companies' debt accumulation. This mechanism has been triggered by external shocks. When reviewing the presence of the financial accelerator as a generator of financial debt of non-financial firms, Prašnikar et al. (2012) confirmed that Mediterranean countries and the Western Balkan countries were the primary candidates. Montenegro, Croatia and Slovenia were particularly affected by the sudden stop and working of the financial accelerator when the crisis started. However, a common denominator for these countries is the fact that the government and bank reactions, including national banks, did not manage the discovered frictions in timely and appropriate manner. This amplified the crisis even more.

Based on comparative analysis Prašnikar et al. (2012) report that companies can adjust the number of employees to the market changes more easily on the long-run. Short-run elasticities were mostly bigger in the boom period. As expected, companies prefer employing workers in favorable business environment to letting workers go in times of an economic downturn. However, Reinhart and Rogoff (2009) note that during the financial crisis, labor adjustments come with a lag. Data for Slovenia in 2011 show that short-run elasticities were increasing in the bust period. Slovenia has above median protection of permanent workers against dismissal (Cazes et al., 2012). Despite the fact that in the last two decades countries tried to increase the flexibility of their labor market by relaxing the level of temporary employment protection, in Slovenia it remains quite regulated to some extent. Slovenia still has an unliberalized labor legislation. The huge pool of temporary employees enabled the fast adjustment of firms in the bust (post crisis) years, while the standard procedures took a lot of time. Prašnikar (2010) finds another fact, suggesting adverse effect of frictions on efficiency of certain companies. According to the results of the research, there was a lack of incentives for managers in non-tradable sector companies to restructure, thus keeping them less efficient than their counterparts from tradable sectors of Slovene economy.

Fiscal balance in Slovenia recovered in 2015. One-time expenditures not taken into account, the government financial balance fell from 3.2% of GDP in 2014 to 2.9% of GDP in 2015 and was re-framed to the Maastricht agreement, below 3%. However, in order to align public finances with the reformed European fiscal framework, Slovenia will have to target both the dynamics of the structural deficit and the level of debt. Debt must be reduced each year for 1/20 excess of 60% of GDP, while the average improvement of deficit should not be less than 0.5 percentage point of GDP per year. Moreover, notwithstanding the dynamics of fiscal revenue, government expenditure should not in real terms rise faster than potential output as long as the government balance will not achieve the medium-term equilibrium (Bole, 2016).

However, according to current EU policy directives, fiscal constraints in Slovenia should not be relaxed even when the government budget balance reaches the level of medium-term equilibrium. When this happens, the annual government spending will have to adapt so that the structural fiscal balance in the medium-term will average at least zero and will never fall below a minimum threshold, which is determined by the commitment (international treaties) of the Slovenian government.

This means that for economic policy makers in Slovenia the growth of potential output as well as corresponding general government structural balance and output gap will be the pillars of fiscal policy and, at the same time, the measure of its appropriateness. Of course, the same applies to fiscal policy makers in other EU countries, particularly in the euro area. Therefore, there is no doubt that potential output signals[12] to the policy makers should be unambiguous, timely, and accurate enough. As suggested by Bole (2016), this is not the case. All three are vague.

Slovenia provides a good environment to monitor the relationship between productivity gaps of non-tradable and tradable sectors. With existing frictions in capital and especially in labor market it is a perfect candidate for testing the consequences of reducing the inefficiencies from imperfect risk sharing in monetary unions on the optimal fiscal policy. Due to mentioned frictions, improvements should not come at the expense of greater output gaps. Slovenia is an exemplary case of small open economy.

1.9 Connecting all parts

The literature review put forward in this chapter shows that there exists a vast body of macroeconomic research and literature on the subject of economic policies. Researchers approach the subject from different perspectives, using different models. In this thesis, we try to provide quantitative support for the idea, that it is possible to positively influence the welfare function through control of non-tradable sectors efficiency and its particular output gap, indirectly controlling the prices of outputs of non-tradable sectors. Authors like Francois (1990) and Arnold et al. (2011) agree on the fact, that the growth of intermediation services is an important determinant of overall economic growth[13].

To link the literature and the main hypothesis of this dissertation, namely that the government can influence the productivity of the firms in the non-tradable sector and thereby affect the efficiency of firms in the tradable sector, we need to connect a chain of events:

1. When a country increases the spending through consumption from its non-tradable services sectors, the sticky prices mechanism keeps the prices relatively unchanged. The same effect can be achieved by other fiscal policy adjustments, that increase the productivity in non-tradable

[12] Output gap and structural deficit

[13] Most non-tradable sectors are selling services.

sectors.

2. The productivity and efficiency of the non-tradable sectors increase as a consequence of increased government spending or more favorable fiscal policy, partly due to rigidities in labor market.

3. Additional funds in the small open economy should increase inflation and thus raise the nominal interest rate and depreciate its currency. However, the raise of nominal interest rate or adjustment of exchange rate does not happen due to externally controlled monetary policy.

4. As a result, the real inflation within economy creates more favorable conditions also for the companies from tradable sectors, that can buy domestic services from non-tradable companies under better conditions and thus become more efficient due to lower costs themselves.

The increase in non-tradable sectors productivity comes without an increase in general output gap and without introducing a beggar-thy-neighbor (Eggertsson et al., 2016a) policy. All this can be achieved within the monetary union, following cooperative international policies.

The research gives encouraging results. Analysis of dynamics in productivity of non-tradable and tradable sectors of individual countries observed in the broader international scope supports the idea, that in a small open economy, that is a member of a monetary union (like Slovenia), it is possible to increase the result of welfare function through control of prices in non-tradable sector. Such support can be established on the basis of proven connection between relative movements of productivity scores of individual country's non-tradable and tradable sectors within international scope. Such reasoning is based on the Calvo (1983) model and proven relationships of DSGE models put forward by Gali and Monacelli (2008) and Hjortsoe (2016).

The European Commission report issued in the autumn of 2015 states some optimistic facts about Slovenia. The economy has been growing for two years, driven primarily by a very solid export growth. Fundamental changes in activity drivers are the end of the post crisis investment contraction. There is a slight growth in the consumption of the population. However, insufficient demand in the services sector is still very strong, as in all previous years after the outbreak of the crisis. The manufacturing sector demand is already close to normal pre-crisis levels. Unemployment fell below 9 percent only in 2015. Despite notable economic growth, prices are still falling. In the euro area, beside Slovenia, only Cyprus has such a low price growth (the December annual price growth was in Slovenia and Cyprus -0.6%). Credits to the business sector continue its falling by 10% per year. Current account surpluses in Slovenia are large, rising each month, exceeding 7% of GDP per year and far outpace the average surplus of the euro area as well as surpluses of some prominent exporters, such as Germany. This surplus is due to the persistent increase in exports and a slow growth or stagnation of imports. All these achievements indicate that the Slovenian economy is performing below its potential. Despite this fact, the European Commission in its autumn report 2015 estimated that economy of Slovenia is already becoming overheated. It predicts further overheating, in 2016 only slightly and during 2017 significantly. According to the report, output gaps in these two years would be positive, 0.7% in 2016 and 1.9% in 2017. In comparison with the situation in

2007, such an assessment seems almost incredible. All the indicators today point to much lower potential capacity utilization compared to the period of explosive growth before 2008. Despite this, the European Commission in its latest report diagnosed overheating of the Slovenian economy for 2016 and 2017, but it did not for 2007. Based on the current estimates of output gap and in line with the European fiscal framework together with the Slovenian own constitutional commitment to the fiscal rule, the European Commission determines the size of the required fiscal effort, that is contraction in the structural deficit, in years 2016 and 2017. Fiscal spending would have to shrink even faster, because, as the Commission claims, the actual output is growing faster than potential (Bole, 2016). Improper estimates of potential output (structural deficit and output gaps) prepared by the European Commission for Slovenia and other EU countries, that are used to implement the timing and design of economic policy actions, can have catastrophic effects on the performance of open economies in monetary union.

Using recent findings from the literature and the results put forward in this thesis, gloom scenarios can be avoided. If the Republic of Slovenia considers the treatment of its non-tradable sectors differently from its tradable sectors, it may leverage the impact of productivity increases in non-tradable sectors to its tradable sectors. Positive results could be achieved with moderated and partly controlled effects on indicators employed by European Commission and even in the absence of monetary policy toolkit.

2 METHODOLOGY

2.1 Productivity

Productivity of a firm is the ratio of the outputs it produces to the inputs that it uses.

$$productivity = outputs/inputs \tag{2.1}$$

When the production process involves a single input and a single output, this calculation is a trivial matter. However, when there is more than one input (which is often the case) then a method for aggregating these inputs into a single index of inputs must be used to obtain a ratio measure of productivity (Coelli et al., 2005).

With productivity a scientist or an analyst can refer to total factor productivity, which is a productivity measure involving all factors of production and also includes all outputs in a multiple-output setting. Other traditional measures of productivity, such as labor productivity in a factory, fuel productivity in power stations, and land productivity (yield) in farming, are often called partial measures of productivity. These partial measures of productivity can provide a misleading indication of overall productivity when considered in isolation (Coelli et al., 2005).

2.1.1 Scopes of productivity analysis

- Firm level data
- Sector level data
- Country level data

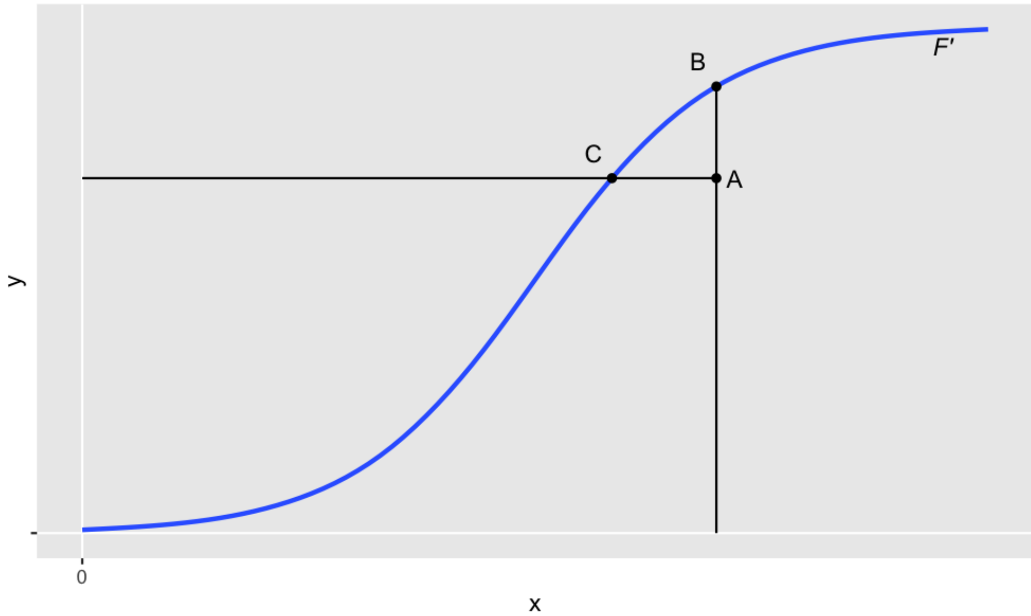
2.2 Efficiency

The terms productivity and efficiency have been used frequently interchangeably in the media. This is unfortunate, because they are not precisely the same things (Coelli et al., 2005). Efficiency can be classified into three categories:

- Technical efficiency
- Scale efficiency
- Allocative efficiency

To illustrate the distinction between the terms productivity and efficiency, it is useful to consider a simple production process in which a single input (x) is used to produce a single output(y). The line 0F' in Figure 2.1 represents a production frontier that may be used to define the relationship between the input and the output. The production frontier represents the maximum output attainable from each input level. Hence it reflects the current state of technology in the industry. Firms in this industry operate either on that frontier, if they are technically efficient, or beneath the frontier if they are not. Point A represents an inefficient point whereas points B and C represent efficient points. A firm operating at point A is inefficient because technically it could increase output to the level associated with the point B without requiring more input (Coelli et al., 2005).

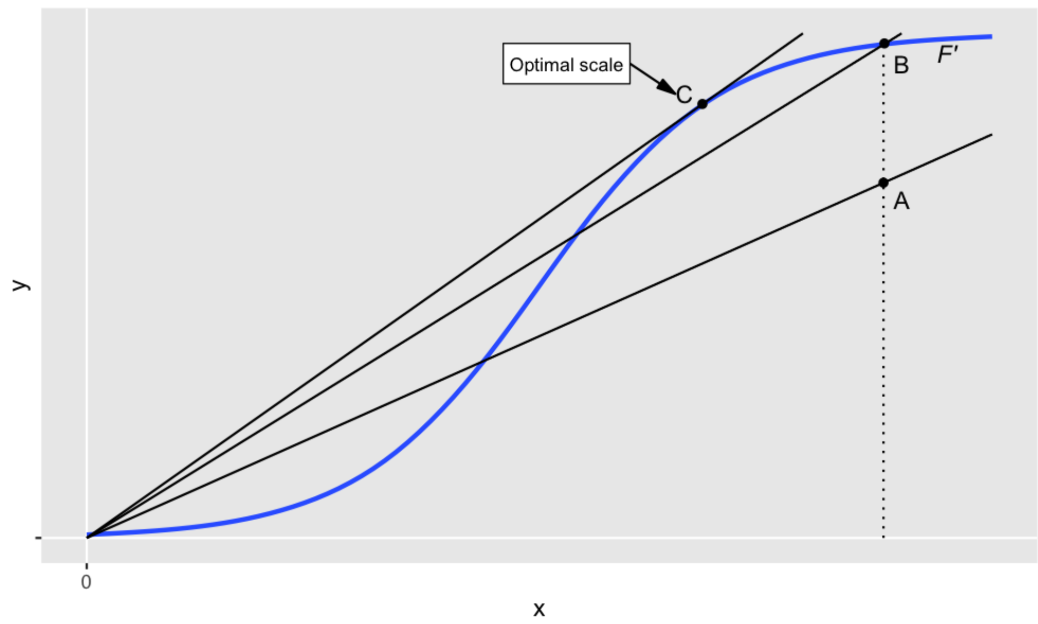
Figure 2.1: Production frontiers and technical efficiency



To illustrate the distinction between technical efficiency and productivity we utilize Figure 2.2. In this figure, we use a ray through the origin to measure productivity at a particular data point. The slope of this ray is y/x and hence provides a measure of productivity. If the firm operating at point A were to move to the technically efficient point B, the slope of the ray would be greater, implying higher productivity at point B. However, by moving to the point C, the ray from the origin is at a tangent to the production frontier and hence defines the point of maximum possible productivity. This latter movement is an example of exploiting scale economies. The point C is the point of (technically) optimal scale. Operation at any other point on the production frontier results in lower productivity (Coelli et al., 2005).

If information on prices is available, and a behavioral assumption, such as cost minimization or profit maximization, is appropriate, then performance measures can be devised which incorporate this information. In such cases it is possible to consider allocative efficiency, in addition to technical efficiency. Allocative efficiency in input selection involves selecting that mix of inputs (e.g. labor and capital) that produces a given quantity of output at minimum cost (given the input prices

Figure 2.2: Productivity, technical efficiency and scale economies



which prevail). Allocative and technical efficiency combine to provide an overall economic efficiency measure (Coelli et al., 2005).

2.3 Overview of measurement methods

There are essentially four major methods for measuring efficiency:

1. least squares econometric production models,
2. total factor productivity (TFP) indexes,
3. data envelopment analysis (DEA),
4. stochastic frontiers (SFA).

The first two methods are most often applied to aggregate time-series data and provide measures of technical change and/or TFP. Both of this methods assume all firms are technically efficient. Methods 3 and 4, on the other hand, are most often applied to data on sample of firms (at one point in time) and provide measures of relative efficiency among those firms. Hence these latter two methods do not assume that all firms are technically efficient. However, multilateral TFP indexes can also be used to compare the relative productivity of a group of firms at one point in time. Also DEA and stochastic frontiers can be used to measure both technical change and efficiency change, if panel data are available.

Thus we see that the above four methods can be grouped according to whether they recognize inefficiency or not. An alternative way of grouping these methods is to note that methods 1 and 4 involve the economic estimation of parametric functions, while methods 2 and 3 do not. These two groups may therefore be termed „parametric“ and „non-parametric“ methods, respectively. These methods may also be distinguished in several other ways, such as by their data requirements, their behavioral assumptions and by whether or not they recognize random errors in the data (Coelli et al., 2005).

2.4 Productivity and efficiency measurement concepts

Analysis of productivity and efficiency has its roots in economical growth research. Some economists were assigning growth to the productivity improvements driven by advances in the technology and the organization of production, while others were stressing the importance of the increase in investments in human capital, knowledge, and fixed capital. An important task for economists was to measure the degree to which output growth is, in fact, due to technological factors ("productivity") versus capital formation. This last undertaking is sometimes called "sources of growth analysis" and is the intellectual framework of the TFP residual (Hulten, 2001).

There is a huge body of theoretical literature explaining the development, problems and entanglement of various productivity measures with the production function. Solow (1957) was not the first to tie the aggregate production function to productivity. This link goes back at least as far as Tinbergen (1942). However, Solow's seminal contribution lay in the simple, yet elegant, theoretical link that he developed between the production function and the index number approach. Where earlier index number studies had interpreted their results in light of a production function, Solow started with the production function and deduced the consequences for (and restrictions on) the productivity index (Hulten, 2001).

Our research is conducted with a combination of set-theoretic approach to analysis of production technology followed by a fixed effects econometric analysis. Set-theoretic representation is the framework underlying the concept of the distance function. Distance functions play a crucial role in productivity measurement.

2.4.1 Production function

Starting in the early 1950's until the late 1970's production function attracted many economists. During the said period a number of specifications or algebraic forms relating inputs to output were proposed, thoroughly analyzed and used for deriving various conclusions. Especially after the end of the 'capital controversy', search for new specification of production functions slowed down considerably (Mishra, 2007). In the literature, production functions are grouped into single output production functions, multiple output production functions and aggregate production functions. Many of them are complex algebraic representations of production models, representing various production system properties, such as constant or variable returns to scale, joint production functions, constant or variable elasticities of substitution, DEA, SFA, etc. Comprehensive overview of historical development of production functions can be found in Mishra (2007). One of the most widely used is Cobb-Douglas production function:

$$Y = AK^{\alpha}L^{\beta} \tag{2.2}$$

where Y represents total production, A represents total factor productivity, K represents capital and L labor input. α and β are the output elasticities of capital and labor, respectively. Total factor productivity can be studied separately. In this case the so called two-step approach is used. If all the factors are explicitly included in the equation, as is the case in equation 2.3 below, one step approach is used. Productivity of a company is defined as the ratio of the outputs it produces to the inputs that it uses. The technological possibilities of such firms can be summarized using very general production function:

$$q = f(x) \tag{2.3}$$

where q represents output and $x = (x_1, x_2, ..., x_n)'$ is a N x 1 vector of inputs and f can become a rather complex function.

The idea of a production function is fundamental to economic analysis. It and its allied concept, the utility function, form the twin pillars of neoclassical economics. Written

$$P = f(L, C, T, ...), \tag{2.4}$$

the production function relates total product P to the labor L, capital C, land T (terrain), and other inputs that combine to produce it. The function expresses a technological relationship. It describes the maximum output obtainable, at the existing state of technological knowledge, from given amounts of factor inputs. Put differently, a production function is simply a set of recipes or techniques for combining inputs to produce output. Only efficient techniques qualify for inclusion in the function, however, namely those yielding maximum output from any given combination of inputs. Production functions apply at the level of the individual firm and the macro economy at large. At the micro level, economists use production functions to generate cost functions and input demand schedules for the firm. The famous profit-maximizing conditions of optimal factor hire derive from such microeconomic functions. At the level of the macro economy, analysts use aggregate production functions to explain the determination of factor income shares and to specify the relative contributions of technological progress and expansion of factor supplies to economic growth (Humphrey, 1997).

Associated with the production function are several properties. Let us denote the production function simply as $q = f(\mathbf{x})$, where q represents output and $\mathbf{x} = (x_1, x_2, ..., x_N)'$ is an $N \times 1$ vector of inputs. Some principal properties are:

Non-negativity: The value of $f(\mathbf{x})$ is a finite, non-negative, real number.

Weak essentiality: The production of positive output is impossible without the use of at least one input.

Nondecreasing in x: (or monotonicity) Additional units of an input will not decrease output. More formally, if $\mathbf{x}^0 \geq \mathbf{x}'$ then $f(\mathbf{x}^0) \geq f(\mathbf{x}')$. If the production function is continuously differentiable, monotonicity implies all marginal products are non-negative.

Concave in x: Any linear combination of the vectors $\mathbf{x}^0$ and $\mathbf{x}'$ will produce an output that is no less than the same linear combination of $f(\mathbf{x}^0)$ and $f(\mathbf{x}')$. Formally, $f(\Theta\mathbf{x}^0 + (1-\Theta)\mathbf{x}') \geq \Theta f(\mathbf{x}^0) + (1-\Theta)f(\mathbf{x}')$ for all $0 \leq \Theta \leq 1$. If the production function is continuously differentiable, concavity implies all marginal products are non-decreasing (i.e. the well-known law of diminishing marginal productivity).

These are not all the properties of production functions. If taken as assumptions, they are sometimes relaxed. For example, the monotonicity assumption is relaxed in cases where heavy input usage leads to input congestion (e.g., when labor is hired to the point where "too many cooks spoil the broth"), and the weak essentiality assumption is usually replaced by a stronger assumption in situations where every input is essential for production (Coelli et al., 2005).

Study of production functions introduces many concepts like *economically feasible region* of production, *point of optimal scale* of operations, *isoquants*, *marginal rate of technical substitution*, increasing or decreasing *returns to scale*, *elasticities*, etc.

Generalizing the simple production function concept to the case of a firm that produces more than one output and uses more than one input, results in a so called *transformation function.* Specifically, the technological possibilities of a firm that uses N inputs to produce M outputs can be summarized by the transformation function:

$$T(\mathbf{x}, \mathbf{q}) = 0, \tag{2.5}$$

where $\mathbf{q} = (q_1, q_2, ..., q_M)'$ is an $M \times 1$ vector of outputs. A special case of a transformation function is the production function $q = f(\mathbf{x})$ expressed in implicit form:

$$T(\mathbf{x}, q) = q - f(\mathbf{x}) = 0. \tag{2.6}$$

Transformation functions have properties that are analogous to properties of basic production function described above. In addition, if they are twice-continuously differentiable we can use calculus to derive expressions for economic quantities of interest. We can view transformation functions as special cases of distance functions, described in the subsection 2.4.3 below. Most applied economists analyze multiple-output technologies in ways that do not involve the specification of transformation functions or their properties. Some simply aggregate the outputs into a single measure using the index number methods and then use the production function to summarize technically-feasible production plans. Others make use of price information and represent the technology using the cost, revenue and profit functions (Coelli et al., 2005).

Textbooks and survey articles largely ignore an extensive body of eighteenth and nineteenth century work on production functions. They typically start with the famous two-factor Cobb-Douglas version:

$$P = bL^kC^{1-k}. \tag{2.7}$$

This equation exhibits constant returns to scale, assumes unchanging technology, and omits land and raw material inputs. With its exponents k and $1-k$ summing to one, the function seemed to embody the entire marginal productivity theory of distribution. The exponents constitute the output elasticities with respect to labor and capital. These elasticities, in competitive equilibrium where inputs are paid their marginal products, represent factor income shares that just add up to unity and so exhaust the national product as the theory contends. The function also seemed to resolve the puzzling empirical constancy of the relative shares. How could those shares remain unchanged in the face of secular changes in the labor force and the capital stock? The function supplied an answer. Increases in the quantity of one factor drive down its marginal productivity and hence its real price. That price falls in the same proportion as the increase in quantity so that the factor's income share stays constant. The resulting share terms k and $1-k$ are fixed and independent of the variables P, L, and C. It follows that even massive changes in those variables and their ratios would leave the shares unchanged. From Cobb-Douglas, textbooks and surveys then proceed to the more exotic CES, or constant elasticity of substitution, function:

$$P = [kL^{-m} + (1-k)C^{-m}]^{-1/m}. \tag{2.8}$$

They observe that the CES function includes Cobb-Douglas as a special case when the elasticity, or flexibility, with which capital can be substituted for labor or vice versa approaches unity. Finally, the texts arrive at functions that allow for technological change. The simplest of these is the Tinbergen-Solow equation. It prefixes a residual term e^{rt} to the simple Cobb-Douglas function to obtain:

$$P = e^{rt}L^kC^{1-k} \tag{2.9}$$

This term captures the contribution of exogenous technological progress, occurring at trend rate r over time t, to economic growth. Should new inventions and innovations fail to materialize exogenously like manna from heaven, however, more complex functions are available to handle endogenous technical change. Studies of these and other post-Cobb-Douglas developments can be found elsewhere and surpass the focus of this work (Humphrey, 1997).

2.4.2 Set theoretic representation of a production technology

One possible way to describe a multi-input, multi-output production technology is to use the technology set, S. By the example of Färe and Primont (1995), $\mathbf{x}$ and $\mathbf{q}$ denote a $N \times 1$ input vector of non-negative real numbers and a non-negative $M \times 1$ vector, respectively. The elements of these vectors are non-negative real numbers. The technology set is then defined as:

$$S = \{(\mathbf{x}, \mathbf{q}) : \mathbf{x} \text{ can produce } \mathbf{q}\}. \tag{2.10}$$

This set consists of all input-output vectors ($\mathbf{x}$,$\mathbf{q}$), such that $\mathbf{x}$ can produce $\mathbf{q}$. This technology can also be represented using a technical transformation function as described in second part of subsection 2.4.1. The production technology can equivalently be represented and described using output and input sets. Let us only list the properties on the basis of input sets. As the output and input sets provide alternative descriptions of the same underlying technology, these two sets are also interrelated. It can be easily seen that if $\mathbf{q}$ belongs to $P(\mathbf{x})$, i.e. $\mathbf{q}$ can be produced using input vector $\mathbf{x}$, then $\mathbf{x}$ belongs to the input set of $\mathbf{q}$, $L(\mathbf{q})$. It is important to realize that these descriptions are equivalent since they contain the same information.

The output set is defined as:

$$P(\mathbf{x}) = \{\mathbf{q} : \mathbf{x} \text{ can produce } \mathbf{q}\} = \{\mathbf{q} : (\mathbf{x}, \mathbf{q}) \in S\}. \tag{2.11}$$

For each $\mathbf{x}$. the output set $P(\mathbf{x})$ has some obvious properties:

- $0 \in P(\mathbf{x})$: no production is necessary, nothing needs to be produced from a given set of inputs;
- non-zero output levels cannot be produced without any inputs, i.e. some input is necessary to produce something;
- $P(\mathbf{x})$ satisfies strong disposability of outputs if $\mathbf{q} \in P(\mathbf{x})$ and $\mathbf{q}^* \leq \mathbf{q}$ then $\mathbf{q}^* \in P(\mathbf{x})$.
- $P(\mathbf{x})$ satisfies strong disposability of inputs if $\mathbf{q}$ can be produced from $\mathbf{x}$), then $\mathbf{q}$ can be produced from any $\mathbf{x}^* \geq \mathbf{x}$.
- $P(\mathbf{x})$ is closed;
- $P(\mathbf{x})$ is bounded; and
- $P(\mathbf{x})$ is convex.

Analogously, the input set is defined as:

$$L(\mathbf{q}) = \{\mathbf{x} : \mathbf{x} \text{ can produce } \mathbf{q}\} = \{\mathbf{q} : (\mathbf{x}, \mathbf{q}) \in S\}. \tag{2.12}$$

The input set consists of all input vectors $\mathbf{x}$, that can produce a given output vector $\mathbf{q}$. Given the basic assumptions on the production technology, the following properties of the input sets can be derived:

- $L(\mathbf{q})$ is closed for all $\mathbf{q}$;
- $L(\mathbf{q})$ is convex for all $\mathbf{q}$;
- Inputs are said to be weakly disposable if $\mathbf{x} \in L(\mathbf{q})$ then, for all $\lambda \geq 1$, $\lambda\mathbf{x} \in L(\mathbf{q})$; and
- Inputs are said to be strongly disposable if $\mathbf{x} \in L(\mathbf{q})$ and if $\mathbf{x}^* \geq \mathbf{x}$ then $\mathbf{x}^* \in L(\mathbf{q})$.

These properties of the input distance function can be derived using the assumptions made with respect to the production technology implicit in the properties of $P(\mathbf{x})$ (Coelli et al., 2005).

2.4.3 Distance function

Distance functions are very useful in describing the technology in a way that makes it possible to measure efficiency and productivity. The concept of a distance function is closely related to production frontiers. The basic idea underlying distance function is quite simple, involving radial contractions and expansions in defining these functions. The notion of a distance function was introduced independently by Malmquist (1953) and Shepherd (1953), but they have gained prominence only in the last three to four decades.

Distance functions allow one to describe a multi-input, multi-output production technology without the need to specify a behavioral objective (such as cost minimization or profit maximization). One may specify both input distance functions and output distance functions. An input distance function characterizes the production technology by looking at a minimal proportional contraction of the input vector, given an output vector. An output distance function considers a maximal proportional expansion of the output vector, given an input vector.

Output distance function is defined on the output set $P(\mathbf{x})$ as:

$$d_o(\mathbf{x}, \mathbf{q}) = min\{\delta : (\mathbf{q}/\delta) \in P(\mathbf{x})\}. \tag{2.13}$$

Properties of $d_o(\mathbf{x}, \mathbf{q})$ follow directly from the axioms on the technology set:

- $d_o(\mathbf{x}, \mathbf{0}) = 0$ for all non-negative $\mathbf{x}$;
- $d_o(\mathbf{x}, \mathbf{q})$ is non-decreasing in $\mathbf{q}$ and non-increasing in $\mathbf{x}$;
- $d_o(\mathbf{x}, \mathbf{q})$ is linearly homogeneous in $\mathbf{q}$;
- $d_o(\mathbf{x}, \mathbf{q})$ is quasi convex [14] in $\mathbf{x}$ and convex in $\mathbf{q}$;
- if $\mathbf{q}$ belongs to the production possibility set of $\mathbf{x}$ (i.e. $\mathbf{q} \in P(\mathbf{x})$), then $d_o(\mathbf{x}, \mathbf{q}) \leq 1$; and
- distance is equal to unity (i.e., $d_o(\mathbf{x}, \mathbf{q}) = 1$) if $\mathbf{q}$ belongs to the "frontier" of the production possibility set (the production possibility curve of $\mathbf{x}$).

The *input distance function*, which involves the scaling of the input vector, is defined on the output set, $L(\mathbf{q})$, as:

$$d_i(\mathbf{x}, \mathbf{q}) = max\{\rho : (\mathbf{q}/\rho) \in L(\mathbf{q})\}, \tag{2.14}$$

where the input set $L(\mathbf{q})$ represents the set of all input vectors $\mathbf{x}$ which can produce the output vector $\mathbf{q}$.

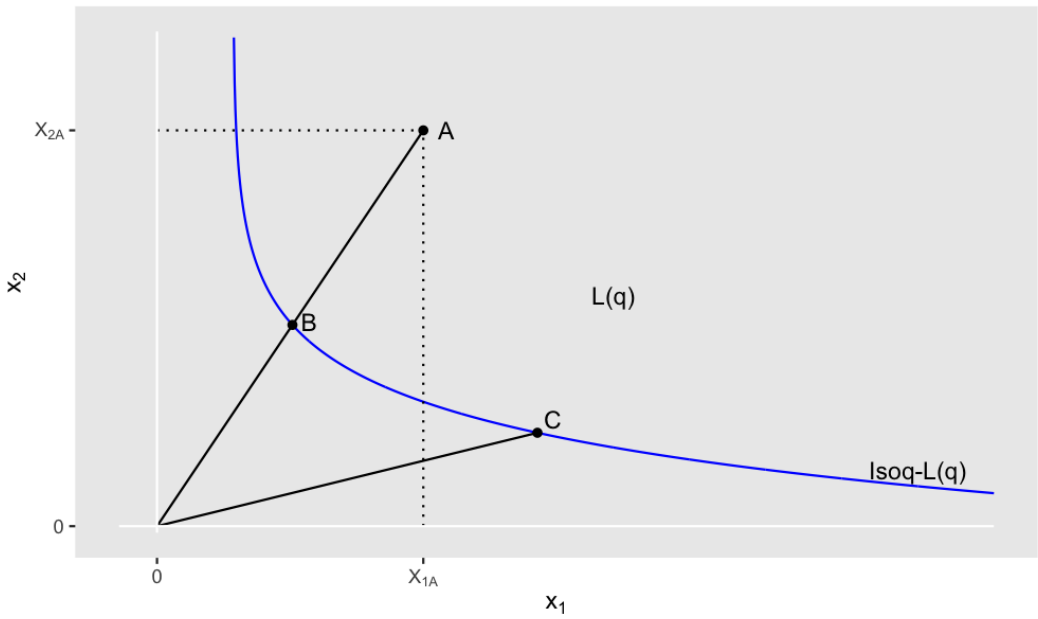
Given the general set of properties listed in subsection 2.4.2, we can show that:

[14] A function $f(\mathbf{x})$ defined in a convex set R_n is said to be quasi-convex if and only if for any pair of distinct points $\mathbf{x}$ and $\mathbf{y}$ in the domain of f and $0 < \lambda < 1$, $f(\mathbf{y}) \geq f(\mathbf{x})$ implies that $f(\lambda\mathbf{x} + (1 - \lambda)\mathbf{y}) \leq f(\mathbf{y})$.

- the input distance is non-decreasing in $\mathbf{x}$ and non-increasing in $\mathbf{q}$;
- it is linearly homogeneous in $\mathbf{x}$;
- $d_i(\mathbf{x}, \mathbf{q})$ is concave in $\mathbf{x}$ and quasi-concave in $\mathbf{q}$;
- if $\mathbf{x}$ belongs to the input set of $\mathbf{q}$ (i.e., $\mathbf{x} \in L(\mathbf{q})$) then $d_i(\mathbf{x}, \mathbf{q}) \geq 1$; and
- distance is equal to unity (i.e., $d_i(\mathbf{x}, \mathbf{q}) = 1$) if $\mathbf{x}$ belongs to the "frontier" of the input set (the isoquant of $\mathbf{q}$).

In Figure 2.3 the production technology is represented in a two dimensional diagram. The input set $L(\mathbf{q})$ is the area bounded from below by the isoquant, Isoq-L($\mathbf{q}$). The value of the distance function for the point A, which defines the production point where firm A uses x_{1A} of input 1 and x_{2A} of input 2, to produce the output vector $\mathbf{q}$, is equal to the ratio $\rho = 0A/0B$.

Figure 2.3: Input distance function and input requirement set



Output and input distance functions are connected in many ways. If $\mathbf{q} \in P(\mathbf{x})$, then $\mathbf{x} \in L(\mathbf{q})$. That means, that if $\mathbf{q}$ belongs to the production possibility set associated with input vector $\mathbf{x}$, then $\mathbf{x}$ belongs to the feasible input set associated with output vector $\mathbf{q}$. If both inputs and outputs are weakly disposable, we can state that

$$d_i(\mathbf{x}, \mathbf{q}) \geq 1 \text{ if and only if } d_o(\mathbf{x}, \mathbf{q}) \leq 1. \tag{2.15}$$

Further, if the technology exhibits global constant returns to scale, then we can state that

$$d_i(\mathbf{x}, \mathbf{q}) = 1/d_o(\mathbf{x}, \mathbf{q}), \text{ for all } \mathbf{x} \text{ and } \mathbf{q}. \tag{2.16}$$

This means that under constant returns to scale, the input distance function is the reciprocal of the output distance function for any $(\mathbf{x}, \mathbf{q})$.

Output and input distance functions have a number of applications. They are used in defining a variety of index numbers. They also provide the conceptual underpinning for various efficiency and productivity measures. These distance functions can be directly estimated using either econometric or mathematical programming methods. Data envelopment analysis (DEA) described in section 2.5 below, is a non-stochastic non-parametric method for identifying production frontiers and for computing input and output distances (Coelli et al., 2005). Other methods for estimating parametric stochastic frontier specification of the distance functions are available but their description is beyond the scope of this text.

2.5 DEA - Data envelopment analysis

DEA is a nonparametric method in operations research and economics for the estimation of production frontiers. It is usually used to empirically measure productive efficiency of decision making units (or DMUs). When analyzing productivity of business entities, it is not prudent to assume, that all entities are fully efficient. DEA excels at analysis and decomposition of various inefficiencies, when the right kind of data is available. In order to analyze inefficiencies and dismantle the sources of it, one has to relax the assumption of fully efficient business entities.

Frontiers have been estimated using different methods over the past 40 years. An excellent introduction on the subject can be found in Lovell (1993). Two most widely used methods are DEA and SFA (Stochastic Frontier Analysis), which involve mathematical programing and econometric methods.

DEA models can be constructed using various assumptions:

- constant returns to scale (CRS) vs. variable returns to scale (VRS);
- input vs. output orientation.

DEA involves the use of linear programming methods to construct a non-parametric piece-wise surface (or frontier) over the data. Efficiency measures are the calculated relative to this surface. Comprehensive explanation of the methodology can be found in the literature (Färe et al. (1994), Färe et al. (2013), Seiford and Thrall (1990), Ali and Seiford (1993), etc.). The piece-wise-linear convex hull approach to frontier estimation was proposed for the first time by Farrell (1957). The task that could be achieved by the use of mathematical programing methods did not receive much attention for twenty years. In 1978 Charnes et al. (1978) introduced the term *data envelopment analysis*. Since then, the method gained popularity and can be found in many papers as the method of choice.

To illustrate, let us consider and input-oriented CRS model, that is most commonly applied DEA model found in research. Let us denote the vector of inputs N and the vector of outputs M, for each of I decision making units. For i-th decision making unit inputs are represented with a column vector $\mathbf{x}_i$ and outputs are represented with a column vector $\mathbf{q}_i$. The $N \times I$ input matrix $\mathbf{X}$ and the

$M \times I$ output matrix $\mathbf{Q}$ contain the data for all decision making units.

An intuitive way to introduce DEA is via the ratio form. For each decision making unit, we would like to calculate a measure of all outputs over all inputs, such as $\mathbf{u}'\mathbf{q}_i/\mathbf{v}'\mathbf{x}_i$, where $\mathbf{u}$ is an $M \times 1$ vector of output weights and $\mathbf{v}$ is a $N \times 1$ vector of input weights. The optimal weights are obtained by solving the mathematical programming problem[15]:

$$\begin{aligned} &max_{u,v} && (\mathbf{u}'\mathbf{q}_i/\mathbf{v}'\mathbf{x}_i), \\ &\text{subject to} && \mathbf{u}'\mathbf{q}_j/\mathbf{v}'\mathbf{x}_j \leq 1, \qquad j = 1, 2, ..., I, \\ &&& \mathbf{u}, \mathbf{v} \geq 0. \end{aligned} \tag{2.17}$$

This involves finding values for $\mathbf{u}$ and $\mathbf{v}$, such that the efficiency measure for the i-th decision making unit is maximized, subject to the constraints that all efficiency measures must be less than or equal to one. Such formulation leads to infinite number of solutions (if $(\mathbf{u}^*, \mathbf{v}^*)$ is a solution, $(\alpha\mathbf{u}^*, \alpha\mathbf{v}^*)$ is also a solution). Adding another constraint $\mathbf{v}'\mathbf{x}_i = 1$ eliminates this problem. The model then becomes:

$$\begin{aligned} &max_{\mu,v} && (\mu'\mathbf{q}_i), \\ &\text{subject to} && \nu'\mathbf{x}_i = 1, \\ &&& \nu'\mathbf{q}_j - \nu'\mathbf{x}_j \leq 0, \qquad j = 1, 2, ..., I, \\ &&& \mu, \nu \geq 0. \end{aligned} \tag{2.18}$$

The change of notation from $\mathbf{u}$ and $\mathbf{v}$ to μ and ν is used to emphasize that this is a different liner programming problem. The form of the DEA model in linear programming (LP) problem 2.18 is known as the multiplier form.

Because of the duality property in linear programming, it is possible to represent the same envelopment problem in a different, but equivalent form:

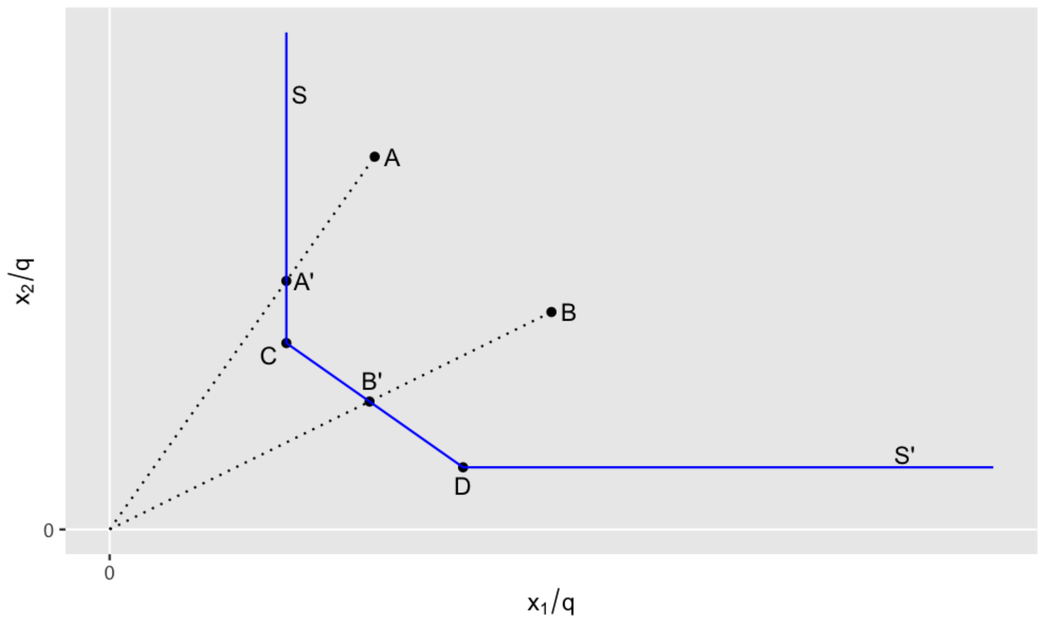
$$\begin{aligned} &min_{\Theta,\lambda} && \Theta, \\ &\text{subject to} && -\mathbf{q}_i + \mathbf{Q}\lambda \geq 0, \\ &&& \boldsymbol{\Theta}\mathbf{x}_i - \mathbf{X}\lambda \geq 0, \\ &&& \lambda \geq 0. \end{aligned} \tag{2.19}$$

Θ is a scalar and λ is a $I \times 1$ vector of constants. This envelopment form involves less constraints then the multiplier form $(N + M < I + 1)$, and hence is generally preferred to solve. The value of Θ obtained is the efficiency score for the i-th decision making unit. It satisfies $\Theta \leq 1$, with a value of 1 indicating a point on the frontier. A decision making unit, operating on the frontier is considered a technically efficient firm (Farrell, 1957). It is important to note that the linear programming problem

[15]Mathematical programming, and especially linear programming, is one of the best developed and most used branches of management science. It concerns the optimum allocation of limited resources among competing activities, under a set of constraints imposed by the nature of the problem being studied. These constraints could reflect financial, technological, marketing, organizational, or many other considerations. In broad terms, mathematical programming can be defined as a mathematical representation aimed at programming or planning the best possible allocation of scarce resources. When the mathematical representation uses linear functions exclusively, we have a linear-programming model (Bradley et al., 1977).

has to be solved I times, once for each decision making unit in the sample. Thus, a value of Θ is obtained for each decision making unit.

Figure 2.4: Illustration of DEA frontier



It is possible to make a nice illustration of the process in solving LP problem 2.19. The problem takes the i-th decision making unit and then radially shrinks the vector of inputs $\mathbf{x}_i$, as much as possible, while still remaining in the feasible input set in order to produce $\mathbf{q}_i$. The inner boundary of this set is a piece-wise isoquant determined by the observed data points, i.e. by all the observed decision making units in the sample. Visual representation can be seen in Figure 2.4. The radial shrinkage of the input vector $\mathbf{x}_i$ produces a projected point $(\mathbf{X}\lambda, \mathbf{Q}\lambda)$ on the surface of current technological boundary, which can be defined as $T = \{(\mathbf{x}, \mathbf{q}) : \mathbf{q} \leq \mathbf{Q}\lambda, \mathbf{x} \geq \mathbf{X}\lambda\}$. This projected point is a linear combination of these observed data points. The constraints in LP 2.19 ensure that this projected point lies within the feasible set (Lovell, 1993). T defines a production set that is closed, convex, exhibits constant returns to scale and strong disposability. *Strong disposability* means, that if inputs are either held the same or are increased, then output will not decrease. Inputs cannot congest output. It is impossible to 'have too much input'.

$$x \geq \hat{x} \in L(y|C, S) \text{ implies that } x \in L(y|C, S). \tag{2.20}$$

Example of a phenomenon, where too much input can reduce the output is a traffic congestion. Too many cars on the road result in less throughput. To allow for the possibility of congestion, it is possible to introduce the concept of *weak disposability*.

$$x \in L(y|C, W) \text{ and } \lambda \geq 1 \text{ imply } \lambda x \in L(y|C, W). \tag{2.21}$$

Weak disposability assumption states that proportional increases in inputs do not decrease outputs (Färe and Grosskopf, 2000).

It is possible to define DEA models with some of assumptions relaxed (Färe et al., 1994). Advanced DEA topics include:

- analyzing allocative efficiency if the price information is available;
- inclusion of non-discretionary variables, that are not under control of the managers;
- adjusting for the environment;
- allowing for input congestion;
- treatment of slacks;
- additional methods (weights restrictions, super efficiency, bootstrap methods).

When conducting a DEA study, the researcher has to be aware of the following possible pitfalls (Coelli et al., 2005):

- DEA is extremely sensitive to measurement error and other noise, which can have huge impact on the position and shape of the frontier, as well as for the DEA scores of individual companies.
- Outliers have large influence on individual DEA scores.
- The exclusion of an important input or output can result in biased results.
- The calculated DEA efficiency scores are only relative to the best observations in the sample. The inclusion of extra observations may reduce all other calculated scores, while exclusion of observations may increase all other calculated scores.
- Comparing mean efficiencies from two samples or studies does not tell us anything about the efficiency of one sample relative to another. It only conveys information about relative dispersion of efficiencies within one individual sample.
- The addition of an extra input or output to a DEA model cannot result in a reduction of technical efficiency scores.
- If the sample is small and each observation has many inputs/outputs, many of the observations will appear on the DEA frontier.
- Treating inputs and/or outputs as homogeneous commodities when they are heterogeneous may produce biased results.
- When analyzing relative managerial competence, one has to account for environmental differences, otherwise the results can be misleading.
- Standard DEA does not account for multi-period optimization nor risk in management decision making. More on dynamic DEA models can be found in Färe and Grosskopf (1996).

Due to the limitations of the dataset used as an input into the research of this thesis, we only scratch the surface of the DEA capabilities. In order for the DEA to show its full potential, it is best to apply it to a dataset of a homogeneous industry, with known quantities of inputs and outputs.

2.6 Fixed effects regression

Estimation of a regression model with fixed effects is a well known method in advanced econometric analysis of panel data. The term fixed effects estimator is also known as the within estimator for the coefficients in the regression model. If we assume fixed effects, we impose a dimension (time, country, industry) independent effects for each entity that are possibly correlated with the regressors.

To illustrate what this method involves, let's consider a model with a single explanatory variable: for each i,

$$y_{it} = \beta_1 x_{it} + a_i + u_{it}, \qquad t = 1, 2, ..., T. \tag{2.22}$$

Now, for each i, average this equation over time. We get

$$\bar{y}_i = \beta_1 \bar{x}_i + a_i + \bar{u}_i, \tag{2.23}$$

where $\bar{y}_i = T^{-1} \sum_{t=1}^{T} yit$, and so on. Because a_i is fixed over time, it appears in both (2.22) and (2.23). If we subtract (2.23) from (2.22) for each t, the equation becomes

$$y_{it} - \bar{y}_i = \beta_1 (x_{it} - \bar{x}_i) + u_{it} - \bar{u}_i, \qquad t = 1, 2, ..., T,$$

or

$$\ddot{y}_{it} = \beta_1 \ddot{x}_{it} + \ddot{u}_{it}, \qquad t = 1, 2, ..., T, \tag{2.24}$$

where $\ddot{y}_{it} = y_{it} - \bar{y}_i$ is the time-demeaned data on y, and similarly for $\ddot{x}_{it}$ and $\ddot{u}_{it}$. The important thing about equation (2.24) is that the unobserved effect, a_i, has disappeared. This suggests that we should estimate (2.24) by pooled OLS[16]. To add more explanatory variables we simply use time-demeaning on each explanatory variable - including things like time period dummies - and then do a pooled OLS regression[17] using all time-demeaned variables. A model

$$y_{it} = \beta_1 x_{it1} + \beta_2 x_{it2} + ... + \beta_k x_{itk} + a_i + u_{it}, \qquad t = 1, 2, ..., T \tag{2.25}$$

represented in general time-demeaned equation for each i is

$$\ddot{y}_{it} = \beta_1 \ddot{x}_{it1} + \beta_2 \ddot{x}_{it2} + ... + \beta_k \ddot{x}_{itk} + \ddot{u}_{it}, \qquad t = 1, 2, ..., T. \tag{2.26}$$

A traditional view of the fixed effects approach is to assume that the unobserved effect, a_i, is a parameter to be estimated for each i. Thus, in equation 2.25, a_i is the intercept for person i (or firm i, city i, and so on) that is to be estimated along with β_j. (Clearly, we cannot do this with a single cross section: there would be $N + k$ parameters to estimate with only N observations. We need at east two time periods.) The way we estimate an intercept for each i is to put in a dummy variable for each cross-sectional observation, along with the explanatory variables (and probably dummy

[16] Ordinary least squares

[17] This approach can be used when the groups to be pooled are relatively similar or homogeneous. Level differences can be removed by ḿean-centeringt́he data across the groups, that is subtracting the mean or average of each group from observations for the group.

variables for each time period). This method is usually called the dummy variable regression. The dummy variable regression has some interesting features. Most importantly, it gives us exactly the same estimates of the β_j that we would obtain from the regression on time-demeaned data, and the standard errors and other major statistics are identical. Therefore, the fixed effects estimator can be obtained by the dummy variable regression. One benefit of the dummy variable regression is that it properly computes the degrees of freedom directly. This is a minor advantage now that many econometrics packages have programmed fixed effects options. The R-squared from the dummy variable regression is usually rather high. This occurs because we are including a dummy variable for each cross-sectional unit, which explains much of the variation in the data. The R-squared from the dummy variable regression can be used to compute F tests in the usual way, assuming, of course, that the classical linear model assumptions hold. In particular, we can test the joint significance of all of the cross-sectional dummies ($N - 1$, since one unit is chosen as base group). The unrestricted R-squared is obtained from the regression with all of the cross-sectional dummies; the restricted R-squared omits these. In the vast majority of applications, the dummy variables will be jointly significant (Wooldridge, 2009).

2.7 Combination of DEA and fixed effects regression

A scientist used to parametric estimation techniques might be tempted to compare average DEA scores between groups. Such comparisons do not make any sense. Average DEA score within group is only telling us something about the relative dispersion of observations within the group. One new very efficient observation can render the rest of observations much less efficient and thus drive the average DEA score down substantially.

Several approaches are possible to compare DEA scores between groups. They depend on the type of the variable, groups are discriminated on (e.g. ordinal or categorical). In the case of empirical model that is described in Section 5, country, year and industry are categorical variables. For such case, Charnes et al. (1981) propose a three stage method:

1. divide the sample into groups based on one categorical variable and solve DEAs for each sub-sample;
2. project all observed data points onto their respective frontiers; and
3. solve a single DEA using the projected points and assess any difference in mean efficiency of the sub-samples.

With projection we take out within group inefficiencies. We basically take one group's production as if it would be conducted efficiently and compare it to efficient productivity curve of the other group. A problem with this method is the fact that it can only accommodate one categorical variable (which can of course be constructed from a set of other categorical variables).

Huge body of literature is dedicated to aggregation issues of DEA analysis (Farrell (1957), Fox (1999), Färe and Zelenyuk (2003), Färe and Grosskopf (2006), Aparicio et al. (2013), Färe et al. (2015), etc.). Since in research DEA is primarily used as a tool for decomposition of (in)efficiencies of observed companies or DMUs, a lot of DEA-aggregation related studies are focused on aggregation issues of inputs and outputs within companies and decision making units. Chambers et al. (1998) introduce a directional distance function as a measure of overall technical inefficiency. Färe and Karagiannis (2014) show that with the assumption of constant returns to scale (CRS) and assuming that all firms in the industry are subject to the same input and output prices, input-based weights are equal to potential output-based weights and vice versa. Under these assumptions, regardless of the DEA orientation, it is possible to weight-aggregate DEA scores as proposed by Farrell (1957) without any loss of aggregation consistency.

Another possibility to compare efficiencies between two groups is to use a two stage method. In the first stage, a DEA problem is solved, using only the traditional inputs and outputs. Then, the efficiency scores from the first stage are regressed upon the group discriminating variables (categorical, ordinal or interval). The signs of the coefficients indicate the direction of the influence of the discriminating variable. Standard hypothesis tests can be used to asses the strength of the relationships. Second stage regression could be used to adjust the initial efficiency scores to the level of discriminating variable (Coelli et al., 2005).

When pooling the data for individual industries, DEA scores are weighted according to the market share and then normalized, so that overall efficiency of the market stays the same.

Since DEA scores are used as input into the fixed effects regression model, not much can be said about relationships and absolute values of any parameters within the industry or within the country. The focus is on global movements. The most important thing that can be observed, is the change of position of individual country's tradable sectors in the global pool, as a consequence of the change of position of that same country's non-tradable sectors in the global pool.

2.8 Outlier detection and treatment

In practice, when a series of replicate measurements is obtained, it is often found that one or more of the values seem to be substantially different from the others. The practical question then posed is clear: should such outlying results be rejected or not before the mean, standard deviation, etc., of the data are calculated (Miller, 1993)? Outliers are present in the data due to data errors, intentional or motivated mis-reporting, sampling error, standardization failure, faulty distributional assumptions and as legitimate cases sampled from the correct population. There is as much controversy over what constitutes an outlier as whether to remove them or not. Simple rules of thumb (e.g., data points three or more standard deviations from the mean) are good starting points. Some researchers prefer visual inspection of the data. Others (e.g., Lornez, 1987) argue that outlier detection is merely a special case of the examination of data for influential data points (Osborne and Overbay, 2004). Ignoring the outliers can introduce mistakes and bias into data. At the same time, removing any observation that seems an outlier from the data can also introduce bias. In case of productivity analysis we might remove the innovative companies that are extremely efficient. Also, market incumbents with a large share of the market may also be exceptionally efficient due to scale of economies.

2.8.1 General outlier detection and removal practices

If a Gaussian or normal distribution is assumed, readings near the mean value are much more likely than readings distant from the mean. Nonetheless, there is some probability of obtaining a value far away from the mean. In practice, such a reading may appear even in the small sample of measurements. If this is so, what justification can there be for rejecting the suspect data point? These issues have caused concern and controversy among experimental scientists (not just analytical scientists) for many years, and indeed continue to generate new research, and further controversy. Three separate statistical approaches to the problem can be identified: (1) use of statistical significance tests that assume a Gaussian (or some other defined) error distribution for the population; (2) use of non-parametric statistical methods, which make no such assumptions; and (3) use of robust statistical methods (Miller, 1993).

Beside the well defined above mentioned methods, scientists in economic literature sometimes resort to rules-of-thumb methods, such as "To deal with outliers, we remove observations with extreme unit values (four times above or below the category mean)" (Faruq, 2006), or "A problem of WorldScope data is the presence of outliers. All balance-sheet variables have therefore been trimmed by dropping observations lower (larger) than the second bottom (top) percentile" (Bortolotti et al., 2004).

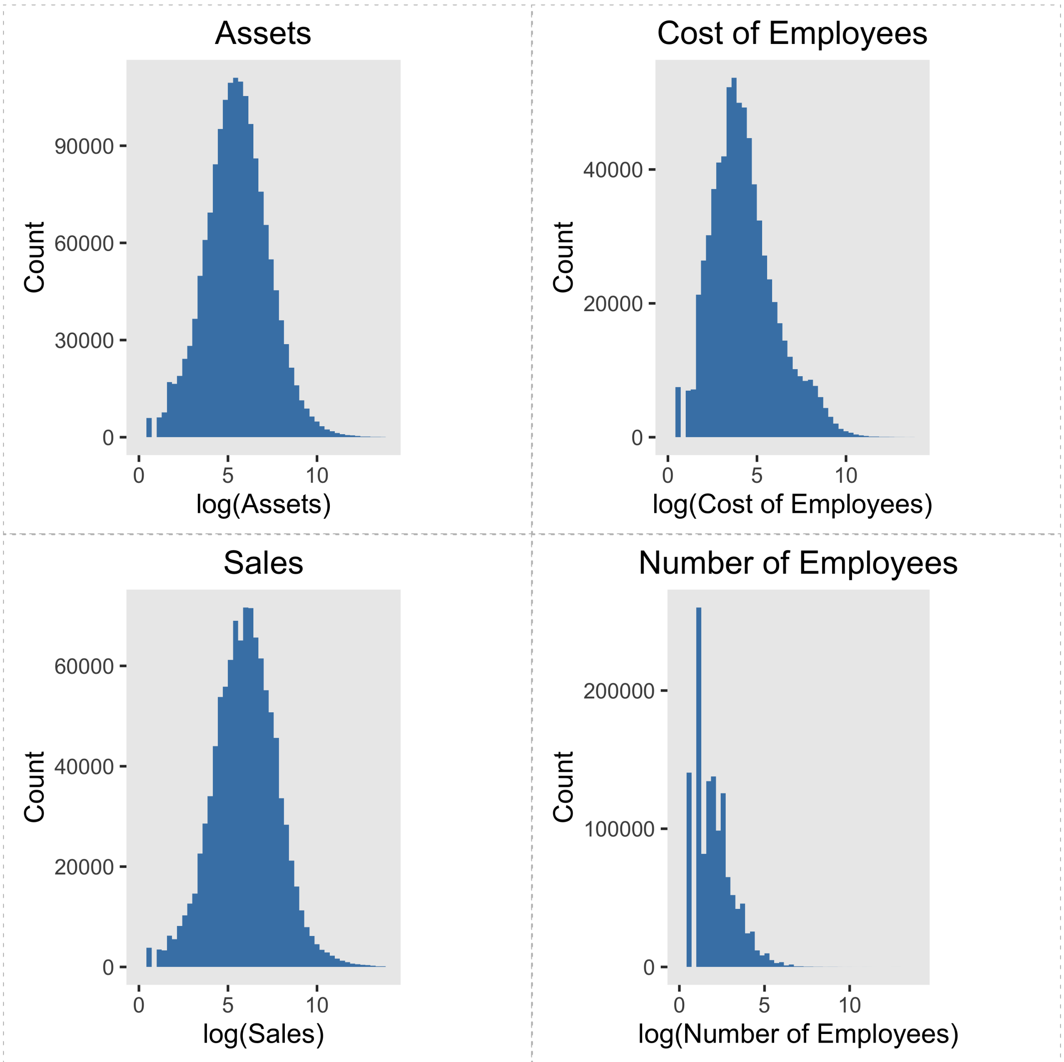
2.8.2 Manifestation of outliers in Amadeus dataset

Since all observed variables in our dataset can only hold positive values and are heavy on the lower end, we expect a log-normal distribution for all of them. This fact is evident from three parts of the Figure 2.5. Since values of $number\_of\_employees$ have lower values and more sparse [18] than the currency values of other variables, log-normal distribution is not as evident in the lower right corner, but still holds in general. This assumption about the distribution of individual variables is the cornerstone of outlier detection in the Amadeus dataset.

Outliers do not manifest themselves only on basic dimensions, that is $sales$, $number\_of\_employees$ and $assets$. Since we are interested in productivity, we should also check sales per employee and sales per assets. We would become suspicious of companies, that exhibited production function with very different ratios than the rest of the companies in the set. Thus, beside the basic dimensions, we also checked for outliers on $salespernumber\_of\_employees$ and $salesperassets$.

[18] Data is presented in discrete values of integer numbers, of which logs are 0, 0.69, 1.10, 1.39, 1.61, ... Spikes can be observed at these values and with some imagination, with a distribution of these spikes among close values, we would be able to observe a nice log-normal distribution.

Figure 2.5: Log-normal distribution of observed variables



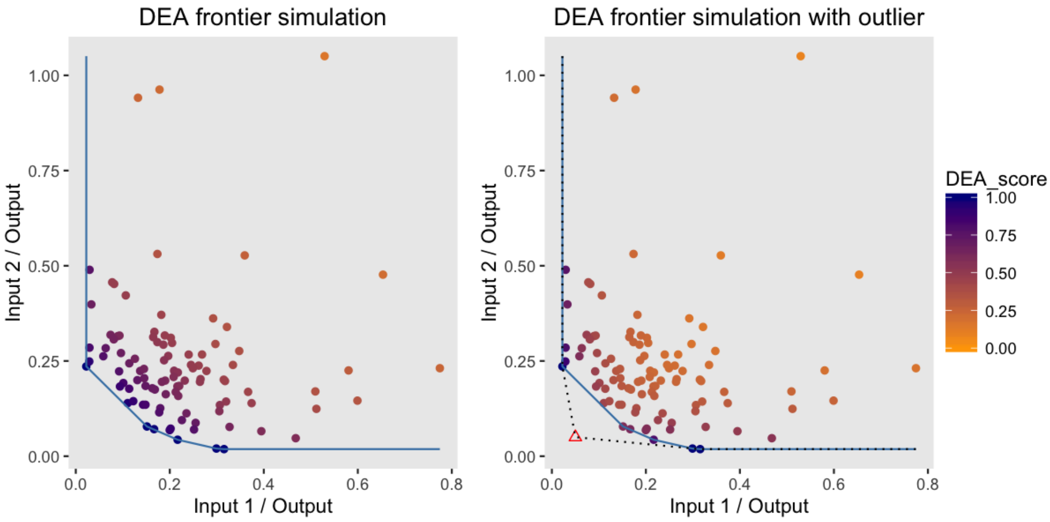
Various sectors of industry exhibit different production functions. Some industries are very capital intensive, while others are more labor intensive. Pooling all the industries and search for outliers could result in keeping too many observations, since observations from one industry would cover up an outlier from another industry. Also, situation varies between years and countries. In order to be as precise as possible, it is reasonable to search for outliers within an industry, within a year, within a country.

An observation can be marked as a candidate for outlier treatment due to various reasons, listed in the introduction of this Subsection 2.8. An outlier can also be a legitimate case sampled from the correct population. If a company exhibits a significant market share in the year-industry-country triplet, it is not prudent to remove it from the analysis. It makes more sense to check it for sensibility and assume, that it has gained some sort of technological or organizational knowledge, that helps it being more efficient and is thus presenting itself as an outlier.

2.8.3 Sensitivity of DEA to outliers

DEA is very sensitive to outliers, therefore it was necessary to implement outlier detection. In the Figure 2.6 we can see, how an introduction of a single outlier changes the DEA score for practically all the points in the dataset. When DEA frontier moves from the solid line to the dotted line through the triangularly shaped outlier, all the points in the lower left corner in the picture get much closer to the orange spectrum, which represents a lower DEA efficiency score.

Figure 2.6: Sensitivity of DEA to outliers



This property of DEA method hints to another important property of DEA: mean of the DEA scores in the dataset does not tell us anything particularly meaningful about the dataset, but rather gives us only some information about the distribution of the data points in the dataset.

2.8.4 Finding and removing outliers in our research

If data is normally distributed, 99.7 percent of mass lies within three standard deviations below and above the mean. Since the number of observations in the dataset is large, we were not too concerned with multiple outliers detection problems.

Since all the variables exhibited log-normal distribution, logarithm was applied to all the variables to get to the normal distribution. Then, we followed the $mean + / - 3 * standard\_deviation$ rule. If an observation, that was marked as a candidate for an outlier had more than 3% market share in year-industry-country triplet, it was kept in the dataset regardless.

This way, we achieved a very precise cut of the observations, without removing important observations, that may be the real drivers of the analyzed phenomena.

3 DATA

The research was executed on a large panel dataset of financial statement data for six (6) industries in fifteen (15) countries in nine (9) years from Amadeus database. Amadeus is a database prepared by Bureau van Dijk. Amadeus contains information on around 21 million companies across Europe. 217194 companies were evaluated on *sales*, *number_of_employees*, *assets* and *costs_of_employees*, all obtained from each company's yearly financial reports. Comparability of data is ensured by Bureau Van Dijk. Dataset is very big for conventional research standards. Because of the size of the dataset it is impossible to manually check for every outlier and every structural peculiarity. Great care was addressed to data treatment methods as described in Subsection 2.8 and Section 4.

3.1 Description of data set

Data contains information on the subset of six different industries (sectors), three from purely tradable sectors, one from pseudo tradable and two from non-tradable[19], as can be seen in Table 3.1.

Table 3.1: Dataset: Industries

NACE rev.2 code	Industry	Number of observations	Type
2511	Manuf. of metal struc. and parts of struc.	14650	Tradable
2229	Manuf. of other plastic products	5997	Tradable
2562	Machining	19008	Tradable
5510	Hotels	40013	Pseudo tradable
3513	Distrib. of electricity	1068	Non-tradable
3811	Collection of non-hazardous waste	3167	Non-tradable

Data was analyzed for fifteen countries: Austria, Croatia, Czech republic, Estonia, Finland, France, Germany, Italy, Latvia, Lithuania, Netherlands, Portugal, Slovak Republic, Slovenia and Spain. Following criteria were applied when choosing the countries:

[19]Industries were classified to tradable and non-tradable sectors on the basis of common classification in the literature. There is no dilemma with both manufacturing industries and machining as tradable industries and non-hazardous waste collection as non-tradable industry. Electricity distribution is considered non-tradable by other authors, e.g. Giannakis et al. (2005). Burstein et al. (2003) explain, that distribution services require local labor and land so they drive a natural wedge between retail prices in different countries. Tourism is another sector that can be classified into both, tradable and non-tradable class. In order to mitigate any doubts regarding the classification of electricity distribution and tourism into their respective classes, two additional models were estimated. Both models have statistically significant coefficients. However, regression assumptions are violated in both cases, rendering both models invalid. Models are reported in Appendix chapter at the end of this dissertation

- country is a member of European Union;
- dataset should include countries with and without EUR;
- dataset should include countries that could be grouped according to various historical and institutional dimensions;
- dataset should include countries that could be grouped according to common markets;
- final size of dataset should be small enough, that despite using advanced programming techniques, research should still be manageable without the use of supercomputer or computer grid in terms of calculation times.

Countries were chosen based to represent various parts of EU market:

- Former transition economies: Estonia, Lithuania, Latvia, Czech republic, Croatia, Slovenia, Slovakia;
- Continental Europe: Austria, Germany, Netherlands;
- Baltic countries: Finland (and also Estonia, Lithuania, Latvia);
- Southwestern countries: Spain, Portugal, Italy, France.

Data was selected for years between and including 2005 and 2013, that is for 9 years. On Table 3.2 we can see the number of observations, that were available for the analysis after the execution of data imputation which was discussed thoroughly in Section 4 and data selection, which is described in Subsection 3.4.

Table 3.2: Dataset: Number of Companies by Country by Year

Country	2005	2006	2007	2008	2009	2010	2011	2012	2013
Austria	270	535	644	728	750	810	862	888	936
Croatia	433	487	530	605	688	711	718	791	800
Czech Rep.	878	1009	1119	1286	1383	1393	1395	1496	1559
Estonia	260	289	318	354	376	402	420	467	508
Finland	597	620	686	787	877	929	979	977	1010
France	7438	7850	8219	8444	7283	12917	8064	10158	9985
Germany	2653	4145	4511	5120	5511	5553	5630	4919	4317
Italy	6142	6959	8805	9613	10349	10942	11573	11779	12293
Latvia	185	227	268	293	335	410	504	554	677
Lithuania	66	86	137	142	151	156	173	177	183
Netherlands	57	62	63	69	77	82	83	80	78
Portugal	595	1640	1759	1849	1954	1964	1964	1985	2082
Slovak Rep.	402	521	581	595	963	1029	1107	1209	1213
Slovenia	229	260	287	302	318	716	740	835	543
Spain	4395	4787	4796	5279	5729	5824	5797	5676	5488

Table 3.3: Average number of Companies by Country by Industry

Cntry	Hotels	Manuf. of metal struc.	Manuf. of other plast. prod.	Machi-ning	Distrib. of electr.	Coll. of non-haz. waste
AT	384.9	200.6	60.9	121.4	2.7	32.1
CZ	376.1	265.7	186.7	375.1	8.4	163.7
DE	1258.6	1178.9	607.7	1692.1	150.6	192.3
EE	112.1	174.6	29.4	71.4	8.3	10.6
ES	2820.3	1176.3	776.6	462.1	74.1	203.3
FI	149.7	280.0	93.7	304.1	9.7	54.9
FR	4852.6	1196.3	580.0	2560.6	6.3	100.0
HR	254.1	222.6	61.9	78.0	3.4	71.9
IT	4111.3	2417.3	339.4	3680.0	10.9	206.0
LT	33.4	57.9	32.1	6.9	3.1	26.4
LV	143.6	141.9	38.4	57.7	7.0	45.9
NL	29.0	25.7	8.9	8.0	1.4	3.0
PT	953.9	399.6	201.1	299.4	1.1	81.6
SI	85.1	133.6	95.3	187.7	5.4	27.3
SK	221.0	190.0	129.4	347.7	6.4	62.1

Since overall quality of the data was very bad for years 2005 and 2006, these years were excluded from the research when analyzing and estimating the models.

In Table 3.3 we can se the average number of companies in each industry in each country. As expected, the number of companies is very low in the sector of electricity distribution. Exceptions in this industry are Germany and Spain, with much higher number of companies. In general, data are for Netherlands are very scarce. Since data are normalized in further steps of the study, data can be left in the dataset[20]

3.2 Description of variables

Due to the fact that Amadeus database is a database of comparable financial information for public and private companies across Europe, we were not able to find any variables that would directly describe input and output data of companies in terms of input and output quantities. We opted to choose *number_of_employees* and (fixed) *assets* as proxies for inputs and *sales* as proxy for output. Since the quality of data on *number_of_employees* was relatively bad for some countries and industries, *costs_of_employees* was used as an input for regression imputation of missing values in *number_of_employees* when necessary. Below, we describe the variables after data imputation and outlier detection have taken place. In variables other than the regression-imputed *number_of_employees* the number of missing values is still quite high. This is due to the fact,

[20]We also ran the final model with Netherlands left out and the results are robust. The test model with Netherlands left out is presented in Appendices chapter at the end of the thesis.

that we opted for an unbalanced panel. Thus, it is expected that there will be no data for certain amount of companies in each year. Without a valid triplet of *assets*, *number_of_employees* and *sales*, an observation did not qualify for analysis in a particular year.

Variable *sales* is reported in thousands of EUR. Summary statistics by year are presented in Table 3.4. As expected, the lower bound for sales is 0. In the first quartile are mostly companies, whose earnings are expected when there are one or two employees. The mean value tells us, that we are dealing with an average sales of 10 million EUR per year. Obviously, some companies in the sample are really big. Usually this are big energy distribution companies. Such companies could not be treated as outliers, because of their market share. Clearly seen is the drop in mean value of sales after the crisis, in the year 2009, and its fast recovery in following years.

Table 3.4: Dataset: Variable *sales* in thousands EUR

SALES	2005	2006	2007	2008	2009
Min	0	0	0	0	0
Q1	58	60	57	57	62
Median	355	366	367	359	325
Mean	8184	8710	9110	9367	8404
Q3	1068	1104	1136	1123	984
Max	$73.7e+6$	$86.1e+6$	$87.3e+6$	$108.1e+6$	$83.5e+6$
Sd	352922	377734	400318	470241	415603
NAs	73405	70629	66961	62945	59206
Total	$616.8e+6$	$680.6e+6$	$745.2e+6$	$803.9e+6$	$752.7e+6$
	2010	2011	2012	2013	
Min	0	0	0	0	
Q1	50	61	65	66	
Median	308	322	313	322	
Mean	8566	8968	9603	9672	
Q3	991	1040	1060	1086	
Max	$98.9e+6$	$109.1e+6$	$126.5e+6$	$114.5e+6$	
Sd	448375	480362	536431	488422	
NAs	53288	49264	47113	42775	
Total	$817.8e+6$	$892.3e+6$	$976.2e+6$	$1025.1e+6$	

Variable *assets* is reported in thousands of EUR. Summary statistics by year are presented in Table 3.5. From huge standard deviation statistic we can see, that there exist vast differences between companies. An interesting effect is the substantial rise in standard deviation after the crisis. Such phenomenon could be observed if, on one side of the spectrum, companies are merging within industries, while on the other side of the spectrum, companies are disinvesting. In our dataset maximal value peaked in 2011 and was set by a French energy distribution company. In terms of missing values data are somewhat better than for sales. However, as noted before, in order for an observation point to be valid, we need all three datums: *assets*, *number_of_employees* and *sales*.

Table 3.5: Dataset: Variable *assets* in thousands EUR

ASSETS	2005	2006	2007	2008	2009
Min	0	0	0	0	0
Q1	142	143	142	142	135
Median	484	495	507	514	491
Mean	10037	10003	10114	11255	11020
Q3	1380	1400	1432	1474	1438
Max	$100.2e+6$	$93.7e+6$	$107.5e+6$	$167.2e+6$	$171.4e+6$
Sd	490254	457243	455767	678858	668450
NAs	54934	51479	47586	43897	39344
Total	$941.8e+6$	$973.2e+6$	$102.3e+7$	$118.0e+7$	$120.6e+7$
	2010	**2011**	**2012**	**2013**	
Min	0	0	0	0	
Q1	137	150	159	160	
Median	505	529	538	537	
Mean	11118	11531	11402	10865	
Q3	1515	1618	1686	1720	
Max	$184.4e+6$	$213.4e+6$	$205.4e+6$	$155.9e+6$	
Sd	708255	782695	743497	617616	
NAs	34978	31257	29805	25124	
Total	$126.5e+7$	$135.5e+7$	$135.6e+7$	$134.3e+7$	

Variable *number_of_employees* is reported as a real number. Summary statistics by year are presented in Table 3.6. Since *number_of_employees* was the only variable where two step data imputation procedure was employed it has no missing values. Two step imputation procedure consisted of a first step with mean imputation and a second step, using regression imputation based on variable *costs_of_employees*. Since we selected only companies, that at least in some year had over 50 employees, we can see that this variable has much less standard deviation than other variables. Even the largest companies in the industries contained in our dataset, do not report very high numbers of employees. Perhaps this is due to the fact, that some sectors are very capital intensive. However, the distribution of this variable is somewhat peculiar, as it can be seen in Figure 2.5. Since in some years, the companies had reported or were imputed a value of less than 50 employees, the distribution visually does not resemble a log-normal one. Logs of small natural numbers tend to become visually sparse on an interval between 0 and 6 as can be seen in Figure 3.1. Since *number_of_employees* is a natural ($\mathbb{N}$) not a real number ($\mathbb{R}$), such distribution is expected. First five logs in a sequence of natural integer numbers 1, 2, 3, 4 and 5 are 0, 0.69, 1.10, 1.39 and 1.61.

Variable *costs_of_employees* is reported in thousands of EUR. Summary statistics by year are presented in Table 3.7. This variable does not represent a key variable in our analysis. It is used only as a proxy for the *number_of_employees*. Considering a large number of missing values, this variable was used as a last resort, when other methods failed, and when regression model for a triplet industry-country-year was valid. We can see a drop in median *costs_of_employees* after the crisis, while mean value shows only a slight decrease in 2009 and then keeps rising. This is most

Figure 3.1: Log of natural numbers in distribution

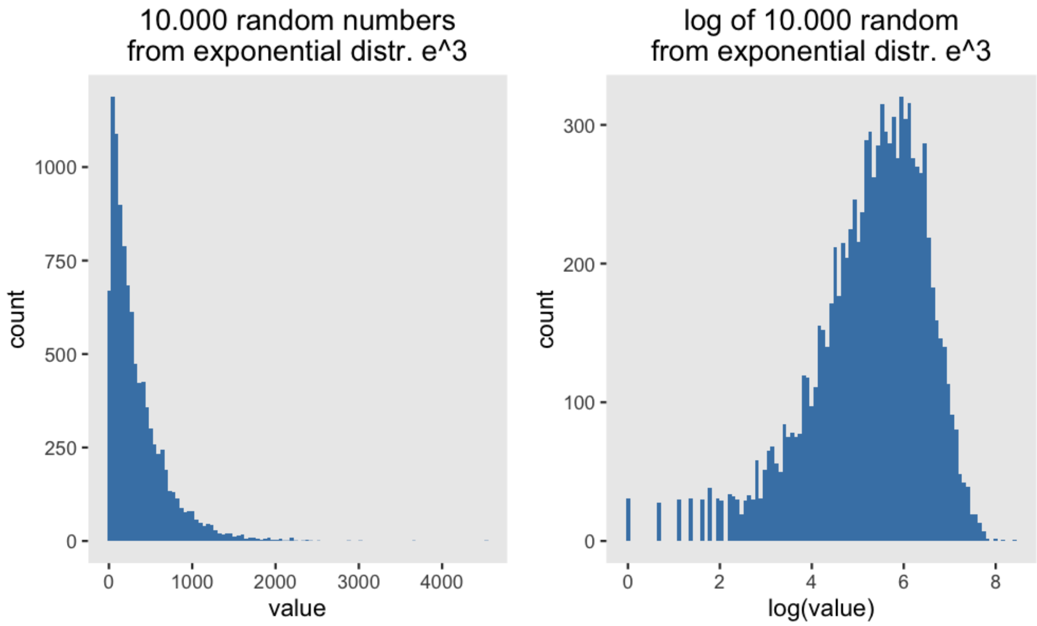


Table 3.6: Dataset: Variable *number_of_employees* real number

NUM. E.	2005	2006	2007	2008	2009
Min	1	1	1	1	1
Q1	2211	2613	2644	2610	2140
Median	2586	3195	3435	3459	2843
Mean	2228	2695	2896	2872	2359
Q3	2586	3195	3435	3459	2843
Max	2587	3196	3436	3460	2844
Sd	683	890	937	966	775
NAs	0	0	0	0	0
Total	$331.5e+6$	$400.9e+6$	$430.8e+6$	$427.3e+6$	$351.0e+6$
	2010	2011	2012	2013	
Min	1	1	1	1	
Q1	3221	1852	2613	2460	
Median	4515	2816	3893	3689	
Mean	3673	2271	3130	2981	
Q3	4515	2816	3893	3689	
Max	4516	2817	3894	3690	
Sd	1251	810	1115	991	
NAs	0	0	0	0	
Total	$546.4e+$	$337.7e+6$	$465.6e+6$	$443.4e+6$	

probably due to the nature of positions that were lost in the crisis and the cluster of positions, where companies reduced the wages.

In general, all variables are approximately log-normally distributed, as can be seen in Figure 2.5. However, if we run formal normality tests such as Shapiro-Wilk test and Kolmogorov-Smirnov test,

Table 3.7: Dataset: Variable *costs_of_employees* in thousands EUR

COSTS E.	2005	2006	2007	2008	2009
Min	0	0	0	0	0
Q1	68	69	69	71	66
Median	180	181	185	191	179
Mean	1260	1304	1310	1460	1450
Q3	403	405	417	424	395
Max	$3.5e+6$	$3.9e+6$	$4.0e+6$	$9.7e+6$	$11.4e+6$
Sd	28987	30845	32078	51937	57347
NAs	101864	99961	97790	95879	93988
Total	$59.1e+6$	$63.6e+6$	$66.8e+6$	$77.2e+6$	$79.4e+6$
	2010	2011	2012	2013	
Min	0	0	0	0	
Q1	64	64	64	60	
Median	179	185	186	182	
Mean	1469	1486	1491	1457	
Q3	402	421	430	433	
Max	$11.7e+6$	$12.8e+6$	$13.2e+6$	$11.6e+6$	
Sd	58660	61475	62257	55381	
NAs	92270	90959	89964	87243	
Total	$83.0e+6$	$85.9e+6$	$87.7e+6$	$89.6e+6$	

results of the test are biased to suggest deviation from normality. These formal tests may be used from small to medium sized samples (e.g., $n < 300$), but may be unreliable for large samples. Also, it should be noted, that on large datasets as the one used in our research, classical statistical tests find significant differences on practically all occasions. It's relatively easy to prove that when n gets large, even the smallest deviation from perfect normality will lead to a significant result. And as every dataset has some degree of randomness, classical tests yield useless results for the huge sample sizes scientists work with today. This is especially inconvenient when visual inspection and formal normality tests show incompatible results for the same data, which is the case with our sample. For each variable 50 runs of Shapiro-Wilk tests were run on a subsample of 1000 data points and results are presented in Table 3.8. All results suggest that the distribution is significantly different from log-normal, which runs contraty to visual inspection expectation that can be seen in Figure 2.5. A combination of visual inspection, assessment using skewness and kurtosis, and formal normality tests can be used to assess whether assumption of normality is acceptable or not (Kim, 2013). More on this subject can be found in Wilcox (2012).

The fact that formal test shows statistically significant discrepancy from the log-normality assumption is explicitly stated in Section 6, Limitations of the study.

As a baseline productivity illustration of average sales in thousand EUR per Employee are presented in aggregated form. They serve mainly as a sanity check. The production functions of industries are different. Expected results are shown - for instance, electricity distribution is capital intensive. Thus, sales per employee are very high, as can be seen in Table 3.9.

Table 3.8: Shapiro-Wilkes test: 50 runs, sample of 1000 values in each run

variable	mean(p-value)	sd(p-value)
Total.assets.th.EUR.	6.245903e-06	3.527585e-05
Number.of.employees.	6.371150e-16	3.380319e-15
Sales.th.EUR.	1.005920e-04	5.237797e-04
Costs.of.employees.th.EUR.	4.924635e-12	2.291633e-11

Table 3.9: Industries - Sales in th. EUR per employee and per assets in th. EUR

Industry	Sales/ Employee (mean)	Sales/ Employee (SD)	Sales/ Assets (mean)	Sales/ Assets (SD)
Hotels	0.69986	0.30673	0.60045	0.08216
Manuf. of metal struc. and parts of struc.	1.12642	0.12306	2.12414	0.37831
Manuf. of other plastic products	1.34332	0.16367	2.39068	0.35387
Machining	0.95805	0.13224	2.08363	0.32855
Distrib. of electricity	11.06758	2.69570	1.34953	0.64196
Collection of non-hazardous waste	0.89522	0.31864	1.33482	0.44809

Comparison between countries does not reveal any new findings about data either. Sample of companies from Netherlands is obviously a misrepresentation of the real situation due to a small numerus. However, as noted before, due to weighting of companies with market shares in further analysis, models are robust to exclusion of Netherlands. Baseline productivities in countries is reported in Table 3.10. Due to different structures of individual economies, direct comparisons between countries should not be made on the basis of this table.

3.3 Possible challenges with AMADEUS data

Data for all countries are not of the same quality. Amadeus database is an agglomeration of databases obtained from various national data providers. In some countries, data for all years are not a sample, but the whole population. For other countries data are from a sample. There is an overview on the collection of data available for every country in Amadeus in the Help Section of the database, but is not available on NACE 4 digit code granularity used in this study. If we want to compare data between countries in absolute terms, we need to check for structural representativeness of the data. An attempt such task on Amadeus dataset was undertaken by Bole et al. (2014a) for several countries for years 2009 and 2010. They obtained We obtained most of the test data from the Eurostat database. Sectoral distribution of revenue per employee calculated from these sectoral (official Eurostat) data was compared for every country with the distribution of sectoral averages of revenue per employee, calculated from data on the Amadeus sample of companies. Among the

Table 3.10: Countries - Sales in th. EUR per employee and per assets in th. EUR

Country	Sales/ Employee (mean)	Sales/ Employee (SD)	Sales/ Assets (mean)	Sales/ Assets (SD)
AT	2.13401	0.46024	1.32932	0.18496
CZ	1.81846	0.23564	1.17307	0.13016
DE	1.22604	0.04885	0.99753	0.09139
EE	1.18235	0.13284	1.75504	0.16516
ES	1.93945	0.39353	1.56244	0.17248
FI	2.16647	0.22156	1.05517	0.08906
FR	1.84728	0.84450	1.20719	0.03741
HR	1.06184	0.12927	2.70668	0.31975
IT	3.73361	0.68827	1.37738	0.12697
LT	1.07093	0.11287	1.86984	0.24289
LV	0.98783	0.10294	1.94818	1.31670
NL	10.02455	4.02378	1.87416	0.92677
PT	0.98787	0.13739	2.90044	1.27341
SI	1.04458	0.23306	1.39076	0.31776
SK	7.32092	1.15897	1.56095	0.18749

countries they tested were Austria, Croatia, Czech Republic, France, Germany, Italy, Portugal, Slovakia, Slovenia and Spain, which account for the majority of data in our dataset also. They got to the conclusion that the values of non-parametric Wilcoxon Man-Whitney (rank-sum) test show that the company structure of the Amadeus sample does not significantly differ from the company structure in the whole economy for analyzed countries and periods. For the countries used in this study, structural summary statistics on Amadeus data are reported in Appendix B at the end of this thesis.

However, many studies (e.g.: Molnár and Bottini (2010), Abrell et al. (2011) and Guillen et al. (2015)) hint at overrepresentation of large companies in Amadeus dataset. Our research is protected against possible structural misrepresentation of the data by two facts.

First, we are concerned only with relative movements of productivity of a sector from one country within productivities of that same sector within a pool of all companies from all countries. Any structural misrepresentation influences the results only if there is a different relative movement in underrepresented / overrepresented parts of the sector across years. A change of the sampling methodology and thus change in the structure of the sample between periods, perhaps due to the change of national data provider could influence the sample composition for individual country. Since the size of the sectors is taken into account when normalizing the research results, smaller sample for some country should not play a key role. Due to the big size of the dataset, it is practically impossible to obtain all the metadata that could influence the results. We are operating in the realm of big data, not in the realm of datasets with couple of hundreds of rows at most.

Second, when choosing industries to be used as proxies for tradable and non-tradable sectors, care was taken to select industries expected to be as homogeneous as possible. Thus, we opted for industries that have higher number of employees in general. Due to expected noise, that small companies could introduce into analysis, companies with less than 50 employees in all observed time periods were eliminated. Such companies' yearly reports are usually not subject to any revisions and are less accurate and consistent in terms of reporting standards. If a company had at least 50 employees at any observed point, it was retained in the dataset. Such decision stems from the expectation, that each individual very small company observed in isolation has no significant effect on national economy as a whole.

Data is treated with best effort. It is tested for suspicious outliers, where companies with significant market share are never treated as an outlier. Any missing values are imputed using a two-step procedure with mean imputation or regression imputation, depending on the availability and quality of relevant data points.

3.4 Methodology based on data

In order to harness as much information from data as possible, it is necessary to first understand the statistical properties of the data. Following the assumptions and limitations of various statistical and econometric methods, we can then choose the best method that will yield valid results.

The data and the chosen methods define the properties of valid scientific claims that can be expected. It is impossible to make consequential claims on the basis of correlation. It is impossible to claim anything about the absolute size of a quantity, if the only time series we can can observe is the index calculated from within group panel dataset[21].

Thus, it is necessary to be aware of the limitations of the data, assumptions and limitations of the methods we can choose and the types of scientific inferences we can make under such conditions.

Because observations (companies) were entering and leaving our problem space (the economy), and we wanted to assess the influence of all available data, we opted for unbalanced panel. Choice of balanced panel would simplify the process, but the analysis would loose a lot of its power due to removal of observations that did not exist at all τ values. As an example, in Table 3.11 are descriptive statistics on data for four selected industries in Austria. Valid data triplet is a tuple of *sales*, *number_of_employees* and *assets* for one company for one year. If any of these three data points is missing, other values are useless in our analysis. Since valid triplets are calculated per year and our dataset has data for 10 years, we have to divide the number of valid triplets with number of years and compare it to amount of complete cases. Complete cases are observations, where we have data for all years. We can see, that opting for balanced panel would leave us with just a quarter of

[21] E.g.: In each separate year, we can set the company with most equal working conditions for both genders as a benchmark and calculate equal working conditions index of all other companies relative to this benchmark. Despite the fact, that index of one particular company may fall through time, its equal working conditions in absolute terms might be increasing, but not as much as the equal working conditions of the benchmark.

available data.

Table 3.11: Amount of useful data - Amadeus, Austria, selected industries

Dataset	Num of observations	Valid triplets	Complete cases
Source	217194	510427	11708
Imputed where possible	148768	771727	22119

Also, the mechanics of fixed effects estimation, that was used as a final step in our research, are not much more difficult than with a balanced panel. If T_i is the number of time periods for cross-sectional unit i, we simply use these T_i observations in doing the time-demeaning. The total number of observations is then $T_1 + T_2 + ... + T_N$. As in the balanced case, one degree of freedom is lost for every cross-sectional observation due to the time-demeaning. Any regression package that does fixed effects makes the appropriate adjustment for this loss. The dummy variable regression also goes through in exactly the same way as with a balanced panel, and the *df* is appropriately obtained. It is easy to see that units, for which we have only a single time period, play no role in a fixed effects analysis. The time-demeaning for such observations yields all zeros, which are not used in the estimation. (If T_i is at most two for all i, we can use first differencing: if $T_i = 1$ for any i, we do not have two periods to difference.) The more difficult issue with an unbalanced panel is determining why the panel is unbalanced. With cities and states, for example, data on key variables are sometimes missing for certain years. Provided the reason we have missing data for some i is not correlated with the idiosyncratic errors, u_{it}, the unbalanced panel causes no problems. When we have data on individuals, families, or firms, things are trickier. Imagine, for example, that we obtain a random sample of manufacturing firms in 1990, and we are interested in testing how unionization affects firm profitability. Ideally, we can use a panel data analysis to control for unobserved worker and management characteristics that affect profitability and might also be correlated with the fraction of the firm's work force that is unionized. If we collect data again in subsequent years, some forms may be lost because they have gone out of business or have merged with other companies. If so, we probably have a nonrandom sample in subsequent time periods. The question is: If we apply fixed effects to the unbalanced panel, when will the estimators be unbiased (or at least consistent)? If the reason a firm leaves the sample (called attrition) is correlated with the idiosyncratic error - those unobserved factors that change over time and affect profits - then the resulting sample section problem can cause biased estimators. This is a serious consideration in this example. Nevertheless, one useful thing about fixed effects analysis is that it does allow attrition to be correlated with a_i, the unobserved effect. The idea is that, with the initial sampling, some units are more likely to drop out of the survey and this is captured by a_i (Wooldridge, 2009). Solving general attrition problems in panel data is complicated. The issue of missing values is addressed in more detail in Section 4.

4 MISSING VALUE IMPUTATION[22]

4.1 Listing and introduction of imputation methods

Methods and procedures concerned with missing values in scientific datasets have been well documented and described. To gain some insight into ad-hoc methods such as complete case analysis[23], available case analysis[24] and single imputation methods like hot deck imputation and mean imputation, one could start with Pigott (2001), Tanguma (2000) and Peugh and Enders (2004). These methods are easily implemented, but they require assumptions about the data that rarely hold in practice (Pigott, 2001). Sloppy use of aforementioned techniques can lead to biased or outright wrong results of scientific analysis. Imputation of missing values increases in complexity with the introduction of a regression model, stochastic regression model and multiple imputation methods, such as bootstrapped stochastic regression. More complex imputation procedures in general also yield much better imputed values. Thus, the amount of work included, pays dividends. With the wide availability of powerful computers, model based methods like Expectation Maximization (EM), and multiple imputation (MI) methods like Expectation Maximization Bootstrap (EMB) and Approximate Bayesian Bootstrap (ABB) are gaining prominence (Siddique and Belin, 2008). Another group are algorithms for autoregressive spectral estimation of lost sample values in discrete-time signals, which can be described with AR and ARMA[25] models (Kazlauskas and Pupeikis, 2014). Genetic Algorithm based, Kernel based, Multi-Layer Perceptron and other Neural Networks based methods have also been evaluated (Andrew and Selamat, 2012).

In the literature a number of studies exist that compare the effectiveness of different missing value imputation mechanisms in various settings (Olinsky et al., 2003; Parwoll and Wagner, 2012; Yeşilova et al., 2011). In these studies authors test different mechanisms of missing data processes, they do however assume some theoretical distribution of the underlying variables, usually the normal distribution. Although this is a fair assumption, corresponding to the standard assumptions of the widely used statistical methods, it does not correspond to empirically observed distributions in social sciences in general and in particular in financial statements data. We will show that the state-of-the-art algorithms that work very well under the assumptions of normal distribution of variables, can be outperformed by a purpose-built algorithm on a real-life non-normal dataset, as the one found in financial reports databases.

The aim of this section is not to review all the data imputation techniques and list all possible methods with their assumptions. A good resource for that is Little and Rubin (2014). Missing data imputation is usually a means to an end of a broader research process. The aim of this section is to show one possible pragmatic approach to research with data that has missing values. The content

[22] This section is going to be published as a paper in Economic and Business review, with a co-author, prof. Marko Pahor, PhD

[23] Also known as the Listwise Deletion method

[24] Also known as the Pairwise Deletion method

[25] AR and ARMA stand for Auto Regressive and Auto Regressive Moving Average, respectively.

and the meaning of the data in the encompassing research project is taken into consideration. With the use of the best imputation procedure according to the properties of the data, imputed values are much closer to the true values than with simple or out of the box solutions. Despite the computational complexity of more elaborate techniques, with the right choice of imputation algorithm, much better results and considerable speed gains can be achieved, especially when using parallel processing capabilities of contemporary computers and other big data technologies.

We compare the performance of the imputation mechanisms first on an artificially created dataset, that follows the conventional normal distribution of variables on two different missing value mechanisms. Then we move to a more realistic case of a large panel dataset of financial statement data for six industries in fifteen countries in nine years from Amadeus[26] database. We use the database to extract the distribution and relations among a set of commonly used variables in economic research and build a simulated dataset with the same distribution and correlation properties, before proceeding to simulating different missing value mechanisms on this dataset.

We continue with a short review of the missing value mechanisms and description of the practical problem at the heart of the research in this dissertation. We then provide the description of the customized two-step imputation algorithm that we used. In the simulation part we first check the performance of different imputation methods on the artificial, normally distributed dataset and then on the simulated dataset that follows the empirically observed distributions and relations. We end the section with a discussion and conclusions.

4.2 Problem description

Missing values are not just blank spaces waiting to be filled with imputed data or somehow removed from the analysis. The pattern of the missing data can contain valuable information. When imputing missing values, one has to be most concerned with the so-called missing data mechanism (Eekhout, 2015; Little and Rubin, 2014). Data imputation methods have different assumptions regarding missing data mechanism. If these assumptions do not match the situation with the data, results of the imputation method may not reflect the real situation and a new reality can be created, which is wrong. Missing data mechanisms can be classified into one of the three categories:

- Missing completely at random (MCAR)
- Missing at random (MAR)
- Not missing at random (MNAR)

MCAR data are missing totally randomly. One could test for MCAR missing data mechanism using Little's test or some other procedures found in cited literature.

[26] Amadeus is a database prepared by Bureau van Dijk. Amadeus contains information on around 21 million companies across Europe.

Data following MAR pattern are missing at random, conditionally. That is, we know of some variable that influences the amount of missing values and we can control for that variable.

MNAR pattern is the most troublesome of all. Missing values are related to some variable for which we can not control. When deducing the missing value pattern, knowledge of the data and the field of research is of great help.

A typical setting in economic research is to use a panel data structure, meaning we have the data for a cross-section of companies for a number of years. If the same cross-section is present in all observed years we talk about a balanced panel, otherwise we have an unbalanced one. Let us assume that in the final analysis we need k interval variables X_k. These interval variables are analyzed separately for each possible combination of values in l categorical variables C_l. One of the categorical variables C_τ for which $l = \tau$ can also serve as a time series index in panel dataset.

In our research we opted for a balanced panel as described in Subsection 3.4. An important reason for using the unbalanced panel lies in the fact that we are not aware of the missing value mechanism. Choosing a balanced panel on available data could thus introduce bias into the analysis, due to removal of observations that is not random, but follows some existing but uncontrolled for pattern.

To check, whether data is valid for certain observation at value τ we used a control variable X_τ, which was *complete_year*[27] in our case. If the data on X_τ was missing or the value was indicating an invalid set of values for observation n at τ then the data was not used in further data imputation process or in final analysis. Such subset of data was invalidated. In our case, it was prudent to assume, that observations at such singular conditions exhibit different characteristics than under ordinary circumstances, e.g. companies behave differently in years when they are entering or leaving the economy than in years of normal business activities.

Let $D_{[n,(l+k-1)]}$ be the matrix of data observations[28]. D is combined as a block matrix from matrix $C_{[n,l\setminus\{\tau\}]}$representing the data points with categorical data and matrix $X_{[n,k]}$ representing the data points with interval data.

$$D_{[n,(l+k-1)]} = \left[C_{[n,l\setminus\{\tau\}]} X_{[n,k]} \right] \tag{4.1}$$

In our case study, data was acquired on the basis of a query to a database, which listed valid values of observed categorical variables C_l as a condition for selection. Thus, a record in the database with a missing value on the observed C_l was automatically excluded from our dataset. This is a clear case where MAR assumption has to be evaluated. MAR is the underlying assumption of many out-of-the-box data imputation algorithms, software packages and programs. If a pattern of missing observations can be suspected, data should be treated accordingly.

Up to this point we know enough about data, that we could brute force execute any out-of-the-box

[27]The variable *complete_year* is telling us, whether the data for a certain company represent the whole year or maybe just some fraction of it.

[28]In our case study n does not represent the number of companies, but rather number of companies * Card(τ). Other categorical variables $C_{l\setminus\{\tau\}}$ like *country* and *industry* are mere descriptors and do not require special attention.

data imputation method like EMB, as described in following subsections.

4.2.1 Parallelism

Many imputation methods, if applied properly, allow for use of parallel computing procedures. Using parallel capabilities of modern computer systems can significantly decrease the amount of time needed to compute the results. However, the problem must be set up in a way, that decouples the processing tasks. Interested reader may refer to Yourdon and Constantine (1979). In order to tackle such problems, many different technologies are available. For datasets that fit into the memory of personal computers, parallel capabilities and libraries of data analysis programs usually suffice. Number of processes, that can be run simultaneously is usually limited with the number of cores available in a CPU[29] of particular personal computer[30], but can sometimes be higher if hyperthreading is available. More advanced users can also utilize the capabilities of computers GPU[31]. For larger datasets and real time applications different free, proprietary and cloud implementations of Big Data technologies such as Hadoop ecosystem, Spark, grid computing, etc. are available. Detailed discussion of available technologies is well beyond the scope of this thesis. Interested reader can start with Li et al. (2015) or Chen et al. (2014).

4.3 Customized missing data imputation

In this subsection we will describe a custom two-step method for missing data imputation that can be used in contexts of unbalanced panel data, as the one usually found in financial statements databases. We will later proceed to show that this method is superior to off-the-shelf methods implemented in contemporary software.

4.3.1 Imputation preparation

Because the values of X_k interval variables have different covariance matrices depending on the combinations in values of C_l, our original dataset gets partitioned into $\prod_{i=1}^{l} Card(C_i)$ independent datasets, some of which may be empty. From the viewpoint of data imputation procedure, computation of independent datasets can be solved in decoupled processes. Such problems are called embarrassingly parallelizable. This fact plays a key role in the employment of big data and other parallel capabilities of IT technology. Usage of parallel computing technology can result in substantial time savings (Kazlauskas and Pupeikis, 2014; Fox et al., 2014).

[29] CPU – Central Processing Unit

[30] Some commercial software packages limit the number of parallel processes as a function of the price of the license.

[31] GPU – Graphical Processor Unit

In the research, where described data imputation procedure was used, we were analyzing the dataset described in details in Section 3. There were 217194 companies for which the step one of the context dependent two-step imputation method was applied to any of the X_k[32] if necessary. In step two, $9 * 15 * 6 = 810$ linear models were estimated. Each of these $217194 * 3 + 810 = 652392$ imputation blocks were independent of each other and could be calculated in parallel.

Similar reasoning can be employed for multiple imputation methods such as EMB algorithm, also used for comparison following in this Section. Multiple imputation techniques use bootstrapping to calculate missing value sets with Bayesian or regression imputation (Honaker et al., 2011). Since each of these has to be independent, they can be calculated in parallel. Well programmed software packages could even use the independent partitions in the data, if provided as function call parameters to further parallelize the computations.

4.3.2 Setting the stage for custom two-step imputation method

With the analysis of the structure and relationships in the underlying dataset, taking into account the subject matter of the broader research topic, we can prepare a custom, tailor made data imputation procedure.

Data can be rewritten to a wide-panel-type of block matrix W. A group of observations where all values of C_l are equal, the only varying categorical column being C_τ can be rewritten to a wide form as:

$$W_{[\frac{n}{\tau},(l-1+k*\tau)]} = \left[C_{[\frac{n}{\tau},l-1]} X_{[\frac{n}{\tau},k*\tau]}\right] \tag{4.2}$$

Each set of values $X_{k,min(\tau)} \ldots X_{k,max(\tau)}$ represents a time series.

In the data with imputed values, we want the relationship between variables X_k to stay unbiased. With the use of regression imputation or various multiple regression imputation techniques, we may increase the correlation between X_k variables, thus introducing bias to our research findings. In our example, we want the relationships between data on *sales*, *number_of_employees* and *assets* to remain clean, i.e. imputation of missing values should not make these variables appear more correlated to each other than they are in reality. Even companies from the same industry are organized differently and create value using different mix of resources. That means that even naïve use of Bayesian imputation methods can give us bad results.

Financial statements data of companies are submitted with a well-defined frequency, once a year in our case. Because the frequency of data sampling is low and transcends seasonal anomalies, and cycles of strong changes in national economic conditions span several decades, it is very easy to extract short term trends from the data. In a decade, a zig-zag curve of rapid swings on any of variables from the set X_k is not likely.

[32]In our case, we were primarily interested in *sales*, *number_of_employees* and *assets*, that are three (3) time series.

The profitability of individual company is in large part dependent on it's own, business specific effects (McGahan and Porter, 1997). Thus, we can assume, that existing data about the company is carrying more information about it's own missing values, than the data about the rest of the industry in a certain country in a certain year, that we have for other companies. To make a good context dependent missing value imputation, below described two-stage method was used.

4.3.3 Context dependent two-step imputation method description

Step 1: If there is enough data present for any partition $C_{l\setminus\{\tau\}}$ in any of the time series from X_k, it makes sense to impute the missing values from this data. Since correlation among time series X_k for individual company is not important in our research, we opted for a simple mean imputation[33]. For all data points where *complete_year* variable was valid, the potential missing value was predicted from neighboring two cells. If no valid values were available on one side of the time series, a trend deduced from former/latter data points was used. At least two valid data points were needed for such imputation to take place. If there was no data for certain observation in a particular time series, or if there was only one data point, regression imputation described in step 2 was used.

Step 2: From data in the source sample[34], based on our domain specific knowledge, we try to find a variable or combination of variables X_r as regressors in linear model for regression estimation of missing values for particular $X_p \subset X_k$. Financial statement data provide us with several variables X_κ, that are a superset of X_k. Thus, some are not included in the research model, i.e. are not in the set X_k. These variables are more or less correlated with the variables in the set X_k and can be used as regressors, i.e. inputs into the regression imputation procedure.

$$X_p \subset X_k \tag{4.3}$$

$$X_p = \vec{X}_r\vec{\beta} + \vec{\epsilon} \tag{4.4}$$

We would still like to keep the relationships between variables X_k that are of interest in our final research to be as similar to the true relationships as possible. Using subset of X_k as predictors X_r for one of $X_{j\in k}$, would result in increased correlation between the variables X_k. It is desirable, that:

$$X_r \cap X_k = \emptyset \tag{4.5}$$

It is possible, that the linear model from equation 4.4, obtained from regression analysis has insignificant p-values for any β or insignificant F-statistic. Such cases can happen, if there are not enough observations with valid data to successfully estimate a model, if there are nonlinear properties in the data, etc. It is necessary, to check for non-significance of coefficients or linear model as a whole and prevent imputation of values for X_p, computed from unreliable regression coefficients[35].

[33] We were not interested in correlation between time series within one company. That is why attenuation of correlation between variables, which is a consequence of mean value imputation, was not problematic in our case.

[34] Another option would be to use the dataset, obtained after execution of imputation in step 1.

[35] In our case, exploratory data has shown that estimating *number_of_employees* from

Final data assembly: If a value was present in the original dataset, we used that value. Next we checked, if it was possible to impute the missing values from each observation's own data. As a last resort, domain adjusted regression imputation was used, if the obtained linear model had statistically significant coefficients and F-statistic. If none of this options provided a value, data point was left empty (missing value was kept) and was accounted for in subsequent analysis.

4.4 Datasets for missing value imputation methods evaluation

The simulations will be conducted on two different datasets that we label as artificial dataset and simulated dataset. Artificial dataset refers to a randomly created dataset where data follow multivariate normal distribution, created purely for testing the results of imputation procedures, accounting for their possible assumptions. This dataset assumes only one time period cross-section and simple correlation among variables.

Simulated dataset is an artificially created dataset, where data distribution and trends in individual time series follow the empirically observed ones found in a dataset of financial statements. The missing value mechanism is controlled within the simulation for both datasets.

The missing data mechanism in the observed real financial dataset is unknown, we do know however that it is not MCAR due to several reasons. For example, when observing the percentage of missing values in individual years we can notice that more data is missing in earlier years of observations. Thus, data is MAR at best. If missing values are in any way correlated with a value of some variable, e.g. smaller companies are less likely to report some datum, data is MNAR. If data is MNAR, it violates the assumption of some missing value imputation techniques.

Data about companies (observations) in Amadeus dataset consist of a set of categorical variables C and a set of interval variables X. From Amadeus dataset with financial statements, let us choose set C to consist of *country* of origin, *industry* in terms of NACE rev. 2 classification[36], *year* and *complete_year*. Financial statements for individual companies consist of several tens of more or less correlated data points[37]. For brevity, let us only focus on *sales*, *number_of_employees*, *costs_of_employees* and *assets*, which are represented in a set of interval variables X.

costs_of_employees yielded strange results if companies with less than 10 employees were taken into account. Since the focus of our research were companies with more than 50 employees, we were able to discard observations with *number_of_employees* value being less than 10. Still, there were combinations of *year*, *industry*, *country*, where no reliable regression model could be estimated.

[36]Statistical Classification of Economic Activities in the European Community, Rev. 2 (2008)

[37]Before analyzing the empirical data for distribution and relations the data was treated in order to ensure consistent representation of decimals, missing value identifiers, etc. Data treatment methods are not the focus of this thesis. Interested readers might want to refer to any introductory text on data analysis. Another important issue in the data preparation process is the decision on detection and treatment of outliers. Readers interested in this topic may refer to Aggarwal (2013) or any other text on the subject of outlier analysis. Ignoring or mistreating of outliers can have strong influence on data imputation accuracy (Quintano et al., 2010)

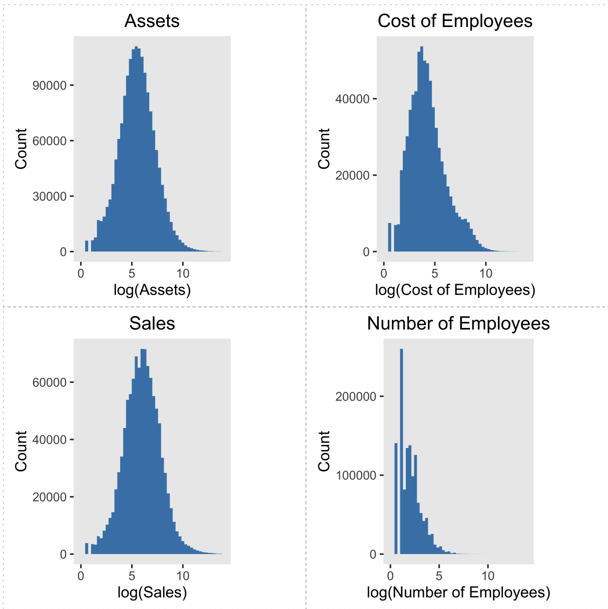
Table 4.1: Correlations between variables from over 3.5M observations of Amadeus data

	Assets	NumOfEmployees	CostsOfEmployees	Sales
Assets	1.00000	0.95954	0.96216	0.95451
NumOfEmployees	0.95954	1.00000	0.90290	0.89875
CostsOfEmployees	0.96216	0.90290	1.00000	0.97925
Sales	0.95451	0.89875	0.97925	1.00000

4.5 Empirical properties of the real-life dataset

Since we are dealing with panel data, we almost always find clear trends observing particular variable for particular observed subject through time. Variables are also quite strongly correlated. Large companies are in general larger than small companies as measured in all variables: number of employees, costs of employees, assets and sales. Correlations vary depending on industry, country and year. Correlations between variables in the original dataset were calculated using pairwise complete observations approach, to keep as much information about original data as possible. Knowing the nature of the dataset is of utmost importance when choosing missing value imputation method, due to assumptions, that imputation methods are based on.

Figure 4.1: Distribution of variables in the observed Amadeus dataset



Due to vast differences in companies sizes the distribution of variables is not normal, thus it is a standard procedure to log the variables, assuming they are log-normally distributed. We found that three variables: *sales*, *costs_of_employees* and *assets* could be approximated by log-normal distribution. It is obvious from the Figure 4.1 that this assumption is not mathematically exact, but can be applied for the sake of brevity. However, *number_of_employees* evades the efforts to be molded into log-normal using the same number of bins as for other observed variables. Many companies have very small number of employees and the log function applied to discrete small natural numbers starting with 1 returns values 0, 0.69, 1.10, 1.39, 1.61, etc. Frequencies of these low numbers are high relative to numbers in other observed variables. With low number of bins in a histogram, cumulative distribution function starts to resemble a cumulative distribution function of Binomial distribution, but further analysis of this phenomenon exceeds the scope of this text. To further complicate the matters, companies are reporting round numbers. Other mechanisms influencing the distributions may exist, e.g. Amadeus may not include data on all companies from one country, but a certain sample[38], which may introduce selection bias.

4.6 Imputation methods analysis

We want to guarantee reproducible results, which are not dependent on particular dataset. Thus, we need the capability to control parameters of data and be able to create several different datasets with the same set of parameters. First, we executed a simplified experiment. We created two normally distributed variables, introduced correlation and applied various missing data patterns and imputation techniques. To be able to control the parameters of data distributions, remove noise and control the missing values mechanism, we prepared a simulation procedure, to create a simulated dataset.

4.7 Artificial data, two variables, correlation = 0.7

We simulated a series of datasets with two normally distributed random variables, each consisting of 10000 observations and correlation between variables set to 0.7. The simulated datasets were created using random number generator and Cholesky root of desired covariance matrix. On average, the measured correlation in the artificial datasets was 0.699 with a standard deviation of 0.007.

4.7.1 Missing pattern: MCAR

The algorithm was set to randomly remove approximately 20% of data points. Some of the cases were afterwards missing one and some both variables, so the procedure left us and average of 6691.7 complete cases in the dataset, with a standard deviation of just above 18 cases. The average measured correlation of complete cases in the MCAR corrupt data set was 0.700 (s.d. 0.009). On average, the MCAR missing data process does not induce bias in the data, although we do observe an increased variability, probably due to smaller datasets.

The results of the simulations are presented in Table 4.2. As expected, mean imputation attenuates the correlation. Both regression imputation and EMB method used in AMELIA II increase the

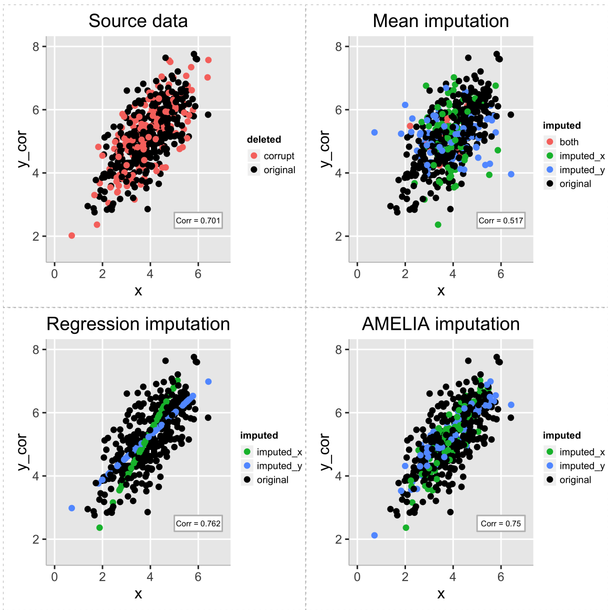
[38]More on this subject is described in Subsection 3.3.

Table 4.2: Results: MCAR missing pattern, two normally distributed variables

Imp. method	mean (Corr.)	mean (Corr. diff.)	sd (Corr. diff.)	mean (%miss. left)
Mean	0.520	0.179	0.009	0.000
Regression	0.760	−0.061	0.003	0.032
Amelia (EMB)	0.747	−0.049	0.003	0.032

correlation, with EMB imputation showing slightly less biased results, since its initial assumptions are satisfied. Visual representation of results is in Figure 4.2.

Figure 4.2: MCAR missing pattern, two normally distributed variables



4.7.2 Missing pattern: MNAR

Setting the data so simulate the MNAR missing data process is just slightly more complicated. Data points should be missing according to same pattern in the data itself, such that we can not control for that with another variable. In our case, there was a probability 0.7 for a data point to get corrupted, if the value in first column in its row was in bottom 4 deciles of the first column's values and zero probability otherwise. After this procedure we were left with an average of 7125.5 complete cases and a standard deviation of 816.7 cases. Measured correlation of complete cases in the MNAR corrupt data set was on average 0.642 with a standard deviation of 0.011. We can see that an MNAR process like the one we simulate can, as opposed to the MCAR process, introduce some bias in the correlation between variables, making it somewhat weaker.

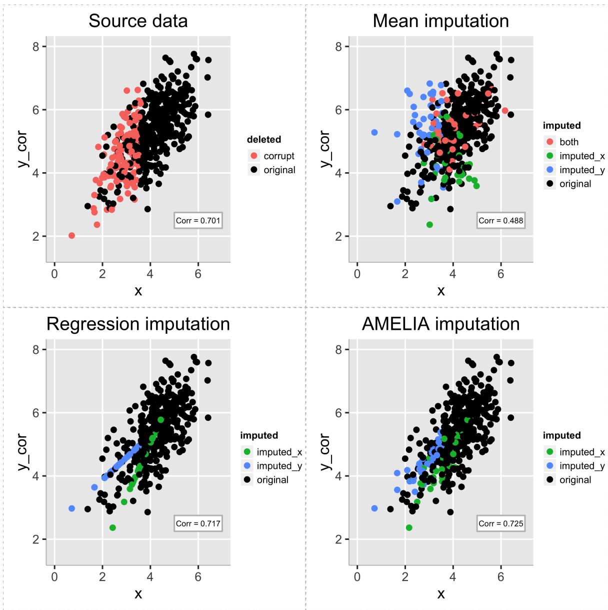
The results of the simulations are presented in Table 4.3. Again, mean imputation further attenuates the correlation. As in the MCAR case, both the regression imputation and the EMB method used

Table 4.3: Results: MNAR missing pattern, two normally distributed variables

Imp. method	mean (Corr.)	mean (Corr. diff.)	sd (Corr. diff.)	mean (%miss. left)
Mean	0.486	0.212	0.024	0.000
Regression	0.713	−0.015	0.015	0.096
Amelia (EMB)	0.723	−0.025	0.018	0.096

in AMELIA II increase the correlation, however in the MNAR case the regression imputation yields slightly less biased results. We can explain this difference with the fact that the EMB algorithm assumes that the missing data process is MCAR, which is in this case clearly violated. Visual representation of results is in Figure 4.3.

Figure 4.3: MNAR missing pattern, two normally distributed variables



4.7.3 Artificial data, conclusion

Despite the fact, that mean imputation leaves no missing values in the final dataset, significant drop in correlation between the variables can be observed. Both regression and EMB imputation methods yield similar results that introduce just a slight bias in the correlation between variables. When the assumptions underlying the EMB method are met, this method proved superior. However, regression method proved to be more robust to violations of the MCAR assumption.

4.8 Simulated data

4.8.1 Creating simulated dataset from parameters

To simulate correlated random variables resembling real Amadeus dataset given a correlation matrix, we could use the following procedure:

- Calculate Cholesky decomposition of correlation matrix, obtained from Amadeus data for particular year, industry and country
- Generate an $n * k$ matrix of standard normals, Z
- Calculate $X = LZ$ to get correlated normals
- Multiply the columns by σ_i and add μ_i to get correlated nonstandard normals

In the above procedure, n represents the number of observations we want to create, k represents number of variables, X is the final simulated dataset, L is the left Cholesky factor of the decomposition, Z is an individual variable with standard normal distribution, σ_i and μ_i are the parameters of target normal distribution of each variable $i \in \{1...k\}$. This procedure was used to introduce the correlation between the variables in artificial dataset in chapter 7.2.

However, such procedure can not reproduce trends that are present in original data. Thus, we opted for a less elegant but simpler algorithm, that produces the data which retains the gist of the phenomenon, i.e. somewhat correlated groups of variables with trends:

- Estimate parameters of log-normal distribution of $number\_of\_employees$ as D_e
- Estimate parameters of log-normal distribution of $assets$ as D_a
- Randomly choose a trend t_e for $number\_of\_employees$ from uniform distribution, chosen to lie between 0 and 1.5
- Randomly choose a trend t_a for $assets$ from uniform distribution, chosen to lie between 0 and 1.2
- Create a random number $rand_{emp}$ from log-normal distribution with parameters from estimated D_e
- Create a vector of $number\_of\_employees$ values for one row using $rand_{emp}$ and t_e, number of elements represents the number of years
- Create a random number $rand_{as}$ from log-normal distribution with parameters D_a
- Create a vector of $assets$ values for one row using $rand_{as}$ and t_a

- Correlate $assets$ to $number\_of\_employees$
- Find by how much does $number\_of\_employees$ deviate from sample mean
- Apply the attenuated deviation to $assets$, we can choose attenuation as parameter
- Create $sales$ which is in linear relationship with $number\_of\_employees$ and $assets$, linear coefficients can be chosen as parameters
- Create $costs\_of\_employees$ vector that in linear relationship to $number\_of\_employees$, linear coefficient can be chosen
- Introduce some noise, parameters and distribution of noise can be controlled
- Repeat steps from third bullet onwards for as many times as there are rows in the simulated data set you are creating

Such procedure gives us total control over parameters of the data. With controlled application of missing values using MCAR, MAR and MNAR patterns, we can measure the success rates of imputation methods, depending on all the parameters, with reproducible results.

4.8.2 Simulated data - MAR missing data pattern

Using a real data controlled simulation procedure described in Subsection 4.8.1, we created a series of datasets with 1000 observations of 4 variables in 10 time periods each. To simulate MAR missing pattern, we chose to delete 20% of points in all rows, where first column had value greater than five. First column was left untouched, so imputation methods were able to use it. Such criterion resulted in an average of 2909.1 (s.d. 17.35) deleted data points and 589.2 (s.d. 17.35) complete cases left out of 1000 in initial simulated dataset.

We would first like to know how closely do the imputed results come to the ones that were deleted using the missing data process. We thus develop a simple metric to measure the difference between the original and the imputed data that takes account of both the share of imputed values as well as the quality of imputation. As the metric we use the sum of differences between the imputed value and the original (deleted) value. Results of the simulations are presented in Table 4.4.

Table 4.4: Simulated data: MAR missing pattern

Imp. method	mean (% miss. left)	mean ($\sum Abs(residuals)$)	sd ($\sum Abs(residuals)$)
Mean	0.010	59525	17507
Regression	0.410	118933	80617
Two step	0.004	61238	16757
Amelia (EMB)	0.005	20497329	3338778

From the Table 4.4 we can see that in terms of the share of imputed data the regression method performs worst, as it is on average only able to replace less than 60 percent of missing data. Mean value imputation replaces 99 percent and both our two-step method and the EMB replace around 99.5 percent of missing values. In terms of the quality of imputation mean imputation and two-step approach yield similarly good results, the two-step method being slightly worse but more consistent. Regression imputation is a somewhat worse and much less consistent. EMB imputation proved to be completely inappropriate for this kind of data, as its imputed value deviate greatly from the deleted originals.

4.8.3 Simulated data - MNAR missing data pattern.

Again, using a real data controlled simulation procedure described in Subsection 4.8.1, we created a dataset with 1000 observations of 4 variables in 10 time periods. To simulate MNAR missing pattern, we chose to delete 20% of points in all rows, where 23rd column had value greater than some quantile of itself. All columns were corrupt with missing values, so imputation methods were unable to find any pattern in missing value mechanism. Such criterion resulted in an average of 2975.7 (s.d. 117.9) deleted data points and 589.3 (s.d. 17.49) complete cases left out of 1000 in initial simulated dataset. Results are given in Table 4.5.

Table 4.5: Simulated data: MNAR missing pattern

Imp. method	mean (% miss. left)	mean ($\sum Abs(residuals)$)	sd ($\sum Abs(residuals)$)
Mean	0.014	66359	19999
Regression	0.410	105235	53220
Two step	0.006	68005	20471
Amelia (EMB)	0.004	20504011	3370479

From the Table 4.5 we can see that in terms of the share of imputed data once more the regression method performs worst, as it is on average only able to replace less than 60 percent of missing data. Mean value imputation replaces 98.6 percent, two-step method 99.4 percent, while the EMB performs best replacing on average 99.6 percent of missing values. In terms of the quality of imputation, mean imputation and two-step approach yield similarly good results, the two-step method being slightly worse but more consistent. EMB imputation managed to impute values to most data points. However, as in the MAR case, the EMB imputation performs worst in terms of imputation quality, having several orders of magnitude higher sum of errors than the next method. Once again, in terms of deviation from true values mean value and the two-step method of imputation perform similarly well, while the regression method lags behind both, but beats EMB imputation.

We have shown that in terms of getting missing data close to the "originals", both mean imputation as well as our two-step procedure perform well regardless of the missing data pattern. However, getting values on average close to the original ones is not yet indicative of whether there will be any bias in the relationships between the variables. As we have seen in the simple simulation in the previous section, mean imputation is prone to introducing bias. Thus we continue the testing by checking the consistency of a common economics relation, namely a Cobb-Douglas type production function after imputation.

4.8.4 Estimating Cobb-Douglas type production function against imputed data.

To test the effects of imputation method on a well known estimation problem, we estimated the α, β and A[39] of a Cobb-Douglas type production function [40].

$$Y = A * L^{\alpha} * K^{\beta} \tag{4.6}$$

For consistency with real-life datasets the observations in the simulated dataset are allowed to have a value zero. That makes the estimation using least squares regression on logged values impossible, thus we use an upgraded model that allows for the production function to be consistently estimated even with some values being zero (Battese, 1997):

$$log(Y) = A + \alpha * log(L) + \beta * log(K) + \kappa_1 * Y_0 + \kappa_2 * L_0 + \kappa_3 * K_0 \tag{4.7}$$

Y_0, L_0 and K_0 are dummy variables representing the cases, when Y, L or K have value zero. With such augmentation of the estimated model, we get unbiased results for the three coefficients we are looking for: A, α and β. Obtained values for the estimation on the MAR data are shown in Table 4.6 and for the MNAR in Table 4.7

In our simulation, mean imputation and two-step imputation give the best results in both cases: MAR and MNAR. In both scenarios mean imputation outperforms the two-step procedure in the accuracy of the estimation of regression coefficient, while mean imputation performs somewhat worse in the estimation of the intercept. Complete case estimation returns estimates that are relatively consistent with non-missing estimation in the slopes but greatly miss the mark for the intercept. Results of both the regression imputation as well as the EMB algorithm are completely biased and as such useless.

[39] A represents total factor productivity

[40] The coefficients estimated using Cobb-Douglas within the chapter describing Missing value imputation methods are obtained from a simulated dataset. Simulation is trying to restore the correlations between variables in original dataset. Important are deviations of estimates after the data were corrupt and imputed, not the values per se (there is no contextual metadata about the coefficients, as is the case when one is estimating Cobb-Douglas production function on a real dataset). To estimate proper elasticities on real data from following chapters of this thesis, one should control for many other measures, such as country, industry, etc.

Table 4.6: Estimated values of Cobb-Douglas production function: MAR

Data set		A	α	β	$\lvert A - A' \rvert$	$\lvert \alpha - \alpha' \rvert$	$\lvert \beta - \beta' \rvert$
Simulated set	mean	0.222	0.667	0.581	0.000	0.000	0.000
	(sd)	(0.040)	(0.018)	0.018)	(0.000)	(0.000)	(0.000)
Complete cases	mean	−0.622	0.696	0.618	−0.843	0.030	0.037
	(sd)	(0.077)	(0.016)	0.023)	(0.097)	(0.007)	(0.010)
Mean imp.	mean	0.223	0.663	0.585	0.002	−0.003	0.003
	(sd)	(0.041)	(0.017)	0.018)	(0.015)	(0.002)	(0.002)
Regression imp.	mean	−0.487	−0.049	0.099	−0.708	−0.715	−0.482
	(sd)	(0.584)	(0.032)	0.037)	(0.612)	(0.032)	(0.039)
Two-step imp.	mean	0.222	0.663	0.584	0.000	−0.004	0.003
	(sd)	(0.041)	(0.017)	0.018)	(0.015)	(0.002)	(0.002)
AMELIA imp.	mean	−0.487	−0.049	0.099	−0.708	−0.715	−0.482
	(sd)	(0.584)	(0.032)	0.037)	(0.612)	(0.032)	(0.039)

Table 4.7: Estimated values of Cobb-Douglas production function: NMAR

Data set		A	α	β	$\lvert A - A' \rvert$	$\lvert \alpha - \alpha' \rvert$	$\lvert \beta - \beta' \rvert$
Simulated set	mean	0.222	0.667	0.581	0.000	0.000	0.000
	(sd)	(0.040)	(0.018)	0.018)	(0.000)	(0.000)	(0.000)
Comp. cases	mean	−0.622	0.696	0.618	−0.844	0.030	0.037
	(sd)	(0.077)	(0.016)	0.023)	(0.096)	(0.007)	(0.010)
Mean imp.	mean	0.216	0.665	0.583	−0.006	−0.001	0.001
	(sd)	(0.048)	(0.017)	0.018)	(0.018)	(0.002)	(0.004)
Regression imp.	mean	−0.621	−0.036	0.084	−0.843	−0.703	−0.497
	(sd)	(0.702)	(0.045)	0.043)	(0.711)	(0.042)	(0.049)
Two-step imp.	mean	0.217	0.665	0.583	−0.004	−0.002	0.002
	(sd)	(0.051)	(0.017)	0.019)	(0.019)	(0.002)	(0.004)
AMELIA imp.	mean	−0.621	−0.036	0.084	−0.843	−0.703	−0.497
	(sd)	(0.702)	(0.045)	0.043)	(0.711)	(0.042)	(0.049)

4.8.5 Discussion of the results for simulated data

As expected, situation with simulated data is more complex than with clean artificial dataset. While the off-the-shelf EMB procedure performed quite well in the artificial, normally distributed case, it completely misses the mark for a dataset simulated to resemble the real-life financial reports data. Caution is thus required in the use of such procedures on real life data. Same goes for some other model-based imputation methods, one of them being the regression imputation that we tested.

While simple approaches as complete-case approach introduce considerable bias in the estimates, simple mean substitution performs surprisingly well beating all other methods in the consistency of model estimations, save for our proposed two-step method, which comes close and partially beats the mean imputation. The main advantage of our proposed method is in the fact that it is able to more than halve the share of non-imputed missing cases on average - an achievement comparable to the EMB, but without sacrificing the consistency of results.

4.9 Conclusion and suggestions for further research

From the results we can see that the described two-step imputation method yields better results than brute force use of available off-the-shelf algorithms. Assumption that data is missing completely at random or less strict assumption that data is missing at random is often wrong. The brute force use of existing data imputation algorithms can lead to invalid research conclusions.

In order to develop a good data imputation method, suited for particular data and research problem, profound knowledge of the dataset and research topic is of utmost importance. It makes sense to spend time assessing the expedience of different data imputation methods for the problem at hand. We may encounter some sort of consistency vs. efficiency tradeoff, as is the case with the two-step method proposed in this paper or as noted by Kmenta (1997).

The two-step method presented in this thesis is a tailor made missing value imputation procedure, suited for imputation of missing values into periodic financial reports. The method is far superior to naïve methods with regard to the amount of missing data points restored, while sacrificing small amount of consistency.

An idea for further research is a possible improvement of the two-step method with the use of some multiple imputation method instead of regression in second step. With such a measure, it would be possible to add another bit of stochastic properties to the procedure and perhaps attenuate the already small loss of consistency or further improve the rate of recovered values.

5 EMPIRICAL MODEL

Before we explicitly specify the empirical model, it is necessary to describe all the data preparation steps, that lead to the inputs into the model. Inputs into the model are the normalized, weighted DEA scores, which conveniently strip the data of any non-homogeneous effects of various components of (in)efficiency. After proper aggregation and normalization of DEA scores on sectoral and country level, the only thing that remains is the information of absolute (in)efficiency of a sector in any point in time.

5.1 Research process description

Research process was conducted with the paradigm of reproducible research in mind. All the steps are well documented and the code is available for possible corrections or reruns. The steps of the process are as follows:

1. load raw data
2. select companies according to described criteria (i.e. $>$ 50 employees, unbalanced panel)
3. impute missing values where applicable
4. test the impact of data imputation
5. prepare working dataset based on availability of data points in each observation
6. calculate DEA first pass
7. calculate total sales by industry in country by year
8. calculate the market share of each company
9. remove outliers, which can not be companies with large market share
10. pool the processed data for each industry
11. calculate DEA second pass
12. pool data for all analyzed industries
13. calculate weight of *industry_country* in *industry_global* through years
14. calculate weighted DEA score of *industry_country* in *global_industry* in years
15. run econometric models (fixed effects, etc.)

After data preparation procedures in steps 1 to 5 have been completed, preliminary DEA scores have been calculated in step 6, to be used in the outlier removal process. After steps 7 to 9 have been completed, data was pooled within an industry and global DEA scores of companies were calculated. These scores were then aggregated using s share-weighting scheme, which also normalizes the DEA inputs into the final regression model. Several econometric models were estimated using linear regression with categorical variables (i.e. country, industry, year) and DEA scores as inputs. Regression assumptions were checked using visual inspection of the residuals with 'Residuals vs Fitted', 'Normal Q-Q', 'Scale-Location' and 'Residuals vs Leverage' plots. Also, assumptions were checked using "gvlma" package (Pena and Slate, 2014).

5.1.1 Lack of variability in non-tradable sector

Many of the non-tradable sectors are the ones operating in the business of utilities (e.g. water supply, electricity distribution, waste collection, etc.). Such is also the case with non-tradable sectors in our research. These companies have very flat fixed assets, number of employees and revenue curves. Thus, it is very hard to sensor any influence of change of these variables, if the changes are small, relative to the absolute scale of the variables. In order to overcome this shortcoming, we conducted our analysis on the effects of relative change of efficiency in non-tradable sectors on the relative change on efficiency in tradable sectors.

5.2 Intuition of the empirical model input preparation

The first obstacle to surmount was the preparation of a suitable aggregation procedure for the DEA scores. If we look at individual industry-year-country average DEA efficiencies, we get no useful data for comparison. We can deduct something about the relative dispersion of companies' efficiencies in industry-time-place map, but that is all. Adding another observation to the dataset could significantly affect the average DEA efficiency, which is thus rendered useless as an aggregation function. More on DEA's sensitivity on individual data points can be read in Section 2.8.3.

In Subsection 2.7 we describe a three step method suggested by Charnes et al. (1981), to compare efficiencies between groups, that uses a projection technique in order to compare the groups. With projection we take out within group inefficiencies. We basically take one group's production as if it would be conducted efficiently and compare it to another groups efficient productivity curve. However, since we are concerned with the relations between sectors, we need to somehow aggregate the data within each sector. When projecting the companies to the DEA frontier we do not account for the size of the companies within the sector. A small efficient company could pull the projected points in one group outward. Executing DEA analysis on each sector first, projecting all companies to the DEA frontier and then rerunning DEA on pooled data from both projected sectors, failing to account for the size of the companies in the sector, would again result in invalid results. Projection to DEA frontier as aggregation function is also not useful for our case.

Comparing groups on the basis of the average or projected scores is thus not a good idea. It might happen that in one group a company with small market share may be very efficient, a company with a big market share very inefficient, but the result would look the same as in other group with the situation reversed (i.e. the big market share company being the efficient one). One small company could drive the DEA curve outwards, making the whole sector seem disproportionately more efficient. The size of the company within group has to be accounted for. It follows naturally to calculate weighted DEA scores for sectors.

Let i be the index of a particular company, ζ_i be the market share of the company in a market and $\widehat{DEA}_i$ be the companies' estimated DEA score. Wighted DEA score of the market M is calculated as:

$$M = \sum_i \widehat{DEA}_i \zeta_i \tag{5.1}$$

Let the weighted market efficiency be denoted by Ξ. If we assume that market size and ζ_i do not change, we can make comparisons beween groups in time t using:

$$\Delta\Xi = \sum_i \widehat{DEA}_{it}\zeta_i - \sum_i \widehat{DEA}_{i(t-1)}\zeta_i \tag{5.2}$$

Since the situation in the markets is changing, we need to analyze various scenarios. For the sake of brevity, assume that the data are pooled from two groups, that we want to compare. As can be seen in Figure 5.1 three different situations are possible where "global" DEA frontier is spanned by:

- only first group points;
- only second group points;
- by points from both groups.

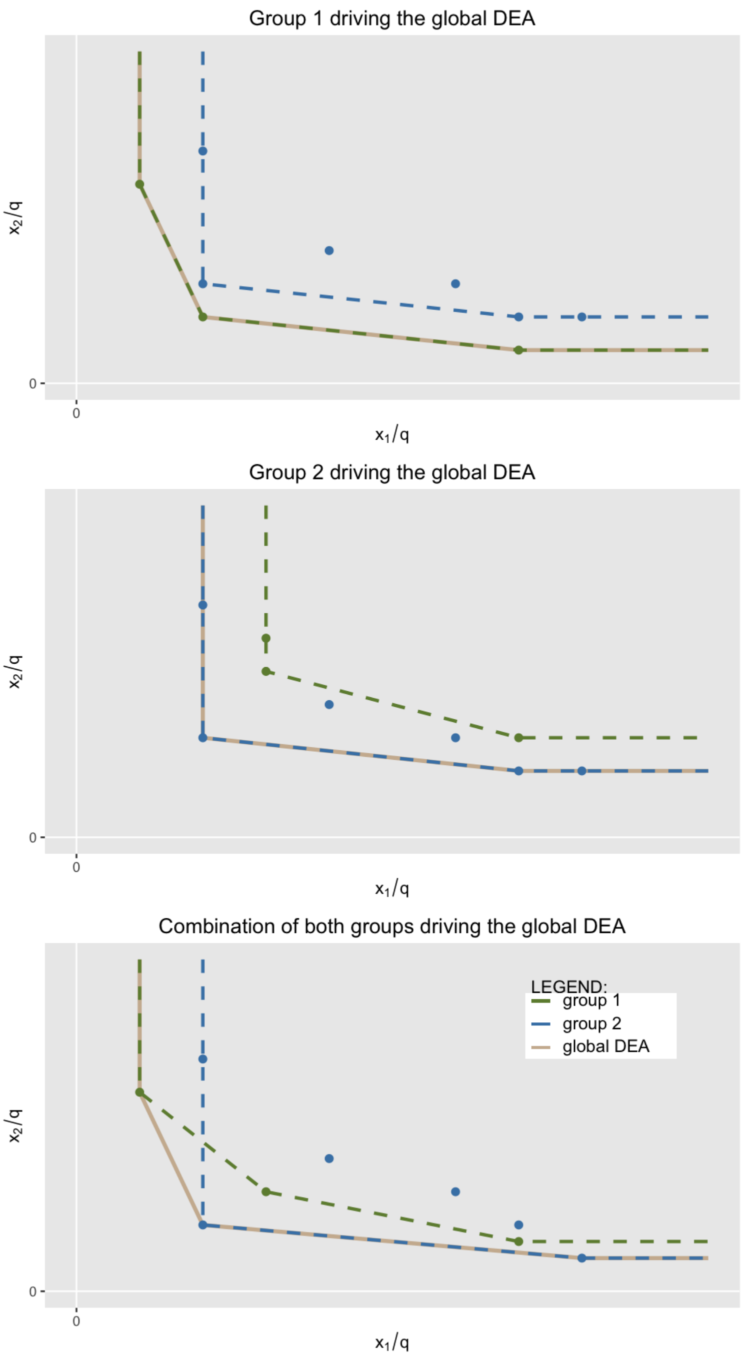
Under the assumption that in Group 1 the productivity is low and the sector is small, efficiency as calculated with the weighted DEA scores may still be high. In Group 2, the productivity in absolute terms can be substantially higher and the sector can be much larger, but the efficiency as calculated with the weighted DEA scores can still be lower as for Group 1. Thus, even a comparison between groups (e.g. years, countries, industries) based on weighted DEA scores discriminated by one categorical variable still does not yield satisfactory results.

To be able to make any valid comparison between groups, we need both: weighted DEA scores and a common (global) frontier.

To find the global frontier, we pool the data on companies within an industry, within a country, for all years $t \in 0...N$. Then we estimate the $\widehat{DEApt}_i$[41] scores on the pooled data. Now, we can calculate the "worth" of the weighted efficiency scores for each year, weights being market shares ζ_{it}

[41] DEApt stands for "DEA pooled within time".

Figure 5.1: DEA between groups scenarios



within each year:

$$\Xi_t = \sum_i \widehat{DEAp}t_{it}\zeta_{it} \tag{5.3}$$

It is important to note that

$$\sum_{t=0}^{N}\sum_i \zeta_{it} = N. \tag{5.4}$$

These results are showing us a much better picture for the efficiency of the sector in a country through time.

By the same line of reasoning, we pool the data within an industry, within one year, across all countries $C \in 0...M$. Then we estimate the $\widehat{DEAps_i}$[42] scores on the pooled data. Now, we can calculate the "worth" of the weighted efficiency scores for each country, weights being market shares ζ_{iC} within each country:

$$\Xi_C = \sum_i \widehat{DEAps}_{iC} \zeta_{iC} \tag{5.5}$$

Again,

$$\sum_{t=0}^{M} \sum_i \zeta_{iC} = M. \tag{5.6}$$

With this approach, we obtain weighted DEA scores with a common frontier, so we can compare the efficiency of a sector in a year between countries.

In the final step, the connection between the time and country dimensions needs to be established. A possible culprit is the fact, that share of the global market each country is taking up can change during the years.

To account for changing shares of countries in the global market for each sector, we also weight the impact of each country in the global picture in each year. This procedure results in *normalized* results with the global weights (i.e. with the market share ζ_{it_pooled} of the company i in the pooled data on companies within an industry, within a country for all years; or with the market share ζ_{iC_pooled} of the company i in the the pooled data within an industry, within one year, across all countries).

$$\sum_i \zeta_{it\_pooled} = 1, \qquad \sum_i \zeta_{iC\_pooled} = 1.$$

Let the global market share of the company i at time t in industry s be denoted as ζ_{its_global}:

$$\sum_i \zeta_{its\_global} = 1.$$

DEA pooled within (industry) sector s in a year t is denoted as $\widehat{DEApst}$. The final aggregated normalized efficiency score for an industry (sector) s in a given country C in a given year t obtained by DEA is:

$$\Xi_{sCt} = \frac{\sum_j \widehat{DEApst}_j \zeta_{jts\_global}}{\sum_i \widehat{DEApst}_i \zeta_{its\_global}} \tag{5.7}$$

or equvalenty:

$$\Xi_{sCt} = \frac{\sum_j \widehat{DEApst}_j \zeta_{jC}}{\sum_{j=0}^{M} \sum_i \widehat{DEApst}_{ij} \zeta_{ij}} \frac{\sum_j \zeta_{jts\_global}}{\sum_i \zeta_{its\_global}} \tag{5.8}$$

where $\{j\} \subset \{i\}$, such that each company with index j originates from country C. Equation 5.7 can

[42]DEAps stands for "DEA pooled within (industry) sector".

be read as:

$$\Xi \quad \text{in cntry C at time t} = \frac{\text{sum of glob. DEA scr} \times \text{glob. mkt shr of each cmpny from cntry C}}{\text{sum of glob. DEA scr} \times \text{glob. mkt shr of each cmpny from all cntrs}},$$

while Equation 5.8 can be read as:

$$\Xi \quad \text{in cntry C at time t} = \left(\frac{\text{sum of glob. DEA scr} \times \text{cntry mkt shr of each cmpny from cntry C}}{\text{sum of glob. DEA scr} \times \text{glob. mkt shr of each cmpny from all cntrs}}\right) \times \left(\frac{\text{sum of glob. mkt shr of companies from cntry C}}{1}\right).$$

The second fraction in Equation 5.8 is representing the share of one countries sector in the global sector in given year.

Calculating Ξ_{sCt} for every year enables us to construct a panel dataset of country-sector scores through time. This panel is then analyzed with regression models.

If global productivity would change and was accompanied by homogeneous response across all groups, we would not be able to detect anything, since relative efficiency would not change. As it turns out, this is not the case. When obtained DEA scores are fed as inputs into regression model, it is shown, that the lagged log DEA score in the global pool at time t of the tradable sectors can be linked to the log DEA score in the global pool at time $t-1$ of the non-tradable sectors.

A phenomenon, that could seriously jeopardise our results is endogeneity. Since in our equations we are changing market share and DEA score at the same time, regression input points could be endogenous by construction. In order to account for this fact, we also tested a model, where we calculated the average market share for each company, during all years.

Let i be the index of a particular company and y_{it} be the market share of the company i in year t. For each company i, we calculate:

$$\bar{y_i} = \sum_t y_i \tag{5.9}$$

The fixed market share is used for the company, at all times t, where company is present in the model. We obtain slightli different final aggregated normalized efficiency scores for an industry (sector) s in a given country C in a given year t as in Equation 5.7 and Equation 5.8:

$$\Xi_{sCt} = \frac{\sum_j \widehat{DEApst}_j \zeta_{js\_global\_fixed}}{\sum_i \widehat{DEApst}_i \zeta_{is\_global\_fixed}} \tag{5.10}$$

or equvalenty:

$$\Xi_{sCt} = \frac{\sum_j \widehat{DEApst}_j \zeta_{jC}}{\sum_{j=0}^{M} \sum_i \widehat{DEApst}_{ij} \zeta_{ij}} \frac{\sum_j \zeta_{js\_global\_fixed}}{\sum_i \zeta_{its\_global\_fixed}} \tag{5.11}$$

Model with fixed market shares returned similar results to the model with market shares varying, which suggests small changes of market shares during the observed period. Such finding is expected in mature industries.

5.2.1 Empirical model specification

Since we are trying to find the effect of efficiency of non-tradable sectors on the efficiency of tradable sectors, with the possible effect of the country, group of countries and years on the results, the general model is specified as:

$$\begin{aligned} log(trad\_glob\_eff)[t] = \\ & \alpha + \\ & \beta_0 * log(nontrad\_glob\_eff)[t-1] + \\ & \sum_j (\beta_j * country_j\_dummy) + \\ & \sum_k (\beta_k * country\_group_k\_dummy) + \\ & \sum_l (year_l\_dummy) \end{aligned} \tag{5.12}$$

As can be seen from Equation 5.12, we assume the lagged effect of the efficiency in non-tradable sectors on the efficiency of tradable sectors. Model with contemporaneous effect was also tested, but did not yield satisfactory results. All normalized weighted DEA scores are given in logs. Results reflect the percent change of the response variable according to percent change in the regressor.

5.3 Hypotheses

Using the model, we want to validate following hypotheses:

1. - H_0: There is no link between productivities of non-tradable and tradable sectors ($\beta_0 = 0$).
   - H_A: There is a link between productivities of non-tradable and tradable sectors ($\beta_0 \neq 0$).
2. - H_0: Strength of the link between productivities of non-tradable and tradable sectors does not vary within the business cycle.
   - H_A: Strength of the link between productivities of non-tradable and tradable sectors is more pronounced during the recession.
3. - H_0: Strength of the link between productivities of non-tradable and tradable sectors does not vary between countries.
   - H_A: Strength of the link between productivities of non-tradable and tradable sectors varies between countries.

5.4 Base models

First, we checked for the direct relationship between logged values of pooled global efficiency DEA scores for tradable sector based in year t and lagged logged pooled global efficiency DEA scores for non-tradable sectors. Base model was specified as:

$$log(trad\_glob\_eff)[t] = \alpha + \beta * log(nontrad\_glob\_eff)[t-1] \tag{5.13}$$

The results are laid out in Table 5.1

Table 5.1: Results: Base model

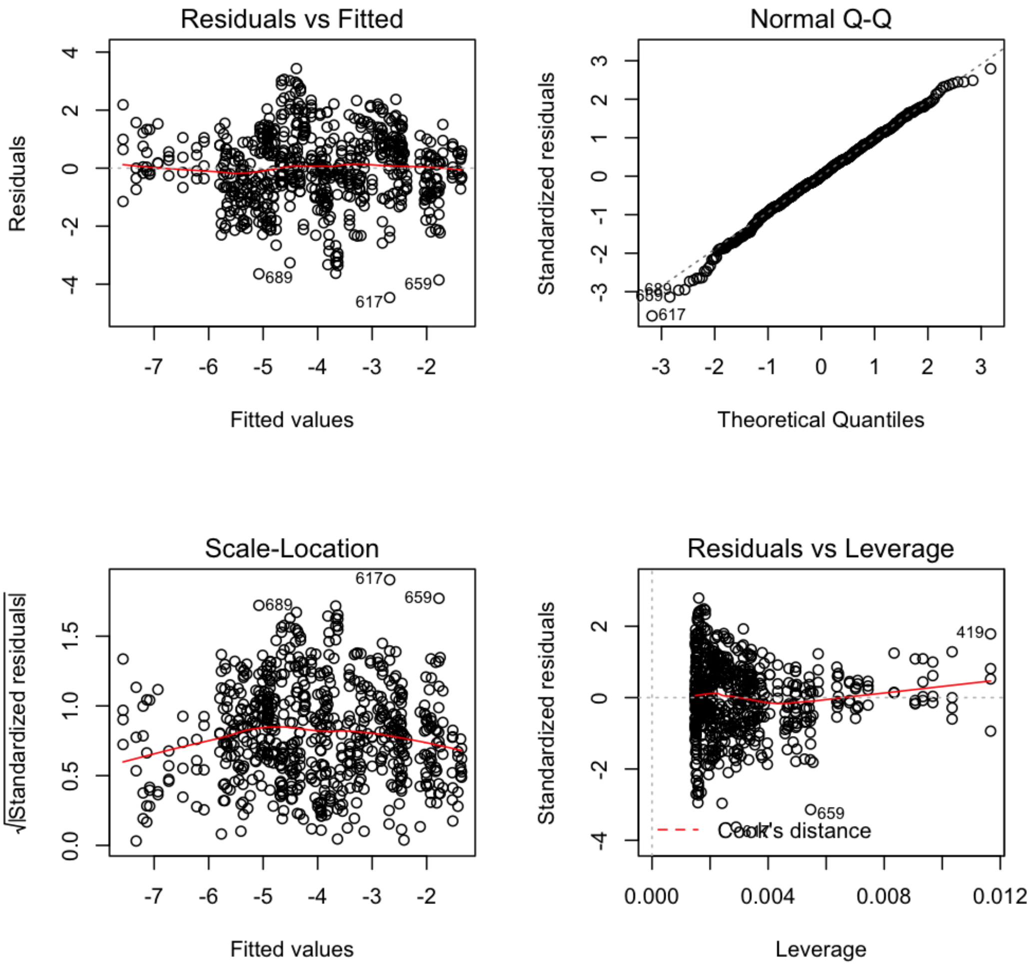
Residuals		Min	-4.4600
		1Q	-0.7657
		Median	0.0082
		3Q	0.8294
		Max	3.4331
Coefficients	Intercept	Estimate	-1.22297
		Std.err	0.10784
		t-value	-11.34
		Pr(> $\|t\|$)	< 2e-16
		Signif.	***
	log(NTG)	Estimate	0.59113
		Std.err	0.02058
		t-value	28.73
		Pr(> $\|t\|$)	< 2e-16
		Signif.	***
Overall		Res.std.err	1.231
		Df	669
		Mult. R-sqared	0.5523
		Adj. R-squared	0.5516
		F-statistic	825.3
		p-value	< 2.2e-16
Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 0			

Assessment of the linear model assumptions using the global test on 4 degrees of freedom at level of significance 0.5 gives the results in the Table 5.2.

Table 5.2: Base model regression assumptions tests

	Value	p-value	Decision
Global Stat	12.48331	0.01410	Assumptions NOT satisfied!
Skewness	5.84545	0.01562	Assumptions NOT satisfied!
Kurtosis	1.87067	0.17140	Assumptions acceptable.
Link Function	0.04786	0.82684	Assumptions acceptable.
Heteroscedasticity	4.71933	0.02983	Assumptions NOT satisfied!

Figure 5.2: Base model regression assumptions plot



From Figure 5.2 and from the linear regression model assumptions checks presented in Table 5.2, we can see that regression assumptions are not satisfied. Thus, even though calculated regression coefficients are marked as statistically significant, results are invalid.

5.4.1 Base model by year

In order to control, whether the results make sense through the whole period, we also checked each year separately, using the relationship from Equation 5.14. The results are collected in Table 5.3.

$$log(trad\_glob\_eff)[t] = \alpha + \beta * log(nontrad\_glob\_eff)[t-1] \tag{5.14}$$

Table 5.3: Results: Base model by year

			2008	2009	2010	2011	2012	2013
Residuals		Min	-2.74313	-3.76168	-3.42525	-2.92223	-4.01368	-2.51344
		1Q	-0.67156	-0.60348	-0.64508	-0.70087	-0.83991	-0.89734
		Median	0.05999	-0.04744	-0.00252	-0.01055	-0.06393	0.13077
		3Q	0.61860	0.87878	0.79440	0.81598	0.87032	0.76966
		Max	2.91399	2.88304	2.92587	2.77610	3.71356	2.83562
Coefficients	Intercept	Estimate	-0.80937	-1.06637	-1.08163	-1.19447	-1.81034	-1.26970
		Std.err	0.23783	0.26431	0.26969	0.23674	0.28456	0.28110
		t-value	-3.4031	-4.0345	-4.0106	-5.0456	-6.3619	-4.5168
		$Pr(>\|t\|)$	0.00092	0.00010	0.00011	0.00000	0.00000	0.00002
		Signif.	***	***	***	***	***	***
	log(NTG)	Estimate	0.64546	0.59575	0.60996	0.58326	0.53385	0.59903
		Std.err	0.04290	0.04966	0.05225	0.04615	0.05468	0.05608
		t-value	15.0465	11.9956	11.6748	12.6382	9.7626	10.6817
		$Pr(>\|t\|)$	< 2e-16	< 2e-16	< 2e-16	< 2e-16	< 2e-16	< 2e-16
		Signif.	***	***	***	***	***	***
Overall		Res.std.err	1.128	1.226	1.238	1.116	1.439	1.155
		Df	114	114	114	114	118	85
		Mult. R-sqared	0.665	0.558	0.545	0.584	0.447	0.573
		Adj. R-squared	0.662	0.554	0.541	0.580	0.442	0.568
		F-statistic	226.4	143.9	136.3	159.7	95.3	114.1
		p-value	7.58e-29	6.13e-22	3.41e-21	2.01e-23	7.33e-17	2.20e-17

Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 0

The results of the base model applied to each year separately are consistent with the expectations. We can see that the general level of $log(trad\_glob\_eff)$ is dropping for four years after the crisis. This might be due to the fact, that the largest trading companies do not manage to adapt to new market conditions as fast as smaller ones. This is a really interesting finding. Another expected result is the response of the main β coefficient to the crisis shock. When the crisis hit in 2008, the efficiency of tradable sectors was most impacted by the efficiency of non-tradable sectors. After the crisis β oscillates about the same value of about 0.57. All measures are significant at 0.001 through all years with R-squared over 0.5 except in year 2011.

From the table we can clearly see, that in the recession, the link is much stronger than in following years. Thus, we can reject Hypothesis 2_0, stated in Section 5.3. The results shown in Table 5.3 suggest, that the strength of the link between productivities of non-tradable and tradable sectors varies during the business cycle and is more pronounced during the recession. Thus, we can accept the alternative Hypothesis 2_A.

5.4.2 Base model by industry

In order to control, whether the results make sense for all industries, we also checked each industry separately, using following relationship:

$$log(trad\_glob\_eff)[t] = \alpha + \beta * log(nontrad\_glob\_eff)[t-1] \tag{5.15}$$

The results are collected in Table 5.4.

Table 5.4: Results: Base model by industry

			Hotels NACE 5510	Metal construct. NACE 2511	Manuf. other plast. prod NACE 2229	Machining NACE 2562
Residuals		Min	-3.05737	-3.41745	-3.35724	-4.24753
		Q1	-0.91580	-0.77640	-0.67023	-0.79537
		Median	0.14323	-0.03134	-0.05010	0.03437
		Q3	0.72911	0.75548	0.77801	1.01982
		Max	2.91124	3.35093	2.30476	3.21427
Coefficients	Intercept	Estimate	-1.15351	-1.24586	-1.15348	-1.34032
		Std.err	0.19950	0.21762	0.19340	0.24159
		t-value	-5.78201	-5.72504	-5.96426	-5.54798
		$Pr(>\|t\|)$	< 2e-16	< 2e-16	< 2e-16	< 2e-16
		Signif.	***	***	***	***
	log(NTG)	Estimate	0.57734	0.57152	0.58330	0.62977
		Std.err	0.03813	0.04126	0.03697	0.04618
		t-value	15.13989	13.85105	15.77875	13.63760
		$Pr(>\|t\|)$	< 2e-16	< 2e-16	< 2e-16	< 2e-16
		Signif.	***	***	***	***
Overall		Res.std.err	1.163	1.158	1.128	1.409
		Df	173	144	173	173
		Mult. R-sqared	0.570	0.571	0.590	0.518
		Adj. R-squared	0.567	0.568	0.588	0.515
		F-statistic	229.2	191.9	249.0	186.0
		p-value	1.613e-33	2.890e-28	2.508e-35	3.161e-29

Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 0

The results of the base model applied to each tradable sector separately shows consistently statistically significant results at 0.001 level for all industries. An interesting observation are slightly higher coefficients for Machining (NACE 2562). This finding suggests, that of all the observed sectors, this is internationally the most competitive one. Again R-squared is over 0.5 for all industries, suggesting that we can explain a lot of variability in efficiency of tradable sectors with the variability in efficiency of non-tradable sectors, with one year lag.

5.5 Fixed effects models

5.5.1 Fixed effects model - basic

Basic fixed effects model with all countries individually expressed as dummy variables does not yield any valuable results. Model is specified as:

$$\begin{aligned}
log(trad_glob_eff)[t] \; = &\\
& \alpha + \\
& \beta_0 * log(nontrad_glob_eff)[t-1] + \\
& \beta_1 * AT_dummy + \beta_2 * CZ_dummy + \beta_3 * EE_dummy + \beta_4 * DE_dummy + \\
& \beta_5 * FI_dummy + \beta_6 * FR_dummy + \beta_7 * HR_dummy + \beta_8 * IT_dummy + \\
& \beta_9 * LT_dummy + \beta_10 * LV_dummy + \beta_11 * NL_dummy + \beta_12 * PT_dummy + \\
& \beta_13 * SK_dummy + \beta_14 * ES_dummy
\end{aligned} \tag{5.16}$$

Results of the basic fixed effects model can be seen in Table 5.5. Slovenia is taken into account as *base_country*.

This is a very attractive model. It has a high adjusted R-sqared with a value 0.87. The shifts between countries are clearly shown. Thus, we can reject Hypothesis 3_0, stated in Section 5.3. This suggests that the strength of the link between productivities of non-tradable and tradable sectors varies between countries, so we can accept the alternative Hypothesis 3_A.

Despite most country fixed effects coefficients being statistically signifficant, the non-tradable global efficiency coefficient is not. This suggests that most of the variability in the tradable global efficiency is due to fixed effects of each individual country and not due to efficiency of non-tradable sectors.

From the linear regression model assumptions checks presented in Table 5.6, we can see that regression assumptions are not satisfied. Thus, even though most of calculated regression coefficients are marked as statistically significant, results are invalid.

Due to relative strength of German economy, we try the model with German data removed from the pool. New **fixed effects model with individual countries without Germany** is thus specified

Table 5.5: Fixed effects basic

	Residuals				
	Min	1Q	Median	3Q	Max
	-2.88627	-0.36140	-0.02831	0.42966	1.87568
	Coefficients				
	Estimate	Std. err.	t-value	$\Pr(>\lvert t\rvert)$	Signif.
(Intercept)	-4.89809	0.16447	-29.781	< 2e-16	***
log_nontrad_global	-0.01275	0.02271	-0.561	0.575	
AT_dummy	2.02132	0.14963	13.509	< 2e-16	***
CZ_dummy	0.80420	0.14216	5.657	2.31e-08	***
EE_dummy	-1.29086	0.14803	-8.720	< 2e-16	***
DE_dummy	3.64109	0.17133	21.252	< 2e-16	***
FI_dummy	1.01998	0.14192	7.187	1.82e-12	***
FR_dummy	2.73365	0.14589	18.738	< 2e-16	***
HR_dummy	-0.71604	0.14233	-5.031	6.33e-07	***
IT_dummy	3.09106	0.16535	18.694	< 2e-16	***
LT_dummy	-2.01841	0.15490	-13.030	< 2e-16	***
LV_dummy	-1.69518	0.14120	-12.006	< 2e-16	***
NL_dummy	2.17887	0.15859	13.739	< 2e-16	***
PT_dummy	0.19949	0.16137	1.236	0.217	
SK_dummy	0.34594	0.14317	2.416	0.016	*
ES_dummy	2.11304	0.16238	13.013	< 2e-16	***
Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 0					
Residual standard error: 0.6768 on 651 degrees of freedom Multiple R-squared: 0.8681, Adjusted R-squared: 0.8651 F-statistic: 285.6 on 15 and 651 DF, p-value: < 2.2e-16					

Table 5.6: Fixed effects by individual country, base county Slovenia, regression assumptions tests

	Value	p-value	Decision
Global Stat	91.0464	0.000000	Assumptions NOT satisfied!
Skewness	19.0435	0.000013	Assumptions NOT satisfied!
Kurtosis	54.5305	0.000000	Assumptions NOT satisfied!
Link Function	0.1135	0.736186	Assumptions acceptable.
Heteroscedasticity	17.3589	0.000031	Assumptions NOT satisfied!

as:

$$
\begin{aligned}
log(trad\_glob\_eff)[t] \; = \; & \\
& \alpha + \\
& \beta_0 * log(nontrad\_glob\_eff)[t-1] + \\
& \beta_1 * AT\_dummy + \beta_2 * CZ\_dummy + \beta_3 * EE\_dummy + \beta_4 * FI\_dummy \\
& \beta_5 * FR\_dummy + \beta_6 * HR\_dummy + \beta_7 * IT\_dummy + \beta_8 * LT\_dummy + \\
& \beta_9 * LV\_dummy + \beta_10 * NL\_dummy + \beta_11 * PT\_dummy + \beta_12 * SK\_dummy + \\
& \beta_13 * ES\_dummy
\end{aligned}
\tag{5.17}
$$

Results are presented in the Table 5.7. Slovenia is taken into account as *base_country*.

Table 5.7: Fixed effects basic without Germany

	Residuals				
	Min	1Q	Median	3Q	Max
	-2.88559	-0.35980	-0.02953	0.42900	1.87564
	Coefficients				
	Estimate	Std. err.	t-value	$Pr(>\|t\|)$	Signif.
(Intercept)	-4.89516	0.17082	-28.657	< 2e-16	***
log_nontrad_global	-0.01224	0.02385	-0.513	0.6081	
AT_dummy	2.02020	0.15288	13.215	< 2e-16	***
CZ_dummy	0.80382	0.14480	5.551	4.25e-08	***
EE_dummy	-1.28986	0.15115	-8.534	< 2e-16	***
FI_dummy	1.01964	0.14454	7.054	4.76e-12	***
FR_dummy	2.73282	0.14884	18.361	< 2e-16	***
HR_dummy	-0.71563	0.14499	-4.936	1.03e-06	***
IT_dummy	3.08913	0.16981	18.192	< 2e-16	***
LT_dummy	-2.01697	0.15857	-12.720	< 2e-16	***
LV_dummy	-1.69508	0.14376	-11.791	< 2e-16	***
NL_dummy	2.17756	0.16217	13.428	< 2e-16	***
PT_dummy	0.19885	0.16446	1.209	0.2271	
SK_dummy	0.34540	0.14589	2.368	0.0182	*
ES_dummy	2.11124	0.16662	12.671	< 2e-16	***
Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 0					
Residual standard error: 0.689 on 606 degrees of freedom					
Multiple R-squared: 0.8462, Adjusted R-squared: 0.8427					
F-statistic: 238.2 on 14 and 606 DF, p-value: < 2.2e-16					

Again, some coefficients in Table 5.7 are not statistically significant, thus the model as a whole is not valid. However, in Table 5.5 and in Table 5.7, we can see that Croatia, a country that is not a member of EMU[43] area, also shows significant coefficients.

On the basis of the analysis of correlations between variables we suspected that multicollinearity is present. We checked for multicollinearity using standard variance inflation factors procedure. Results are presented in Table 5.8 and suggest no multicollinearity is present.

However, there is a chance that economically interwoven countries are responding as groups. In order to overcome this obstacle, a new model is prepared with countries grouped on the basis of geographical, historical or current economic and legislative constellation.

[43] Economic and Monetary Union of the European Union

Table 5.8: Variance inflation factors for fixed effects by individual country

Variable	Variance inflation
log_nontrad_global	4.01567
AT_dummy	2.09339
CZ_dummy	1.88959
EE_dummy	2.04884
DE_dummy	2.74452
FI_dummy	1.88335
FR_dummy	1.99012
HR_dummy	1.89417
IT_dummy	2.55633
LT_dummy	2.24357
LV_dummy	1.86410
NL_dummy	2.01621
PT_dummy	1.62887
SK_dummy	1.91647
ES_dummy	2.46544

5.5.2 Fixed effects model, groups

First, the grouping was made **according to historical and institutional similarities** between the countries. Countries were grouped as follows:

- Germanic: AT, DE, NL
- Romanic: IT, FR
- Pyraeneus: ES, PT
- Slavic: SI, HR, CZ, SK
- Baltic: LT, LV, EE, FI

Model is specified as:

$$\begin{aligned} log(trad\_glob\_eff)[t] \; = & \\ & \alpha + \\ & \beta_0 * log(nontrad\_glob\_eff)[t-1] + \\ & \beta_1 * romanic\_dummy + \beta_2 * slavic\_dummy + \\ & \beta_3 * pyraeneus\_dummy + \beta_4 * baltic\_dummy \end{aligned} \tag{5.18}$$

Results are presented in the Table 5.9. *Germanic_group* is taken into account as base group. Assessment of the linear model assumptions using the global test on 4 degrees of freedom at level of significance 0.5 gives the results in the Table 5.10. All coefficients are statistically significant and presented in the Table 5.9. Measurements of regression assumptions presented in Table 5.10 show, that all the regression assumptions are not satisfied. Thus, the results are invalid.

Table 5.9: Fixed effects grouped on historical and istitutional environment

	Residuals				
	Min	1Q	Median	3Q	Max
	-3.8210	-0.6158	-0.0185	0.6373	2.7620
	Coefficients				
	Estimate	Std. err.	t-value	Pr(> $\|t\|$)	Signif.
(Intercept)	-1.46999	0.10639	-13.817	< 2e-16	***
log_nontrad_global	0.27849	0.02381	11.697	< 2e-16	***
romanic_dummy	0.37120	0.13175	2.817	0.00499	**
slavic_dummy	-1.71565	0.12896	-13.303	< 2e-16	***
pyraeneus_dummy	-1.16173	0.13975	-8.313	5.3e-16	***
baltic_dummy	-2.43266	0.14781	-16.458	< 2e-16	***
Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 0					
Residual standard error: 0.9669 on 661 degrees of freedom					
Multiple R-squared: 0.7267, Adjusted R-squared: 0.7246					
F-statistic: 351.4 on 5 and 661 DF, p-value: < 2.2e-16					

Table 5.10: Fixed effects grouped on historical and institutional characteristics, regression assumptions tests

	Value	p-value	Decision
Global Stat	15.1180	0.004463	Assumptions NOT satisfied!
Skewness	2.0283	0.154392	Assumptions acceptable.
Kurtosis	0.8424	0.358716	Assumptions acceptable.
Link Function	9.3792	0.002195	Assumptions NOT satisfied!
Heteroscedasticity	2.8681	0.090349	Assumptions acceptable.

To make the picture about Germany as clear as possible, we tried another variant of the **model with grouping made in a way to isolate German influence** as much as possible. Thus, Austria and Germany are grouped together. Netherlands is observed individually, and this is also the case for Slovenia. Especially for Slovenia, we suspect that its economy is highly intertwined with the German economy. Despite the late historical and institutional similarities with Slavic group, Slovenia is observed separately. Countries were grouped as follows:

- Slovenia: SI
- Netherlands: NL
- Germanic: AT, DE
- Romanic: IT, FR
- Pyraeneus: ES, PT

- Slavic: HR, CZ, SK
- Baltic: LT, LV, EE, FI

Model is specified as:

$$\begin{aligned} log(trad\_glob\_eff)[t] \ = \\ \alpha + \\ \beta_0 * log(nontrad\_glob\_eff)[t-1] + \\ \beta_1 * SI\_dummy + \beta_2 * NL\_dummy + \\ \beta_3 * romanic\_dummy + \beta_4 * slavic\_dummy + \\ \beta_5 * pyraeneus\_dummy + \beta_6 * baltic\_dummy \end{aligned} \tag{5.19}$$

Results are presented in the Table 5.11. *Germanic_group* is taken into account as base group.

Table 5.11: Fixed effects with German influence isolated

	Residuals				
	Min	1Q	Median	3Q	Max
	-3.8174	-0.6320	-0.0141	0.6347	2.7650
	Coefficients				
	Estimate	Std. err.	t-value	Pr(> $\|t\|$)	Signif.
(Intercept)	-1.34556	0.11710	-11.491	<2e-16	***
log_nontrad_global	0.27312	0.02384	11.457	<2e-16	***
SI_dummy	-1.90660	0.19033	-10.018	<2e-16	***
NL_dummy	-0.46698	0.18477	-2.527	0.0117	*
romanic_dummy	0.23040	0.14262	1.615	0.1067	
slavic_dummy	-1.85736	0.14698	-12.637	<2e-16	***
pyraeneus_dummy	-1.30293	0.15004	-8.684	<2e-16	***
baltic_dummy	-2.59383	0.16038	-16.173	<2e-16	***
Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 0					
Residual standard error: 0.9636 on 659 degrees of freedom					
Multiple R-squared: 0.7293, Adjusted R-squared: 0.7264					
F-statistic: 253.7 on 7 and 659 DF, p-value: < 2.2e-16					

Again, not all coefficients in Table 5.11 are not significant. We test for multicollinearity again. The results presented in Table 5.12.

Variance inflation factors do not suggest any multicollinearity.

We continue with the search for plausible model with the **fixed effects model with grouping according to common markets**. Countries were grouped as follows:

- Germany focused markets: AT, DE, SI, NL
- Romanic markets: IT, FR

Table 5.12: Variance inflation factors for fixed effects with isolated Germany effect

Variable	Variance inflation
log_nontrad_global	2.18336
SI_dummy	1.67077
NL_dummy	1.35010
romanic_dummy	1.73737
slavic_dummy	2.54630
pyraeneus_dummy	1.63269
baltic_dummy	3.69076

- Pyraeneus markets: ES, PT
- Predominantly slavic markets: HR, CZ, SK
- Baltic markets: LT, LV, EE, FI

Model is specified as:

$$\begin{aligned} & log(trad\_glob\_eff)[t] \ = \\ & \quad \alpha + \\ & \quad \beta_0 * log(nontrad\_glob\_eff)[t-1] + \\ & \quad \beta_1 * romanic\_dummy + \beta_2 * slavic\_dummy + \\ & \quad \beta_3 * pyraeneus\_dummy + \beta_4 * baltic\_dummy \end{aligned} \tag{5.20}$$

Results are presented in Table 5.13. $Germany\_focused\_markets$ are taken into account as base group.

Assessment of the linear model assumptions using the global test on 4 degrees of freedom at level of significance 0.5 gives the results in the Table 5.14.

From Figure 5.3 and from the Table 5.14, we can see that regression assumptions are satisfied. All regression coefficients in Table 5.13 are higly statistically significant. Based on the evidence we can conclude, that the model is valid. Multiple R-squared is also very high.

This result proves a strong connection between the change relative efficiency of non-tradable sectors from one country on a lagged relative efficiency of tradable sectors form one country in the global market. There is clearly a link between productivities of non-tradable and tradable sectors, we reject Hypothesis 1_0 and accept the alternative Hypothesis 1_A, stated in Section 5.3.

Romanic dummy coefficients are positive in *fixed effects model, grouped according to common market focus*. This may be counterintuitive, since one would expect the coefficient belonging to Germany to be the highest. Because we are observing change of efficiency in tradable sectors in response to change of efficiency in non-tradable sectors, despite its expected highest productivity, the German

Figure 5.3: Fixed effects model, groups according to common market focus, regression assumptions plot

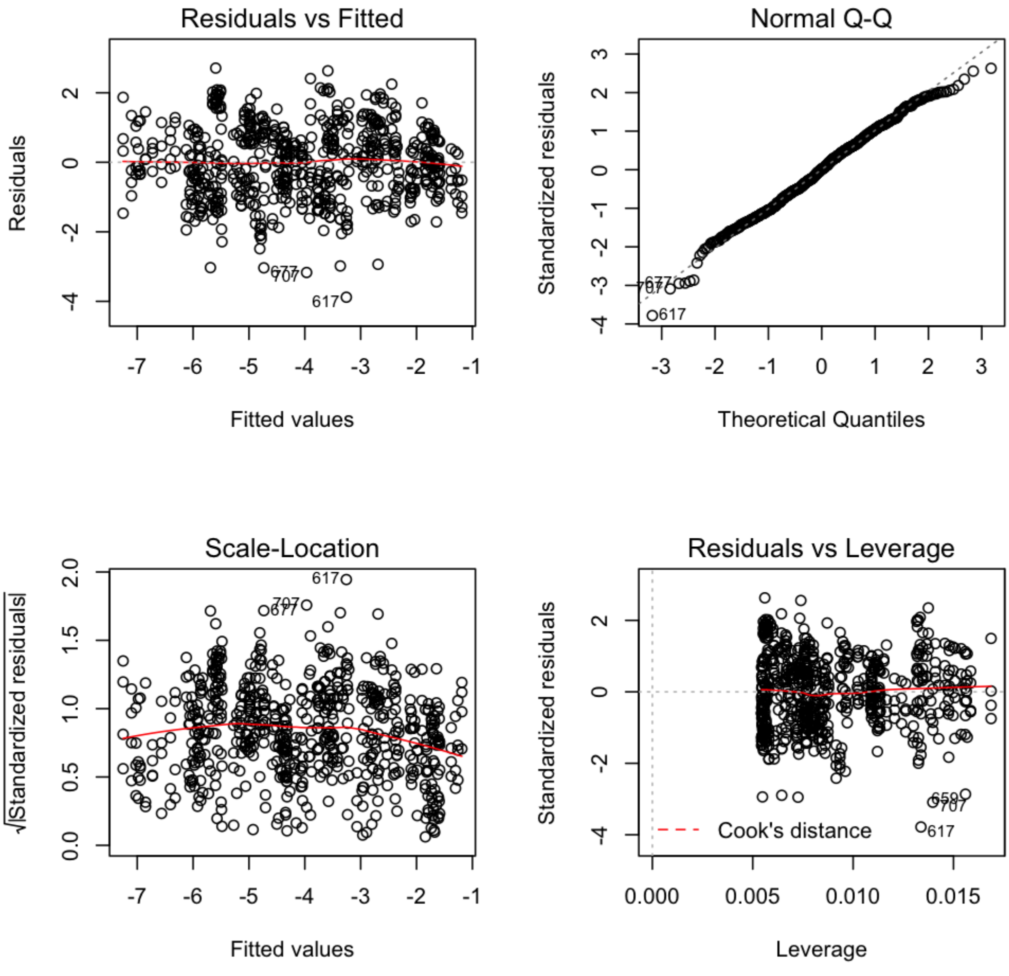


Table 5.13: Fixed effects grouped by common market focus

	Residuals				
	Min	1Q	Median	3Q	Max
	-3.8817	-0.6998	0.0136	0.7105	2.7093
	Coefficients				
	Estimate	Std. err.	t-value	Pr(> $\|t\|$)	Signif.
(Intercept)	-1.60171	0.11281	-14.198	< 2e-16	***
log_nontrad_global	0.37071	0.02334	15.886	< 2e-16	***
romanic_dummy	0.78377	0.13323	5.883	6.4e-09	***
slavic_dummy	-1.07187	0.12557	-8.536	< 2e-16	***
pyraeneus_dummy	-0.74227	0.14198	-5.228	2.3e-07	***
baltic_dummy	-1.67030	0.13370	-12.493	< 2e-16	***
Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 0					
Residual standard error: 1.033 on 661 degrees of freedom					
Multiple R-squared: 0.6879, Adjusted R-squared: 0.6855					
F-statistic: 291.4 on 5 and 661 DF, p-value: < 2.2e-16					

Table 5.14: Fixed effects grouped on common market focus, regression assumptions tests

	Value	p-value	Decision
Global Stat	4.7034	0.3191	Assumptions acceptable.
Skewness	2.0758	0.1497	Assumptions acceptable.
Kurtosis	0.2977	0.5853	Assumptions acceptable.
Link Function	0.0511	0.8212	Assumptions acceptable.
Heteroscedasticity	2.2788	0.1312	Assumptions acceptable.

change has lower response to increase of efficiency of already very efficient tradable sector on change of efficiency in already very efficient non-tradable sector, as is the case in Romanic countries. It is possible, that Romanic countries are operating in the range of efficiencies, where the response of tradable sector efficiency change to non-tradable sector efficiency change is higher.

To further test our findings, we specify a model with interaction terms:

$$\begin{aligned}
&log(trad_glob_eff)[t] = \\
&\quad \alpha + \\
&\quad \beta_0 * log(nontrad_glob_eff)[t-1] + \\
&\quad \beta_1 * romanic_dummy + \beta_2 * slavic_dummy + \\
&\quad \beta_3 * pyraeneus_dummy + \beta_4 * baltic_dummy + \\
&\quad \beta_5 * log(nontrad_glob_eff)[t-1] * romanic_dummy + \\
&\quad \beta_6 * log(nontrad_glob_eff)[t-1] * slavic_dummy + \\
&\quad \beta_7 * log(nontrad_glob_eff)[t-1] * pyraeneus_dummy + \\
&\quad \beta_8 * log(nontrad_glob_eff)[t-1] * baltic_dummy
\end{aligned} \tag{5.21}$$

Results are presented in Table 5.15. *Germany_focused_markets* are taken into account as base group.

Table 5.15: Fixed effects grouped by common market focus with interaction terms

	Residuals				
	Min	1Q	Median	3Q	Max
	-3.8596	-0.6807	-0.0085	0.6849	2.8646
	Coefficients				
	Estimate	Std. err.	t-value	$\Pr(>\lvert t\rvert)$	Signif.
(Intercept)	-1.15906	0.15320	-7.566	1.31e-13	***
log_nontrad_global	0.49694	0.03791	13.107	< 2e-16	***
romanic_dummy	-0.57295	0.28066	-2.041	0.0416	*
slavic_dummy	-1.84939	0.42404	-4.361	1.50e-05	***
pyraeneus_dummy	-1.28966	0.29217	-4.414	1.19e-05	***
baltic_dummy	-2.17843	0.32567	-6.689	4.81e-11	***
log_NT_glob*r_dum	-0.42637	0.07873	-5.416	8.57e-08	***
log_NT_glob*s_dum	-0.18797	0.08062	-2.332	0.0200	*
log_NT_glob*p_dum	-0.15980	0.08006	-1.996	0.0463	*
log_NT_glob*b_dum	-0.13580	0.05554	-2.445	0.0147	*
Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 0					
Residual standard error: 1.013 on 657 degrees of freedom					
Multiple R-squared: 0.702, Adjusted R-squared: 0.6979					
F-statistic: 171.9 on 9 and 657 DF, p-value: < 2.2e-16					

Table 5.16: Fixed eff. grouped common market focus with interactions, reg. assump. tests

	Value	p-value	Decision
Global Stat	6.7769	0.14816	Assumptions acceptable.
Skewness	1.7255	0.18899	Assumptions acceptable.
Kurtosis	0.1251	0.72352	Assumptions acceptable.
Link Function	1.5602	0.21164	Assumptions acceptable.
Heteroscedasticity	3.3661	0.06655	Assumptions acceptable.

Again, all coefficients are significant at least at 5%. Also, all regression assumptions are satisfied.

5.5.3 Fixed effects model, groups, fixed market shares

At the end of Subsection 5.2, concern is expressed that computation of regression input scores by varying market shares and DEA scores at the same time may result in endogeneity. In order to make sure, that the validity of the models is not a consequence of endogenous construction, below we estimate models with fixed, average market shares of companies. Thus, the only quantity varying is DEA score.

The first model is a fixed effects model with grouping according to common markets, as described in the previous subsection. Country grouping is the same, the only thing that is changed are the computed regression input scores, which are based on fixed market shares.

Model is again specified as:

$$
\begin{aligned}
log(trad\_glob\_eff)[t] \;=\; & \\
& \alpha + \\
& \beta_0 * log(nontrad\_glob\_eff)[t-1] + \\
& \beta_1 * romanic\_dummy + \beta_2 * slavic\_dummy + \\
& \beta_3 * pyraeneus\_dummy + \beta_4 * baltic\_dummy
\end{aligned} \tag{5.22}
$$

Table 5.17: Fixed effects grouped by common market focus, fixed market shares

	Residuals				
	Min	1Q	Median	3Q	Max
	-2.8006	-0.6791	-0.0136	0.6637	2.6212
	Coefficients				
	Estimate	Std. err.	t-value	$Pr(>\|t\|)$	Signif.
(Intercept)	-1.55496	0.10498	-14.812	< 2e-16	***
log_nontrad_global	0.37490	0.02177	17.220	< 2e-16	***
romanic_dummy	0.78149	0.12373	6.316	4.92e-10	***
slavic_dummy	-1.08363	0.11648	-9.303	< 2e-16	***
pyraeneus_dummy	-0.70312	0.13170	-5.339	1.29e-07	***
baltic_dummy	-1.63792	0.12400	-13.209	< 2e-16	***
Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 0					
Residual standard error: 0.9586 on 661 degrees of freedom					
Multiple R-squared: 0.719, Adjusted R-squared: 0.7169					
F-statistic: 338.3 on 5 and 661 DF, p-value: < 2.2e-16					

Table 5.18: Fixed effects common market focus, fixed mkt. shares, regression assumptions tests

	Value	p-value	Decision
Global Stat	8.3867106	0.078397	Assumptions acceptable.
Skewness	0.5051987	0.477225	Assumptions acceptable.
Kurtosis	7.6190440	0.005776	Assumptions NOT satisfied!
Link Function	0.0002915	0.986378	Assumptions acceptable.
Heteroscedasticity	0.2621764	0.608629	Assumptions acceptable.

As we can see from the Table 5.17, all coefficients are still highly significant. However, regression assumptions tests in Table 5.18 show, that kurtosis assumption is violated. This suggests, that there are outliers - companies that with average market shares have larger than expected impact on the results.

We proceed with the fixed effects model with above model augmented with interaction terms.

Table 5.19: Fixed effects grouped by common market focus with interaction terms, fixed market shares

	Residuals				
	Min	1Q	Median	3Q	Max
	-2.7916	-0.6405	-0.0616	0.6169	2.6270
	Coefficients				
	Estimate	Std. err.	t-value	Pr(> $\|t\|$)	Signif.
(Intercept)	-1.11810	0.14242	-7.851	1.69e-14	***
log_nontrad_global	0.49947	0.03531	14.147	< 2e-16	***
romanic_dummy	-0.54906	0.25726	-2.134	0.03319	*
slavic_dummy	-1.91403	0.39033	-4.904	1.19e-06	***
pyraeneus_dummy	-1.17785	0.27703	-4.252	2.43e-05	***
baltic_dummy	-2.14172	0.30065	-7.124	2.77e-12	***
log_NT_glob*r_dum	-0.42391	0.07298	-5.808	9.83e-09	***
log_NT_glob*s_dum	-0.19731	0.07444	-2.651	0.00823	**
log_NT_glob*p_dum	-0.13662	0.07613	-1.795	0.07317	.
log_NT_glob*b_dum	-0.13439	0.05151	-2.609	0.00928	**
Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 0					
Residual standard error: 0.9364 on 657 degrees of freedom					
Multiple R-squared: 0.7335, Adjusted R-squared: 0.7299					
F-statistic: 200.9 on 9 and 657 DF, p-value: < 2.2e-16					

As we can see from the Table 5.19, all coefficients are significant. Only one interaction term is weakly significant. However, this time all the regression assumptions shown in Table 5.20 are satisfied.

Table 5.20: Fixed effects grouped by common market focus with interactions and fixed market shares, regression assumptions tests

	Value	p-value	Decision
Global Stat	5.8074754	0.21399	Assumptions acceptable.
Skewness	0.7832184	0.37616	Assumptions acceptable.
Kurtosis	3.1260890	0.07705	Assumptions acceptable.
Link Function	1.8972367	0.16839	Assumptions acceptable.
Heteroscedasticity	0.0009313	0.97565	Assumptions acceptable.

Despite the fact that all variations of fixed effects models where countries are grouped according to the common market show that there is a positive relationship between $log(trad\_glob\_eff)[t]$ and $log(nontrad\_glob\_eff)[t-1]$, conclusions should be further verified as specified in Section 6.

6 LIMITATIONS OF THE STUDY

6.1 Assumption regarding distributions of variables

In Section 4 on missing value imputation and in Subsection 2.8 on outlier detection some assumptions of log-normality if the variables are stated. Due to large sample size formal Shapiro-Wilkes and Komogorov-Smirnov tests yielded results that suggest a distribution different from log-normal. Results for Shapiro-Wilkes test are reported in Table 3.8.

Because the two-step imputation method we used to impute missing values does not rely on normality assumptions, failing normality tests should not be seen as a major concern.

The story is a bit different for outlier detection, since we do not know how much exactly does $mean + / - 3 * standard\_deviation$ rule cut away. Expected impact of this problem is again small, since companies with significant market share were kept in the sample anyway.

6.2 Missing regressors of substance

In the models presented throughout the study, we do not include exchange rates, interest rates, inflation, quality of infrastructure or elements of the I-O matrices. We looked into the possibility of inclusion of I-O matrices, but the granularity of available data does not correspond to NACE 4 digit code used to identify the industries in this study. We are aware that these are very important variables that impact the productivities of tradable and non-tradable sectors. As a consequence, our models may suffer from endogeneity introduced through omitted variable bias.

6.3 Unbalanced panel estimated using OLS

As described in the thesis, the panel we analyze is unbalanced. Despite this fact, we were estimating the regression coefficients using OLS. The results of such procedure are only valid, provided that firms are entering and leaving the dataset at random. In real life this is hardly the fact. In order to estimate regression coefficients of the unbalanced panel better, more advanced methods could be used.

7 CONCLUSION

7.1 Theoretical implications

As described in the Chapter 1, economic relationship and relative prices between non-tradables and tradables play an important role in increasingly reduced set of tools that are at disposal to policy makers in small open economies, that are members of monetary and trade unions. In order to maximize a utility function describing *welfare*, countries used to keep their inflation in check with exchange rates and interest rates. This monetary policy drivers are gone with a membership of a country in a monetary union. The only set of levers available is the set of fiscal policy tools.

Taking into account frictions in labor market and nominal prices of non-tradable sectors, with an aim to increase the productivity of economy, countries can control the relative prices in non-tradable sectors and lower the *output gap*. Without the ability to control inflation through the instrument of *interest rates*, this provides an option to increase the utility in the welfare function.

The research results presented in this thesis provide an empirical proof of the relationship between efficiencies of non-tradable and tradable sectors of any national economy in relation to global market efficiency. It is a microeconomical support for ideas that are based on the macroeconomic literature.

7.2 Policy implications

From the available literature and empirical findings it is possible to conclude, that in a small open economy, with exchange rates and interest rates being out of its control, the country can focus on improving the productivity of its non-tradable sectors. This way it can indirectly control the relative prices, that in effect influence the real exchange rate, PPP and result in higher utility scores of the welfare function.

Each country's fiscal authority needs to trade-off between the supply of an efficient level of public goods and the stabilization of domestic inflation and output gap. Such a stabilizing role for fiscal policy is desirable not only from the viewpoint of each individual country, but also from that of the union as a whole and does not result in beggar-thy-neighbor policies. The strength of the countercyclical fiscal response increases with the importance of nominal rigidities. If the goods and services are less substitutable like it is the case in non-tradable sectors, it is optimal from a cooperative perspective to set fiscal policy such as to reduce intra-union imbalances. When prices are sticky, or when the re-allocation of labor across sectors within countries is inefficient, reducing the inefficiencies from imperfect risk sharing does not come at the expense of greater output gaps (Gali and Monacelli, 2008; Hjortsoe, 2016). Such finding may call into question the desirability of imposing external constraints on a currency union's members ability to conduct countercyclical fiscal policies, when the latter seek to limit the size of the domestic output gap and inflation differentials resulting from idiosyncratic shocks.

A small open economy like Slovenia should explicitly target the efficiency of its non-tradable sectors. Since the trading companies are already operating at a more efficient level, this is a possible way to correct the amplitude of the inappropriate signals or indicators used by European Union to measure the status of national economies. Otherwise, a misinformed policy authority may require fiscal policy restrictions, that can have disastrous effects in the years to come.

7.3 Suggestions for further research

It would be interesting to conduct such research on a dataset with input and output data of the companies. The decomposition of (in)efficiencies that can be conducted with the help of DEA is offering a well of research opportunities. It provides an augmentation to the "sources of growth analysis", which used to be concerned primarily with the degree to which output growth is due to technological factors (productivity) versus capital formation (Hulten, 2001).

Models in our research were checked for multicollinearity using variation inflation factors analysis. No multicollinearity was found. However, the interesting results of models with grouped countries suggest, that there is some mechanism at work. Producing an analysis using methodology that can account for the panel data cointegration as suggested by Banerjee and Carrion-i Silvestre (2006) might produce empirical basis for grupation of countries.

There is by now a relatively large literature measuring the cross border effects of conventional and unconventional monetary policies. Latest research on monetary policy cooperation puts forward a key conclusion, that the desirability of cooperation is highly model specific and some potentially important shocks and propagation channels are still poorly understood. Given the state of our knowledge, it is better to be cautious before drawing policy conclusions. More research is thus needed (Claessens et al., 2015).

If we assume a small open economy, that is a part of monetary union, monetary policy variables can be assumed fixed. Beside the interest rate and exchange rates, inflation can also be assumed fixed for some practical purposes. Under a given technology and the target of minimal output gap, possibly the only thing that can change in order to increase efficiency, is the decrease in costs of labor in non-tradable sectors. This is worth investigating.

REFERENCES

Abramovitz, M. (1956). Resource and output trends in the united states since 1870. In *Resource and output trends in the United States since 1870* (pp. 1–23)NBER.

Abrell, J., Ndoye, A., & Zachmann, G. (2011). Assessing the impact of the eu ets using firm level data. *Brussels: Bruegel*.

Aggarwal, C. C. (2013). An introduction to outlier analysis. In *Outlier Analysis* (pp. 1–40)Springer.

Ali, A. I. & Seiford, L. M. (1993). The mathematical programming approach to efficiency analysis. *The measurement of productive efficiency* (pp. 120–159).

Andrew, B. & Selamat, A. (2012). Systematic literature review of missing data imputation techniques for effort prediction,[in:] 2012 international conference on information and knowledge management.

Aparicio, J., Pastor, J. T., & Ray, S. C. (2013). An overall measure of technical inefficiency at the firm and at the industry level: The 'lost profit on outlay'. *European Journal of Operational Research*, *226*(1), 154–162.

Arnold, J. M., Javorcik, B. S., & Mattoo, A. (2011). Does services liberalization benefit manufacturing firms?: Evidence from the czech republic. *Journal of International Economics*, *85*(1), 136–146.

Auguie, B. (2016). *gridExtra: Miscellaneous Functions for "Grid" Graphics*. R package version 2.2.1.

Bacchetta, P. & Van Wincoop, E. (2000). Does exchange-rate stability increase trade and welfare? *American Economic Review* (pp. 1093–1109).

Baily, M. N., Hulten, C., Campbell, D., Bresnahan, T., & Caves, R. E. (1992). Productivity dynamics in manufacturing plants. *Brookings papers on economic activity. Microeconomics*, *1992*, 187–267.

Banerjee, A. & Carrion-i Silvestre, J. L. (2006). Cointegration in panel data with breaks and cross-section dependence.

Battese, G. E. (1997). A note on the estimation of cobb-douglas production functions when some explanatory variables have zero values. *Journal of agricultural Economics*, *48*(1-3), 250–252.

Benigno, G. & Benigno, P. (2003). Price stability in open economies. *The Review of Economic Studies*, *70*(4), 743–764.

Bernanke, B. S., Gertler, M., & Gilchrist, S. (1999). The financial accelerator in a quantitative business cycle framework. *Handbook of macroeconomics*, *1*, 1341–1393.

Bernanke, B. S. & Mishkin, F. S. (1997). Inflation targeting: a new framework for monetary policy?, National bureau of economic research.

Betts, C. & Devereux, M. (2001). The international effects of monetary and fiscal policy in a two-country model. *Money, capital mobility, and trade: Essays in honor of Robert A. Mundell* (pp. 9–52).

Betts, C. M. & Kehoe, T. J. (2008). Real exchange rate movements and the relative price of non-traded goods, National Bureau of Economic Research.

Boeri, T. & Garibaldi, P. (2012). Financial shocks and the labor markets: should economic policy save jobs? In Canuto, O., Leipziger, D., & Bank, W. (Eds.), *Ascent After Decline: Regrowing Global Economies After the Great Recession*, The growth dialogue (pp. 201–217)World Bank Publications.

Bogetoft, P. & Otto, L. (2015). *Benchmarking with DEA and SFA*. R package version 0.26.

Bole, V. (2006). Fiscal policy in slovenia after entering euro, new goals and soundness. *The Journal for Money and Banking*, *55*(11), 91–98.

Bole, V. (2016). Unpublished.

Bole, V., Oblak, A., Prašnikar, J., & Trobec, D. (2014a). Financial frictions and indebtedness of firms: Balkan countries vs. mediterranean and central european countries.

Bole, V., Prašnikar, J., & Trobec, D. (2012). Debt accumulation: dynamics, structure and mechanisms. *Unpublished paper, Faculty of Economics, Ljubljana.*

Bole, V., Prašnikar, J., & Trobec, D. (2014b). Policy measures in the deleveraging process: A macroprudential evaluation. *Journal of Policy Modeling*, *36*(2), 410–432.

Bortolotti, B., Faccio, M., et al. (2004). *Reluctant privatization*Fondazione ENI Enrico Mattei.

Bradley, S., Hax, A., & Magnanti, T. (1977). *Applied mathematical programming*Addison Wesley.

Buiter, W. H. (2009). The unfortunate uselessness of most'state of the art'academic monetary economics. *VoxEU, Research-based policy analysis and commentary from leading economists.*

Burstein, A. T., Neves, J. C., & Rebelo, S. (2003). Distribution costs and real exchange rate dynamics during exchange-rate-based stabilizations. *Journal of monetary Economics*, *50*(6), 1189–1214.

Calvo, G. A. (1983). Staggered prices in a utility-maximizing framework. *Journal of monetary Economics*, *12*(3), 383–398.

Cazes, S., Khatiwada, S., & Malo, M. (2012). Employment protection and collective bargaining: Beyond the deregulation agenda, International Labour Organization.

Chambers, R. G., Chung, Y., & Färe, R. (1998). Profit, directional distance functions, and nerlovian efficiency. *Journal of Optimization Theory and Applications*, *98*(2), 351–364.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European journal of operational research*, *2*(6), 429–444.

Charnes, A., Cooper, W. W., & Rhodes, E. (1981). Evaluating program and managerial efficiency: an application of data envelopment analysis to program follow through. *Management science*, *27*(6), 668–697.

Chen, H., Kondratowicz, M., & Yi, K.-M. (2005). Vertical specialization and three facts about us international trade. *The North American Journal of Economics and Finance*, *16*(1), 35–59.

Chen, M., Mao, S., Zhang, Y., & Leung, V. C. (2014). *Big data: related technologies, challenges and future prospects*Springer.

Christiano, L. J., Motto, R., & Rostagno, M. (2004). The great depression and the friedman-schwartz hypothesis, National Bureau of Economic Research.

Christiano, L. J., Trabandt, M., & Walentin, K. (2011). Introducing financial frictions and unemployment into a small open economy model. *Journal of Economic Dynamics and Control*, *35*(12), 1999–2041.

Christoffel, K. P. & Linzert, T. (2005). The role of real wage rigidity and labor market frictions for unemployment and inflation dynamics.

Claessens, S., Stracca, L., & Warnock, F. E. (2015). International dimensions of conventional and unconventional monetary policy. *Journal of International Money and Finance.*

Clarida, R. & Gali, J. (1994). Sources of real exchange-rate fluctuations: How important are nominal shocks? In *Carnegie-Rochester conference series on public policy*, volume 41 (pp. 1–56). Elsevier.

Clarida, R., Gali, J., & Gertler, M. (1999). The science of monetary policy: a new keynesian perspective, National bureau of economic research.

Clarida, R., Gali, J., & Gertler, M. (2001). Optimal monetary policy in closed versus open economies: An integrated approach, National Bureau of Economic Research.

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., & Battese, G. E. (2005). *An introduction to efficiency and productivity analysis*Springer Science & Business Media.

Corsetti, G., Dedola, L., & Leduc, S. (2010). Optimal monetary policy in open economies.

Corsetti, G. & Pesenti, P. (2001). Welfare and macroeconomic interdependence. *Quarterly Journal of Economics*, *CXVI(2)*, 421–446.

Damijan, J. P., Polanec, S., & Prašnikar, J. (2004). Self-selection, export market heterogeneity and productivity improvements: Firm level evidence from slovenia, LICOS Discussion paper.

Davis, S. J. & Haltiwanger, J. (1991). Wage dispersion between and within us manufacturing plants, 1963-1986, National Bureau of Economic Research.

Domadenik, P., Farčnik, D., & Trobec, D. (2012). Slovenia. In Prašnikar, J. (Ed.), *Comparing Companies' Success in Dealing with External Shocks: The Case of the Western Balkans, Mediterranean Countries and Core European Countries* (pp. 45–68)Časnik Finance.

Domadenik, P., Prašnikar, J., & Svejnar, J. (2003). Defensive and strategic restructuring of firms during the transition to a market economy.

Domar, E. D. (1961). On the measurement of technological change. *The Economic Journal*, *71*(284), 709–729.

Duranton, G. & Overman, H. G. (2005). Testing for localization using micro-geographic data. *The Review of Economic Studies*, *72*(4), 1077–1106.

Eekhout, I. (2015). *Don't Miss Out!: Incomplete data can contain valuable information*. PhD thesis.

Eggertsson, G. B., Mehrotra, N. R., Singh, S. R., & Summers, L. H. (2016a). A contagious malady? open economy dimensions of secular stagnation, National Bureau of Economic Research.

Eggertsson, G. B., Mehrotra, N. R., & Summers, L. H. (2016b). Global reserve assets in a low interest rate world secular stagnation in the open economy. *The American Economic Review*, *106*(5), 503–507.

Eichhorst, W., Escudero, V., Marx, P., & Tobin, S. (2010). The impact of the crisis on employment and the role of labour market institutions.

Enders, W. & Lee, B.-S. (1997). Accounting for real and nominal exchange rate movements in the post-bretton woods period. *Journal of International Money and finance*, *16*(2), 233–254.

Engel, C. (1999). Accounting for u.s. real exchange rate changes. *Journal of Political Economy*, *107*(3), 507–538.

Engel, C. (2011). Currency misalignments and optimal monetary policy: a reexamination. *The American Economic Review*, *101*(6), 2796–2822.

Fagiolo, G. & Roventini, A. (2016). Macroeconomic policy in dsge and agent-based models redux: New developments and challenges ahead. *Available at SSRN.*

Färe, R. & Grosskopf, S. (1996). *Intertemporal production frontiers: With dynamic DEA*Kluwer Academic Publishers.

Färe, R. & Grosskopf, S. (2000). Reference guide to onfront. *Economic Measurement and Quality Corporation.*

Färe, R. & Grosskopf, S. (2006). *New directions: efficiency and productivity*, volume 3Springer Science & Business Media.

Färe, R., Grosskopf, S., & Karagiannis, G. (2015). More on aggregating efficiency and productivity indicators.

Färe, R., Grosskopf, S., & Lovell, C. K. (1994). *Production frontiers*Cambridge University Press.

Färe, R., Grosskopf, S., & Lovell, C. K. (2013). *The measurement of efficiency of production*, volume 6Springer Science & Business Media.

Färe, R. & Karagiannis, G. (2014). A postscript on aggregate farrell efficiencies. *European Journal of Operational Research*, *233*(3), 784–786.

Färe, R. & Primont, D. (1995). *Multi-output production and duality: theory and applications*Kluwer Academic Publishers, Boston.

Färe, R. & Zelenyuk, V. (2003). On aggregate farrell efficiencies. *European Journal of Operational Research*, *146*(3), 615–620.

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society. Series A (General)*, *120*(3), 253–290.

Faruq, H. (2006). New evidence on product quality and trade.

Fisher, I. (1933). The debt-deflation theory of great depressions. *Econometrica: Journal of the Econometric Society* (pp. 337–357).

Fox, G. C., Williams, R. D., & Messina, G. C. (2014). *Parallel computing works!*Morgan Kaufmann.

Fox, K. J. (1999). Efficiency at different levels of aggregation: public vs. private sector firms. *Economics Letters*, *65*(2), 173–176.

Francois, J. F. (1990). Producer services, scale, and the division of labor. *Oxford Economic Papers*, *42*(4), 715–729.

Fratzscher, M., Lo Duca, M., & Straub, R. (2013). On the international spillovers of us quantitative easing.

Froot, K. A. & Rogoff, K. (1995). Perspectives on ppp and long-run real exchange rates. *Handbook of international economics*, *3*, 1647–1688.

Gali, J. & Monacelli, T. (2005). Monetary policy and exchange rate volatility in a small open economy. *The Review of Economic Studies*, *72*(3), 707–734.

Gali, J. & Monacelli, T. (2008). Optimal monetary and fiscal policy in a currency union. *Journal of international economics*, *76*(1), 116–132.

Giannakis, D., Jamasb, T., & Pollitt, M. (2005). Benchmarking and incentive regulation of quality of service: an application to the uk electricity distribution networks. *Energy Policy*, *33*(17), 2256–2271.

Griliches, Z. (1994). Productivity, r&d, and the data constraint. *The American Economic Review*, *84*(1), 1–23.

Guillen, J., Natale, F., & Polanco, J. M. F. (2015). Estimating the economic performance of the eu aquaculture sector. *Aquaculture International*, *23*(6), 1387–1400.

Hall, B. H., Mansfield, E., & Jaffe, A. B. (1993). Industrial research during the 1980s: Did the rate of return fall? *Brookings papers on economic activity. Microeconomics*, *1993*(2), 289–343.

Hjortsoe, I. (2016). Imbalances and fiscal policy in a monetary union. *Journal of International Economics*, *102*, 225–241.

Honaker, J., King, G., Blackwell, M., et al. (2011). Amelia ii: A program for missing data. *Journal of statistical software*, *45*(7), 1–47.

Hulten, C. R. (2001). Total factor productivity: a short biography. In *New developments in productivity analysis* (pp. 1–54)University of Chicago Press.

Humphrey, T. M. (1997). Algebraic production functions and their uses before cobb-douglas. *FRB Richmond Economic Quarterly*, *83*(1), 51–83.

Institute of macroeconomic analysis and development of Republic of Slovenia (2013). Development report 2013.

Jensen, J. B., Kletzer, L. G., Bernstein, J., & Feenstra, R. C. (2005). Tradable services: Understanding the scope and impact of services offshoring [with comments and discussion]. In *Brookings trade forum* (pp. 75–133). JSTOR.

Justiniano, A. & Preston, B. (2010). Monetary policy and uncertainty in an empirical small open-economy model. *Journal of Applied Econometrics*, *25*(1), 93–128.

Kapelko, M. & Lansink, A. O. (2015). An international comparison of productivity change in the textile and clothing industry: a bootstrapped malmquist index approach. *Empirical Economics*, *48*(4), 1499–1523.

Kazlauskas, K. & Pupeikis, R. (2014). Missing data restoration algorithm. *Informatica*, *25*(2), 209–220.

Kenen, P. (1969). The theory of optimum currency areas: an eclectic view. *Monetary problems of the international economy* (pp. 41–60).

Kim, H.-Y. (2013). Statistical notes for clinical researchers: assessing normal distribution (2) using skewness and kurtosis. *Restorative dentistry & endodontics*, *38*(1), 52–54.

Kmenta, J. (1997). *Elements of Econometrics*. Number v. 1University of Michigan Press.

Krugman, P. et al. (2011). The profession and the crisis. *Eastern Economic Journal*, *37*(3), 307.

Krugman, P. R. (1991). *Geography and trade*. MIT press.

Lastrapes, W. D. (1992). Sources of fluctuations in real and nominal exchange rates. *The review of economics and statistics* (pp. 530–539).

Li, K.-C., Jiang, H., Yang, L. T., & Cuzzocrea, A. (2015). *Big data: algorithms, analytics, and applications*CRC Press.

Little, R. J. & Rubin, D. B. (2014). *Statistical analysis with missing data*John Wiley & Sons.

Lovell, C. K. (1993). Production frontiers and productive efficiency. *The measurement of productive efficiency: techniques and applications* (pp. 3–67).

MacDonald, R. (2000). Concepts to calculate equilibrium exchange rates: an overview.

Maddison, A. (2007). *Contours of the World Economy 1-2030 AD: Essays in Macro-Economic History*Oxford University Press.

Malmquist, S. (1953). Index numbers and indifference surfaces. *Trabajos de Estadistica y de Investigacion Operativa*, *4*(2), 209–242.

McGahan, A. M. & Porter, M. E. (1997). How much does industry matter, really? *Strategic management journal* (pp. 15–30).

Mendoza, E. G. (2000). On the instability of variance decompositions of the real exchange rate across exchange-rate-regimes: evidence from mexico and the united states, National bureau of economic research.

Miller, J. N. (1993). Tutorial review—outliers in experimental data and their treatment. *Analyst*, *118*(5), 455–461.

Miller, M. & Stiglitz, J. (2010). Leverage and asset bubbles: averting armageddon with chapter 11? *The Economic Journal*, *120*(544), 500–518.

Mishra, S. K. (2007). A brief history of production functions. *Available at SSRN 1020577.*

Molnár, M. & Bottini, N. (2010). How large are competitive pressures in services markets?–estimation of mark-ups for selected oecd countries. *OECD Economic Studies, forthcoming.*

Monacelli, T. & Perotti, R. (2010). Fiscal policy, the real exchange rate and traded goods. *The Economic Journal*, *120*(544), 437–461.

Olinsky, A., Chen, S., & Harlow, L. (2003). The comparative efficacy of imputation methods for missing data in structural equation modeling. *European Journal of Operational Research*, *151*(1), 53–79.

Osborne, J. W. & Overbay, A. (2004). The power of outliers (and why researchers should always check for them). *Practical assessment, research & evaluation*, *9*(6), 1–12.

Ouyang, A. Y. & Rajan, R. S. (2013). Real exchange rate fluctuations and the relative importance of nontradables. *Journal of International Money and Finance*, *32*, 844–855.

Parwoll, M. & Wagner, R. (2012). The impact of missing values on pls model fitting. In *Challenges at the interface of data analysis, computer science, and optimization* (pp. 537–544)Springer.

Pena, E. A. & Slate, E. H. (2014). *gvlma: Global Validation of Linear Models Assumptions.* R package version 1.0.0.2.

Peugh, J. L. & Enders, C. K. (2004). Missing data in educational research: A review of reporting practices and suggestions for improvement. *Review of educational research*, *74*(4), 525–556.

Pigott, T. D. (2001). A review of methods for missing data. *Educational research and evaluation*, *7*(4), 353–383.

Prašnikar, J. (2010). *The role of intangible assets in exiting the crisis*Časnik Finance.

Prašnikar, J. (2011). *The Slovenian Economy: Stranded in Recovery*Časnik Finance.

Prašnikar, J., Farčnik, D., Trobec, D., & Marinšek, D. (2012). A comparison of the analyzed countries. In Prašnikar, J. (Ed.), *Comparing Companies' Success in Dealing with External Shocks: The Case of the Western Balkans, Mediterranean Countries and Core European Countries* (pp. 11–30)Časnik Finance.

Quintano, C., Castellano, R., & Rocca, A. (2010). Influence of outliers on some multiple imputation methods. *Metodoloski zvezki*, *7*(1), 1.

R Core Team (2016). *R: A Language and Environment for Statistical Computing.* R Foundation for Statistical Computing, Vienna, Austria.

Reinhart, C. M. & Rogoff, K. S. (2009). The aftermath of financial crises, National Bureau of Economic Research.

Restuccia, D. & Rogerson, R. (2008). Policy distortions and aggregate productivity with heterogeneous establishments. *Review of Economic dynamics*, *11*(4), 707–720.

Ricci, M. L. A., Lee, M. J., & Milesi-Ferretti, M. G.-M. (2008). *Real exchange rates and fundamentals: A cross-country perspective.* Number 8-13International Monetary Fund.

Rogers, J. H. (1999). Monetary shocks and real exchange rates. *Journal of International Economics*, *49*(2), 269–288.

Rogoff, K. (1996). The purchasing power parity puzzle. *Journal of Economic literature*, *34*(2), 647–668.

Rotemberg, J. J. & Woodford, M. (1999). Interest rate rules in an estimated sticky price model. In *Monetary policy rules* (pp. 57–126)University of Chicago Press.

Seiford, L. M. & Thrall, R. M. (1990). Recent developments in dea: the mathematical programming approach to frontier analysis. *Journal of econometrics*, *46*(1), 7–38.

Shepherd, R. W. (1953). *Cost and production functions*Princeton University Press.

Siddique, J. & Belin, T. R. (2008). Using an approximate bayesian bootstrap to multiply impute nonignorable missing data. *Computational statistics & data analysis*, *53*(2), 405–415.

Solow, R. M. (1957). Technical change and the aggregate production function. *The review of Economics and Statistics* (pp. 312–320).

Statistical office of Republic of Slovenia (2014). Gross domestic product 2014.

Stiglitz, J. E. (2011). Rethinking macroeconomics: What failed, and how to repair it. *Journal of the European Economic Association*, *9*(4), 591–645.

Tanguma, J. (2000). A review of the literature on missing data.

Taylor, J. B. (1993). Discretion versus policy rules in practice. In *Carnegie-Rochester conference series on public policy*, volume 39 (pp. 195–214). Elsevier.

Tinbergen, J. (1942). Zur theorie der langfristigen wirtschaftsentwick lung. *Weltwirtschaftliches Archiv*, *55*(1), 511–49.

Wagner, J. (2007). Exports and productivity: A survey of the evidence from firm-level data. *The World Economy*, *30*(1), 60–82.

Wickham, H. (2009). *ggplot2: Elegant Graphics for Data Analysis*Springer-Verlag New York.

Wilcox, R. R. (2012). *Introduction to robust estimation and hypothesis testing*Academic Press.

Wooldridge, J. (2009). *Introductory Econometrics: A Modern Approach.* ISE - International Student EditionSouth-Western Cengage Learning.

Yeşilova, A., Yilmaz, K., & Almali, M. N. (2011). A comparison of hot deck imputation and substitution methods in the estimation of missing data. *Gazi University Journal of Science*, *24*(1), 69–75.

Yourdon, E. & Constantine, L. L. (1979). *Structured design: Fundamentals of a discipline of computer program and systems design*Prentice-Hall, Inc.

APPENDICES

LIST OF APPENDICES

Appendix A:
Other evaluated models

A.1 Netherlands excluded

Table A.1: Fixed effects basic without Netherlands, base Slovenia

	Residuals				
	Min	1Q	Median	3Q	Max
	-2.88206	-0.35641	-0.03516	0.38419	1.87543
	Coefficients				
	Estimate	Std. err.	t-value	Pr(> $\lvert t \rvert$)	Signif.
(Intercept)	-4.87998	0.16767	-29.104	< 2e-16	***
log_nontrad_global	-0.00960	0.02348	-0.409	0.6828	
AT_dummy	2.01442	0.14936	13.487	< 2e-16	***
CZ_dummy	0.80183	0.14134	5.673	2.16e-08	***
EE_dummy	-1.28467	0.14764	-8.701	< 2e-16	***
DE_dummy	3.62763	0.17250	21.030	< 2e-16	***
FI_dummy	1.01789	0.14109	7.215	1.60e-12	***
FR_dummy	2.72852	0.14535	18.772	< 2e-16	***
HR_dummy	-0.71347	0.14152	-5.041	6.10e-07	***
IT_dummy	3.07912	0.16614	18.533	< 2e-16	***
LT_dummy	-2.00956	0.15500	-12.965	< 2e-16	***
LV_dummy	-1.69454	0.14030	-12.078	< 2e-16	***
PT_dummy	0.19554	0.16055	1.218	0.2237	
SK_dummy	0.34260	0.14242	2.405	0.0164	*
ES_dummy	2.10191	0.16299	12.896	< 2e-16	***
Signif. codes: ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 0					
Residual standard error: 0.6725 on 613 degrees of freedom					
Multiple R-squared: 0.872, Adjusted R-squared: 0.8691					
F-statistic: 298.4 on 14 and 613 DF, p-value: < 2.2e-16					

Table A.2: Fixed eff. basic wo NL, base Slovenia, reg. assumptions tests

	Value	p-value	Decision
Global Stat	111.5891	0.000000	Assumptions NOT satisfied!
Skewness	17.7595	0.000025	Assumptions NOT satisfied!
Kurtosis	71.1665	0.000000	Assumptions NOT satisfied!
Link Function	0.0597	0.807008	Assumptions acceptable.
Heteroscedasticity	22.6035	0.000002	Assumptions NOT satisfied!

Table A.3: Fixed effects grouped by common market focus NL excluded

	Residuals				
	Min	1Q	Median	3Q	Max
	-3.8817	-0.6998	0.0136	0.7105	2.7093
	Coefficients				
	Estimate	Std. err.	t-value	Pr(> $\|t\|$)	Signif.
(Intercept)	-1.60171	0.11281	-14.198	< 2e-16	***
log_nontrad_global	0.37071	0.02334	15.886	< 2e-16	***
romanic_dummy	0.78377	0.13323	5.883	6.4e-09	***
slavic_dummy	-1.07187	0.12557	-8.536	< 2e-16	***
pyraeneus_dummy	-0.74227	0.14198	-5.228	2.3e-07	***
baltic_dummy	-1.67030	0.13370	-12.493	< 2e-16	***
Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 0					
Residual standard error: 1.033 on 661 degrees of freedom					
Multiple R-squared: 0.6879, Adjusted R-squared: 0.6855					
F-statistic: 291.4 on 5 and 661 DF, p-value: < 2.2e-16					

Table A.4: Fixed eff. grouped by common market focus wo NL, regr. assump. tests

	Value	p-value	Decision
Global Stat	4.7034	0.3191	Assumptions acceptable.
Skewness	2.0758	0.1497	Assumptions acceptable.
Kurtosis	0.2977	0.5853	Assumptions acceptable.
Link Function	0.0511	0.8212	Assumptions acceptable.
Heteroscedasticity	2.2788	0.1312	Assumptions acceptable.

A.2 Reclassification of Hotels to non-tradable sectors

Table A.5: Fixed effects Hotels classified as non-tradable

	Residuals				
	Min	1Q	Median	3Q	Max
	-2.43957	-0.68700	-0.00359	0.68058	2.22111
	Coefficients				
	Estimate	Std. err.	t-value	$\Pr(>\|t\|)$	Signif.
(Intercept)	-1.28459	0.09891	-12.988	< 2e-16	***
log_nontrad_global	0.41788	0.02153	19.410	< 2e-16	***
romanic_dummy	0.37120	0.11449	3.242	0.00124	**
slavic_dummy	-1.22797	0.10645	-11.535	< 2e-16	***
pyraeneus_dummy	-1.36852	0.11829	-11.569	< 2e-16	***
baltic_dummy	-1.82560	0.11276	-16.190	< 2e-16	***
Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 0					
Residual standard error: 0.9271 on 742 degrees of freedom					
Multiple R-squared: 0.7383, Adjusted R-squared: 0.7365					
F-statistic: 418.6 on 5 and 742 DF, p-value: < 2.2e-16					

Table A.6: Fixed eff. Hotels classified as non-trad, reg. assumptions tests

	Value	p-value	Decision
Global Stat	15.26883	0.0041749	Assumptions NOT satisfied!
Skewness	0.02063	0.8857783	Assumptions acceptable.
Kurtosis	11.79510	0.0005939	Assumptions NOT satisfied!
Link Function	3.38725	0.0657025	Assumptions acceptable.
Heteroscedasticity	0.06584	0.7974965	Assumptions acceptable.

A.3 Reclassification of Electricity distribution to tradable sectors

Table A.7: Fixed effects Electricity distribution classified as tradable

	Residuals				
	Min	1Q	Median	3Q	Max
	-4.3005	-0.6369	0.0610	0.7796	2.7814
	Coefficients				
	Estimate	Std. err.	t-value	Pr(> $\|t\|$)	Signif.
(Intercept)	-1.53858	0.16262	-9.461	< 2e-16	***
log_nontrad_global	0.51712	0.03986	12.973	< 2e-16	***
romanic_dummy	0.61474	0.19157	3.209	0.00143	**
slavic_dummy	-0.92588	0.18218	-5.082	5.60e-07	***
pyraeneus_dummy	-0.51022	0.19389	-2.632	0.00881	**
baltic_dummy	-1.22329	0.20602	-5.938	6.02e-09	***
Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 0					
Residual standard error: 1.181 on 424 degrees of freedom					
Multiple R-squared: 0.6458, Adjusted R-squared: 0.6417					
F-statistic: 154.6 on 5 and 424 DF, p-value: < 2.2e-16					

Table A.8: Fixed eff. Electr. distr. classified as trad, reg. assumptions tests

	Value	p-value	Decision
Global Stat	119.5882	0.000e+00	Assumptions NOT satisfied!
Skewness	30.5175	3.309e-08	Assumptions NOT satisfied!
Kurtosis	13.1593	2.861e-04	Assumptions NOT satisfied!
Link Function	0.8436	3.584e-01	Assumptions acceptable.
Heteroscedasticity	75.0679	0.000e+00	Assumptions NOT satisfied!

A.4 Switch of basic independant and dependant variable

Model is specified as:

$$\begin{aligned} & log(non - trad\_glob\_eff)[t] \ = \\ & \quad \alpha + \\ & \quad \beta_0 * log(trad\_glob\_eff)[t-1] + \\ & \quad \beta_1 * romanic\_dummy + \beta_2 * slavic\_dummy + \\ & \quad \beta_3 * pyraeneus\_dummy + \beta_4 * baltic\_dummy \end{aligned} \tag{A.1}$$

Table A.9: Fixed effects, switched indep. and dep. variable:
Is non-tradable dependant on tradable?

	Residuals				
	Min	1Q	Median	3Q	Max
	-4.215	-1.046	0.036	1.099	3.809
	Coefficients				
	Estimate	Std. err.	t-value	Pr(> |t|)	Signif.
(Intercept)	-1.34397	0.17510	-7.675	5.94e-14	***
log_nontrad_global	0.74535	0.04692	15.886	< 2e-16	***
romanic_dummy	-0.25032	0.19355	-1.293	0.19635	
slavic_dummy	-0.58840	0.18620	-3.160	0.00165	**
pyraeneus_dummy	0.83312	0.20286	4.107	4.52e-05	***
baltic_dummy	-1.16598	0.20584	-5.665	2.20e-08	***
Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 0					
Residual standard error: 1.465 on 661 degrees of freedom					
Multiple R-squared: 0.6023, Adjusted R-squared: 0.5993					
F-statistic: 200.2 on 5 and 661 DF, p-value: < 2.2e-16					

Table A.10: Switched indep. and dep. variable, reg. assumptions tests

	Value	p-value	Decision
Global Stat	12.87261	0.011915	Assumptions NOT satisfied!
Skewness	0.04714	0.828110	Assumptions acceptable.
Kurtosis	7.17957	0.007374	Assumptions NOT satisfied!
Link Function	3.69788	0.054482	Assumptions acceptable.
Heteroscedasticity	1.94802	0.162801	Assumptions acceptable.

Appendix B:
Amadeus database coverage

B.1 Amadeus coverage of 44 countries by size

Table B.1: Amadeus coverage - 44 countries - by size and year

Year	Very large	Large	Medium	Small	Total
2013	75952	370706	2475607	13866406	16788671
2012	74452	360674	2330007	12728502	15493635
2011	70688	339795	2059033	11131536	13601052
2010	66607	325362	1970336	10313921	12676226
2009	62672	301885	1800043	8771401	10936001
2008	58166	275661	1577937	6831499	8743263
2007	54117	256492	1438676	5961440	7710725
2006	49105	231674	1255795	4702705	6239279
2005	15649	76852	460818	2009463	2562782

B.2 Amadeus coverage by number of employees

Table B.2: Amadeus coverage - companies by number of employees

Country	< 50	50 - 149	150 - 499	500 - 999	1000 - 4999	> 5000	NA	Total
AT	239519	5822	2379	565	431	114	4283	253113
FI	277974	3332	1304	298	254	57	12224	295443
FR	2175910	28148	10332	2101	1631	415	256148	2474685
DE	1547522	50989	17753	3934	3087	639	32510	1656434
IT	1066507	20615	6910	1417	1028	199	4456	1101132
NL	1138213	14740	5531	1345	1196	309	6140	1167474
PT	419032	5377	1558	271	243	37	4663	431181
ES	954006	14914	5195	1114	867	226	22204	998526
HR	122441	1737	643	114	63	8	1898	126904
CZ	445576	13115	8001	1389	925	145	36145	505296
EE	131187	950	305	47	15	1	2297	134802
LV	155180	1522	413	65	25	3	1604	158812
LT	107181	3614	841	131	58	7	456	112288
SK	213848	3807	1116	217	113	17	24275	243393
SI	78395	941	315	62	32	2	5556	85303

B.3 Amadeus coverage by operating revenue

Table B.3: Amadeus coverage - companies by operating revenue in th. EUR

Country	< 1000	1000 - 1999	2000 - 4999	5000 - 19999	> 20000	NA	Total
AT	164351	21411	16773	8718	4422	37443	253118
FI	262334	12926	8369	7260	2951	1618	295458
FR	2158701	148100	93480	50677	23781	91	2474830
DE	956472	139128	117553	72318	29596	341370	1656437
IT	879157	89992	72040	43836	18212	24	1103261
NL	909723	71976	46409	25303	14345	99900	1167656
PT	391121	16538	10928	6325	2459	4424	431795
ES	837113	63632	47293	27071	11596	11821	998526
HR	118569	3584	2696	1511	544	0	126904
CZ	413638	16751	11656	7950	3098	52285	505378
EE	126891	3074	2350	1311	472	708	134806
LV	150627	3376	2346	1392	432	639	158812
LT	98272	5296	4777	2175	632	1136	112288
SK	189417	7507	5576	3212	1218	36471	243401
SI	71847	3425	2453	1497	534	5556	85312

Appendix C:
Extended summary in Slovenian language
Daljši povzetek v Slovenskem jeziku

C.1 Uvod

To doktorsko delo skozi prizmo optimalnih monetranih in fiskalnih politik držav v okviru monetarnih unij raziskuje medsebojni vpliv nemenjalnih in menjalnih sektorjev gospodarstva.

V monetarnih unijah odločitve in interne politike tako majhnih držav kot je Republika Slovenija nimajo praktičnih učinkov na parametre celotnega sistema. Večina ekonomskih modelov, ki obravnava tematiko medsebojnih učinkov monetarnih in fiskalnih politik posameznih držav je utemeljena na poenostavljenih sistemih dveh držav. Kot boljši in za tak namen primeren makroekonomski model predlagata Gali and Monacelli (2008). V njunem modelu je vključenih več držav, vse pa so modelirane kot infinitezimalno majhne. Tako kot drugod po svetu lahko klasične gospodarske sektorje v Republiki Sloveniji uvrstimo med tržne sektorje gospodarstva. Sektorji bančništva, zavarovalništvam, telekomunikacij in energetike se v Republiki Sloveniji nagibajo k uvrstitvi v netržne sektorje, kar v mednarodnem okolju ni pravilo. Tako stanje je moč pripisati nacionalnemu gospodarskemu protekcionizmu. V Republiki Sloveniji lahko opazujemo primer, ko so podjetja iz storitvenih dejavnosti neučinkovita. Niso razvrščena v tržne sektorje, ampak delujejo kot podjetja iz nemenjalnih sektorjev gospodarstva. Ta podjetja imajo previsoko število zaposlenih glede na produktivnost (Domadenik et al., 2003).

Učinkovitost je možno izboljšati z ustvarjanjem večje količine izdelkov oziroma storitev (izložkov) z danimi produkcijskimi tvorci (vložki) ali z zmanjšanjem produkcijskih tvorcev pri ustvarjanju enake količine izložkov. Ob enakih ostalih pogojih so cene izložkov neučinkovitih podjetij višje od cen izložkov konkurenčnih učinkovitih podjetij. Z več produkcijskimi tvorci oziroma več vloženega dela in kapitala neučinkovita podjetja namreč proizvedejo enako količino izdelkov in storitev kot učinkovita podjetja.

Če nemenjalni sektorji proizvajajo količine nižje od teoretičnih zmogljivosti glede na vezan kapital in število zaposlenih delavcev, imajo široko proizvodno vrzel. Ta se manifestira kot nizka učinkovitost. Posledice za gospodarstvo nastanejo na dveh področjih. V prvem primeru gre za možnost napačne ocene in sprejemanja napačne politike na nivoju države. Če država nadzira proizvodno vrzel v okviru bruto domačega proizvoda (BDP) kot eno količino, lahko namreč napačno izmeri oziroma spregleda razliko med neproporcionalno učinkovitostjo tržih in neučinkovitostjo nemenjalnih sektorjev gospodarstva, ki sta dve količini. Z eno mero domače proizvodne vrzeli lahko na ta način napačno oceni dejansko situacijo v gospodarstvu in sprejeme neustrezne monetarne in fiskalne politike, ki zadevajo vse sektorje v državi. Politike država lahko primerno prikroji dejanski situaciji, če ločeno ugotavlja proizvodne vrzeli za netržne in tržne sektorje gospodarstva. Drugo področje, kjer neučinkovitost nemenjalnih sektorjev vpliva na gospodarstvo, je bolj mikroekonomkske narave. Izdelki in storitve neučinkovitih nemenjalnih sektorjev so običajno potrošeni kot vhodne storitve oziroma surovine v praviloma bolj učinkovitih menjalnih sektorjih. Podjetja iz menjalnih sektorjev plačujejo nepotrebno premijo za izdelke in storitve, ki jih ponujajo nemenjalni sektorji. Podjetja iz menjalnih sektorjev so namreč te vhodne storitve oziroma surovine primorana kupovati v lastni državi, kjer imajo svoje proizvodne zmogljivosti. To slabo vpliva na njihovo konkurenčnost na zunanjih trgih.

Prispevek tega doktorskega dela znanosti je razdeljen na dva dela. Osnovna ideja vsebuje nov pristop k analizi možnih posledic fiskalne politike z ločitvijo nadzora nad proizvodno vrzelijo nemenjalnih in menjalnih sektorjev gospodarstva. Drugi del je pretežno metodološki. Za izvedbo raziskave je uporabljen niz metod za obdelavo velikih količin podatkov. Zelo pomemben je prispevek o analizi in vstavljanju majkajočih podatkov, ki je opisan v poglavju 4. Niz je zaključen s kombinacijo metode DEA v povezavi s standardnimi regresijskimi modeli.

Cilj naloge je izvesti in predstaviti kvantitativno ekonomsko raziskavo, ki dokazuje *vpliv ekonomske politike na povečanje učinkovitosti netržnih sektorjev in s tem na učinkoviost tržnih sektorjev gospodarstva.* V majhnih odprtih menjalnih gospodarstvih v okviru monetarnih unij, kakršno je Evrsko območje, kjer klasična orodja nominalnih menjalnih tečajev in nominalnih obrestnih mer niso pod nadzorom državnih inštitucij, je tak vpliv možno vršiti samo s fiskalnimi vplivi na povečanje produktivnosti nemenjalnih sektorjev.

Rezultati raziskave potrjujejo primernost povečanja učinkovitosti nemenjalnih sektorjev gospodarstva kot inštrumenta fiskalne politike v posameznih državah. Raziskava dokazuje vpliv učinkovitosti nemenjalnih sektorjev na učinkovitost menjalnih sektorjev posameznih držav izmerjenih v globalnem okolju. Obstoječea makroekonomska literatura na temo monetarne in fiskalne politike v denarnih unijah in literature na temo nominalnih togosti na trgu dela, cen in plač ponuja primerne teoretične okvire, ki so osnova za zaključke, izpeljane iz rezultatov raziskave. Zmanjšanje proizvodne vrzeli nemenjalnih sektorjev gospodarstva bi bilo smiselno uvrstiti med kazalnike, inštrumente in cilje, ki jih snovalci gospodarskih politik uporabljajo s ciljem maksimiziranja družbene blaginje oziroma minimiziranja poslabšanja družbene blaginje. Povečanje učinkovitosti nemenjalnih sektorjev gospodarstva je možno dosegati brez hkratnega negativnega vpliva na druge ekonomske entitete znotraj države ali v drugih državah znotraj denarne unije. Tako z vidika vsake posamezne države, kot tudi z vidika denarne unije kot celote, je vloga fiskalne politike kot inštrumenta za stabilizacijo zaželjena. S primernimi ukrepi jo je moč izvajati tako, da nima negativnih vplivov na druge države v sistemu.

Majhna država z odprtim menjalnim gospodarstvom, kakršna je Republika Slovenija, bi morala izrazito ciljati učinkovitost v nemenjalnih sektorjih lastnega gospodarstva. Ker podjetja iz menjalnih sektorjev že poslujejo (bolj) učinkovito, je ločen pogled na učinkovitost v nemenjalnih sektorjih lastnega gospodarstva bistven. V nasprotnem primeru lahko pride do situacije, ko ima centralna evropska oblast, ki določa politiko v celotni uniji in bdi nad posameznimi državnimi gospodarstvi, napačne informacije zaradi napačno zastavljenih meritev. Možen način, da se popravijo meritve neprimernih signalov in indikatorjev, ki jih za nadzor nad stanjem v posameznih državnih gospodarstvih trenutno uporablja Evropska unija, je ravno v primerno oblikovanih merilih. V primeru, da bi se evropske inštitucije odločale na podlagi napačnih informacij, bi lahko od posamezne države zahtevale fiskalne omejitve, ki bi imele zelo slabe posledice v prihodnosti.

C.2 Motivacija in makroekonomski kontekst

Ljudje v zgodnjem 19. stoletju so bili za današnje standarde zelo revni. Bruto domači proizvod (BDP) na prebivalca v Evropi je po grobih ocenah znašal okrog 1.000 EUR (Maddison, 2007). Industrijska revolucija je v naslednjih 200 letih povzročila strm vzpon produktivnosti. Do začetka novega tisočletja je BDP na prebivalca v razvitih državah zrasel čez 20.000 EUR letno. Rast je bila skozi odobje razgibana, vendar konsistentna. V Združenih državah Amerike je povprečna letna rast BDP znašala 1,7 odstotka. Poleg tega se je, kot posledica avomatizacije in drugih inovacij, ki jih je prinašala industrijska revolucija, odvijala tudi transformacija delovnih nalog na delovnih mestih. Prosta delovna mesta so pritegnila ljudi iz kmetijstva, da so šli delat v industrijske in kasneje vedno bolj tudi v storitvene sektorje gospodarstva (Hulten, 2001; Chen et al., 2005).

Ekonomisti, ki so raziskovali opisana pojava, so se problema lotevali pretežno z dvema tipoma modelov. Zagovorniki Marksistične in neoklasične teorije rasti so najpomembnejše vzroke za povečano produktivnost iskale v tehnološkem napredku in boljši organizaciji proizvodnje. Druga struja, zagovorniki nove teorije rasti in drugi del neoklasičnih teoretikov pa je povečano produktivnost pojasnjevala s teorijo kapitala in investicij. Med investicije so poleg klasičnega pojmovanja uvrščali tudi investicije v človeški kapital in znanje. Ta razlika med raziskavami, utemeljenimi na tehnologiji in organizaciji proizvodnje, ter raziskavami, utemeljenimi na kreiranju kapitala, se je prenesla tudi na področje empiričnih raziskav gospodarske rasti.

Predmet raziskovanja je postala *analiza virov gospodarske rasti*, ki predstavlja intelektualno ogrodje residuala skupne faktorske produktivnosti (TFP)[44]. BDP v trenutnih cenah kot edina metrika gospodarskega napredka ni dovolj. Ekonomska blaginja namreč temelji tako na kvantiteti kot kvaliteti potrošenih proizvodov in storitev, ob upoštevanju trajnostnih načel ohranjanja naravne in kulturne dediščine (Hulten, 2001).

V preteklih desetletjih so ekonomisti razvili več različnih kompleksnih modelov za nadziranje in predikcijo učinkov različnih ekonomskih politik na narodno in družbeno blaginjo. Ti modeli vsebujejo in merijo ali manipulirajo različne ekonomske koncepte: vedenje gospodinjstev, vedenje podjetij, mednarodne tržne pogoje, elastičnosti substitucije, mednarodno deljenje tveganja, menjalne tečaje, inflacijo, proizvodno vrzel, BDP, različne nominalne togosti, sodelovanje med snovalci politik, itd.

TFP je načeloma možno izračunati za vse nivoje gospodarske aktivnosti, od posamezne poslovne enote do agregata za celotno gospodarstvo. Kljub temu te izračunane količine TFP med seboj niso neodvisne. Produktivnost podjetja kot celote vsebuje in v neki meri odraža produktivnost posameznih poslovnih (proizvodnih) enot. Enako produktivnost panoge oziroma sektorja odraža produktivnost podjetij, ki v panogi poslujejo. Kot rezultat produktivnost v agregatu (gospodarstvu) zraste, če zrastejo produktivnosti posameznih panog, ali če se spremenijo menjalni deleži panog

[44] *angl.* Total Factor Productivity

oziroma sektorjev z visoko produktivnostjo. Celotna slika grafa dinamike gospodarstva bi morala vsebovati medsebojno konsistentne meritve TFP residualov na vsakem nivoju v mreži robov, ki povezujejo nivoje agregacije. Izgradnje takega grafa se je moč lotiti od vrha navzdol, ali od posameznih enot navzgor. Domar (1961) se je prvi lotil problema z vrha navzdol in identificiral težavo z vpeljavo vmesnih (pol)izdelkov. Do te težave pride, ker tovarne in podjetja v svojem proizvodnem procesu uporabljajo surovine in storitve, ki so izložek drugih podjetij. Strategija od posameznih enot navzgor vzame celotno množico posameznih poslovnih (proizvodnih) enot kot osnovni okvir. Pri agregaciji ta način analize ne postavlja nikakršnih omejujočih predpostavk, da lahko doseže konsistentno mero skupne produktivnosti. Namesto tega poudarja temeljno heterogenost mikroprodukcijskih enot. Pomemben cilj tega pristopa je pogosto pojasniti to heterogenost s faktorji kot so raziskave in razvoj, patentiranje, razlike v finančni strukturi, razlike v strukturi panoge, itd. Pionirji tega pristopa so Davis and Haltiwanger (1991), Hall et al. (1993) in Griliches (1994).

Analiza produktivnosti na makro nivoju lahko predstavlja pomemben vir informacij za snovalca ekonomske politike. Razporeditev nacionalnih gospodarskih virov med entitete, ki se razlikujejo po produktivnosti je lahko pomemben dejavnik v raziskavah meddržavnih razlik v proizvodnji na prebivalca. Restuccia and Rogerson (2008) sta pokazala, da lahko politika, ki ustvarja različnost cen, po katerih so storitve in surovine dosegljive različnim proizvajalcem, vodi do znatnega zmanjšanja v izložkih in izmerjenem residualu skupne faktorske produktivnosti (TFP). Konkurenčnost panoge (sektorja) pogosto temelji na doseganju produkcijskega potenciala v podjetjih, ki sektor sestavljajo (Kapelko and Lansink, 2015). Baily et al. (1992) ocenjujeta, da je približno polovico celotnega povečanja produktivnosti v ZDA industrijskih panogah v desetletju po 1980 posledica prerazporeditve produkcijskih virov od nizkoproduktivnih k visokoproduktivnim proizvodnim enotam. Ta in drugi dokazi govorijo vprid pomembnosti alokacije kapitala in dela med entitetami kot pomembne determinante agregatne produktivnosti.

Znatna količina pozornosti sodobnih državnih vlad in centralnih finančnih inštitucij kot ustvarjalcev in izvajalcev raznovrstnih politik je posvečena monetarni in fiskalni politiki, v zadnjih letih pogosto pod pogoji, ki veljajo v okviru monetarnih unij. Usklajenost monetarnih politik je do neke mere zaželjena, vendar zahtevna. Jasno je, da so finančno samozadostne države manj odvisne od vplivov tujih monetarnih politik skozi neposredne finančne kanale direktnih, kot finančno odprte države (Claessens et al., 2015). Večina modelov za analizo medsebojnih vplivov monetarnih in fiskalnih politik temelji na idealiziranih modelih z dvema državama, v praksi pa so majhne države najverjetneje najbolj prizadete zaradi pomanjkanja usklajenosti. Bolj so izpostalvjene denarnim tokovom, ki jih povzročijo spremembe politik večjih držav, obenem pa imajo same majhen vpliv in nizko pogajalsko moč ob odločanju o različnih parametrih politik v okviru denarnih unij. To vrzel nekoliko zapolni model, ki ga predlagata Gali and Monacelli (2008) in služi kot temelj razmisleka za preostanek naloge. Kljub nekaterim nejasnostim med ekonomisti obstaja konsenz, da je zaradi omejitev pri sprejemanju usklajenih mednarodnih monetarnih politik, v vsaki državi posamično potrebno ojačati odpornost gospodarstva z drugimi mehanizmi in tako povečati skupno globalno ekonomsko trdnost. Večja makroekonomska preudarnost in nadzor nad kapitalskimi tokovi predstavljata eno od možnosti, s katero države iščejo zaščito pred gospodarskimi pregrevanji in krizami (Bole et al., 2014b; Claessens et al., 2015).

V nalogi je razložen pomen monetarne in fiskalne politike, ter omejitve, ki jih morajo upoštevati države članice denarnih unij, ki nimajo neposrednega vpliva na menjalne tečaje in nominalno obrestno mero. Dalje je nakazan uvod v makroekonomsko modeliranje z dinamičnimi stohastičnimi modeli splošnega ravnotežja (DSGE)[45], z namenom predstavitve modela, ki sta ga razvila (Gali and Monacelli, 2008). Bistvena je ločitev med zaprtimi in majhnimi odprtimi gospodarstvi. Pri slednjih gre za gospodarstva z denarjem, nepopolno konkurenco, nominalnimi censkimi togostmi in togostmi na trgu dela (Clarida et al., 2001). Togosti na finančnem trgu, trgu dela in t.i. lepljive cene izdelkov in storitev so nepogrešljive za uspešno izvajanje nekaterih politik, ki iz modelov sledijo kot optimalne. S togostmi na različnih področjih so se ukvarjali Bernanke et al. (1999), Christiano et al. (2004), Christiano et al. (2011), izpostaviti pa je potrebno še Calvo (1983), ki je uvedel koncept lepljivih cen.

C.3 Metodologija

Poglavje o metodologiji opiše splošne koncepte in metode, ki se uporabljajo za analizo produktivnosti in učinkovitosti. Produktivnost je enostavno definirana z naslednjo formulo:

$$produktivnost = \frac{proizvedeni\_proizvodi\_in\_storitve}{uporabljena\_stredstva\_surovine\_in\_vstopne\_storitve} \tag{C.1}$$

Kadar je produkcijski proces sestavljen iz ene vhodne in ene izhodne količine, je tak izračun preprost. V praksi se problem običajno zaplete vsaj z več različnimi vhodnimi količinami. V takih primerih je pomembna izbira metod za agregacijo vhodnih in izhodnih količin Coelli et al. (2005).

Izraza produktivnost in učinkovitost[46] se v angleškem jeziko pogosto zamenjujeta, v slovenščini pa zadevo dodatno zakomplicira še izraz efektivnost[47]. Ti izrazi ne označujejo natančno iste reči (Coelli et al., 2005). Učinkovitost lahko razčlenimo na tri kategorije:

Tehnološka učinkovitost

Učinkovitost obsega

Alokacijska učinkovitost

Za ilustracijo razlike med izrazoma učinkovitost in produktivnost si lahko ogledamo sliko Figure 2.1 na strani 28. Gre za preprost proces v katerem se ena vhodna količina (x) troši za proizvodnjo ene izhodne količine (y). Črta 0F' predstavlja mejo produktivnosti, ki jo lahko uporabimo za definicijo preslikave med vhodno in izhodno količino. Produkcijska meja predstavlja maksimalno možno količino izložka x, pri določeni količini y. Odraža torej trenutno stanje tehnologije v panogi (sektorju). Podjetja v panogi, ki poslujejo na tej produkcijski meji, so tehnološko učinkovita. Če podjetje posluje pod mejo, je do neke mere neučinkovito. Točka A predstavlja neučinkovito podjetje, točki

[45] *angl.*Dynamic Stochastic General Equillibrium model
[46] *angl.* efficiency - ali reč počnemo prav
[47] *angl.* effectiveness - ali počnemo pravo reč

B in C pa predstavljata učinkoviti podjetji. Podjetje, ki posluje na točki A je neučinkovito, ker bi z obstoječo tehnoloijo lahko poslovalo na točki B brez zahtev po povečani vhodni količini y.

Metode, ki so v uporabi za analizo produktivnosti so:

1. Ekonometrični produkcijski modeli ocenjevani z regresijo
2. Indeksi skupne faktorske produktivnosti (TFP)
3. Metoda podatkovne ovojnice (DEA[48])
4. Stohastične meje (SFA[49])

Prvi dve metodi se običajno uporabljata na agregiranih časovnih vrstah in ugotavljata mero tehnološkega razvoja in/ali skupne faktorske produktivnosti (TFP). Obe metodi predpostavljata, da so vsa podjetja tehnološko učinkovita. Metodi 3 in 4 se največ uporabljata na vzorcu podjetij v enem časovnem obdobju in analizirata relativno učinkovitost med temi podjetji in ne predpostavljata tehnološke učinkovitosti. Poleg običajnih načinov uporabe se tudi multilateralni TFP indeksi občasno uporabljajo za primerjavo relativne produktivnosti skupine podjetij v enem časovnem obdobju. Prav tako se DEA in SFA lahko uporabljata tako za merjenje tehnološkega razvoja, kot za merjenje učinkovitosti, če imamo na voljo panelne podatke.

Raziskava v nalogi je opravljena z uporabo kombinacije teorije množic, ki ji sledi linearna regresija s fiksnimi učinki. Teorija množic predstavlja okvir, ki definira funkcijo razdalje (metrike). Metrike[50] predstavljajo ključni element pri merjenju produktivnosti. So temeljni koncept DEA analize. Pomemben metodološki korak predstavlja agregacija DEA rezultatov, s katero se izračunajo vhodni podatki za linearno regresijo.

Podatki, ki so zajeti iz baze Amadeus imajo veliko napak v obliki manjkajočih podatkov in osamelcev[51]. Na sliki Figure 2.5 na strani 45 si lahko ogledamo porazdelitve spremenljivk. Ker je metoda DEA zelo občutljiva na osamelce, smo podatke pred analizo usterzno obdelali. Ker je vse spremenljivke moč predstaviti z log-normalno porazdelitvijo, smo vse spremeljivke logaritmirali, ter nato za vse vrednosti, ki so bile od srednje vrednosti oddaljene več kot tri standardne odklone[52] preverili, če nimajo več kot 3% tržnega deleža. V takem primeru smo točko označili kot osamelec in je v raziskavi nismo upoštevali. Vsa podjetja z znatnim menjalnim deležem smo v vzorcu obdržali.

C.4 Podatki

Analizo smo izvedli na veliki množici podatkov, ki je vsebovala šest (6) panog v petnajstih (15) državah za devet (9) let in je bila črpana iz velike baze Amadeus, ki jo pripravlja Bureau van Dijk.

[48] *angl.* Data Envelopment Analysis
[49] *angl.* Stochatic Frontier Analysis
[50] *angl.* Distance function
[51] *angl.* Outlier
[52] To pomeni, da smo zadržali najmanj 99,7% vseh točk.

Amadeus vsebuje podatke o približno 21 milijonih podjetij v celotni Evropi. V naši raziskavi smo uporabili podatke o 217194 podjetjih, z dimenzijami $prodaja$, $stevilo\_zaposlenih$, $osnovna\_sredstva$ in $stroski\_zaposlenih$. Bireau van Dijk zagotavlja primerljivost podatkov. Množica podatkov je zelo velika za konvencionalne raziskovalne standarde v ekonomskih znanostih. Nemogoče je bilo "ročno" preveriti vsak osamelec in vsako strukturno posebnost. Za zagotavljanje čim večje kakovosti podatkov je bilo veliko pozornosti posvečene njihovi pripravi, kar je opisano v poglavjih C.3 in C.5.

C.5 Analiza in vstavljanje manjkajočih podatkov[53]

Običajne metode in procedure za vstavljanje manjkajočih podatkov[54] so dobro razložene v več člankih in knjigah. Ad-hoc metode, kot so analiza celotnih primerov[55] in analiza obstoječih primerov[56] ter metode enojnega vstavljanja kot so vstavljanje srednje vrednosti[57] in vstavljanje zadnje vrednosti so opisane v Pigott (2001), Tanguma (2000) in Peugh and Enders (2004). Te metode je lahko uporabiti, problematične pa so zaradi predpostavk o podatkih, na katerih temeljijo in redko držijo v praksi (Pigott, 2001). Površna uporaba omenjenih metod lahko vodi do pristranskih ali celo popolnoma napačnih rezultatov znanstvenih raziskav. Z vpeljavo regresijskih modelov, stohastičnih regresijskih modelov in metod večkratnega vstavljanja[58] kompleksnost metod hitro narašča. Kompleksnejše metode običajno vračajo bistveno boljše rezultate. S široko dostopnostjo zmogljivih računalnikov pa so se razmahnile tudi metode, ki bazirajo na modelih[59] (Siddique and Belin, 2008). Obstajajo tudi drugi eksperimentalni algoritmi, ki bazirajo na metodah umetne inteligence (Andrew and Selamat, 2012).

Za potrebe raziskave, ki je predstavljena v tej disertaciji, je bila pripravljena nova metoda, ki se problema loteva v dveh korakih in upošteva kontekstualne informacije, ki jih imamo o podatkih.

V disertaciji so predstavljene osnovne predpostavke metod za vstavljanje manjkajočih podatkov, ki opisujejo vzorec manjkajočih podatkov. Manjkajoče podatke lahko razdelimo v tri razrede:

- Manjkajoči popolnoma naključno (MCAR[60])
- Manjkajoči naključno (MAR[61])
- Manjkajoči nenaključno (MNAR[62])

[53] To poglavje bo objavljeno v reviji Economic and Business review. Pri pisanju članka je sodeloval soavtor, prof. dr. Marko Pahor

[54] *angl.* Missing value imputation methods

[55] *angl.* Complete case analysis

[56] *angl.* Available case analysis

[57] *angl.* Mean imputation

[58] kot npr. stohastična regresija z metodo ponovnega vzorčenja *angl.* Bootstrapped stochastic regression

[59] kot npr. maksimizacija pričakovanja *angl.* expectation maximization (EM), večkratno vstavljanje *angl.* multiple imputation (MI), maksimizacija pričakovanja z metodo ponovnega vzorčenja *angl.* expectation maximization bootstrap (EMB) in približa Bayesianska metoda s ponovnim vzorčenjem *angl.* approximate Bayesian bootstrap (ABB)

[60] *angl.* Missing Completely At Random

[61] *angl.* Missing At Random

[62] *angl.* Missing Not At Random

Analiza je izvedena na dveh množicah podatkov. Pri prvi množici gre za popolnoma umetno statistično distribucijo in korelacijo med spremeljivkama, pri drugi pa za množico s simuliranimi distribucijami in korelacijami med spremelnjivkami na podlagi računovodskih podatkov iz baze, ki je uporabljena v glavni raziskavi te disertacije. Na obeh množicah so kreirani podatki "pokvarjeni" z različnimi mehanizmi, nato pa so testirane metode, ki poizkušajo manjkajoče podatke ponovno uganiti. V poglavju 4 pokažemo, da se v določenih okoliščinah nova metoda, razvita prav za namen vstavljanja manjkajočih podatkov v panelno zbirko računovodskih izkazov, obnaša bistveno bolje od običajnih metod, ki so na voljo v vseh sodobnih programskih paketih za statistične obdelave podatkov.

C.6 Empirični model

Pred specifikacijo empirčinega modela je nujno potrebno razumeti korake, ki vodijo do izračuna vhodnih podatkov, ki so podlaga za empirični model:

1. Pripravimo surove podatke
2. Izberemo podjetja skladno z začrtanimi kriteriji (vsaj enkrat v opazovanem ondobju je v podjetju nad 50 zaposlenih), dobimo neuravnovešeni panel
3. Vstavimo manjkajoče podatke, kjer je to mogoče
4. Testiramo učinek vstavljenih manjkajočih podatkov
5. Pripravimo podatke za analizo glede na razpoložljivost vseh opazovanih dimenzij v vsakem opazovanem podjetju
6. Izračunamo DEA količnike prvič
7. Izračunamo skupno prodajo po posameznih panogah v državi po letih
8. Izračunamo menjalni delež vsakega podjetja
9. Odstranimo osamelce, ki ne morejo biti podjetja z velikim menjalnim deležem
10. Združimo podatke za vsako panogo
11. Izračunamo DEA količnike drugič
12. Združimo podatke za vse analizirane panoge
13. Izračunamo obtežitve panoge iz vsake države v panogi globalno, za vsa leta
14. Izračunamo obtežene DEA količnike panoge v državi glede na panogo globalno, za vsa leta
15. Izvedemo regresijsko analizo

Koraki 1 do 5 predstavljajo pripravo podatkov. V koraku 6 izračunamo prve DEA količnike, ki jih uporabimo za odstanitev osamelcev v korakih 7 do 9. Od 10 koraka naprej, podatke najprej združimo znotraj posamezne panoge in izračunamo lokalne in globalne DEA količnike za vsako podjetje. Te količnike potem agregiramo s pomočjo uteži, ki odražajo delež vsakega podjetja v okviru opazovane enote (lokalno/globalno). Ta korak normalizira DEA količnike, ki so uporabljeni kot vstopni podatki v končni regresijski model. Brez te normalizacije so rezultati pristranski, saj lahko zelo majhno podjetje, ki je kratek čas zelo učinkovito, popolnoma izkrivi celostno sliko, na kateri ostala večja podjetja neupravičeno izmerimo kot zelo neučinkovita.

Testiranih je bilo več regresijskih modelov z analizo različnih kategoričnih spremenljivk (država, panoga, leto). Predpostavke regresijskih modelov so bile preverjene z R paketom "gvlma", (Pena and Slate, 2014). Prav tako so bile predpostavke preverjene z vizualno oceno grafov 'primerjava residulov z izračunanimi ocenami[63]', 'normalni Q-Q[64]', 'velikost-lokacija[65]' in 'primerjava residualov glede na vzvod[66]'.

Mnoge netržne panoge poslujejo na infrastrukturnih področjih (voda, elektrika, odpadki,...). Podjetja tega tipa imajo običajno zelo nespremenljiva osnovna sredstva, število zaposlenih in prihodke. Zelo težko je torej zaznati vpliv spremembe katerekoli od teh spremeljivk, saj je njihova variabilnost praviloma nizka. Spremembe so majhne, glede na absolutno vrednost spremenljivk. Da bi se izognili temu problemu, se v naši raziskavi osredotočamo na relativne spremembe učinkovitosti v nemenjalnih sektorjih glede na relativne spremembe v menjalnih sektorjih.

Osnovi empirični model je definiran kot:

$$\begin{aligned} log(trzni\_glob\_ucinkovitost)[t] = \; & \\ & \alpha + \\ & \beta_0 * log(netrzni\_glob\_ucinkovitost)[t-1] + \\ & \sum_j (\beta_j * drzava_j\_indikator) + \\ & \sum_k (\beta_k * skupina\_drzav_k\_indikator) + \\ & \sum_l (leto_l\_indikator) \end{aligned} \tag{C.2}$$

Kot izhaja iz enačbe C.2 pričakujemo, da se efekt (ne)učinkovitosti nemenjalnih sektorjev prenese na učinkovitost menjalnih sektorjev z zamikom. Model, ki je testiral odnos na sočasnih količinah ni deloval. Vsi DEA količniki so logaritmirani. Rezultat torej odraža odstotkovno spremembo odvisne spremelnjivke glede na odstotkovno spremembo neodvisne spremenljivke.

[63] *angl.* Residuals vs Fitted
[64] *angl.* Normal Q-Q
[65] *angl.* Scale-Location
[66] *angl.* Residuals vs Leverage

C.6.1 Hipoteze

V nalogi preizkušamo naslednje hipoteze:

1.
   - H_0: Povezava med učinkovitostima nemenjalnih in menjalnih panog ne obstaja ($\beta_0 = 0$).
   - H_A: Obstaja povezava med učinkovitostima nemenjalnih in menjalnih panog ($\beta_0 \neq 0$).
2.
   - H_0: Jakost povezave med učinkovitostima nemenjalnih in menjalnih panog se ne spreminja skozi gospodarski cikel.
   - H_A: Jakost povezave med učinkovitostima nemenjalnih in menjalnih panog je bolj izrazita med recesijo.
3.
   - H_0: Jakost povezave med učinkovitostima nemenjalnih in menjalnih panog med državami je enaka.
   - H_A: Obstajajo razlike v jakosti povezave med učinkovitostima nemenjalnih in menjalnih panog.

V vseh primerih je hipoteza H_0 ovržena. Sprejete so vse tri alternativne hipoteze H_A.

C.6.2 Testiranje modelov in končni rezultati

Po testiranju različnih modelov (posamezno po letih, posamezno po menjalnih panogah, s sočasnima neodvisno in odvisno spremenljivko, s fiksiranimi učinki posameznih držav, z izločenimi posameznimi državami) se je kot najbolj primeren izkazal model, ki države grupira po skupinah z usmeritvijo na podoben geografski trg. Skupine so:

- Germanski trg: AT, DE, SI, NL
- Romanski trg: IT, FR
- Pirenejski trg: ES, PT
- Večinoma slovanski trgi: HR, CZ, SK
- Baltski trg: LT, LV, EE, FI

Model je specificiran kot:

$$\begin{aligned} log(trzni\_glob\_ucinkovitost)[t] \; = \; & \\ & \alpha + \\ & \beta_0 * log(netrzni\_glob\_ucinkovitost)[t-1] + \\ & \beta_1 * romanski\_indikator + \beta_2 * slovanski\_indikator + \\ & \beta_3 * pirenejski\_indikator + \beta_4 * baltski\_indikator \end{aligned} \tag{C.3}$$

Rezultati so predstavljeni v Tabeli C.1. Kot bazna skupina so upoštevane države, osredotočene na *germanski_trg*.

Table C.1: Regresija s fiksnimi učinki skupin držav glede na usmeritev na geografski trg

	Residuali				
	Min	1Q	Mediana	3Q	Maks
	-3.8817	-0.6998	0.0136	0.7105	2.7093
	Koeficienti				
	Ocena	Std. odkl.	t-vrednost	$\Pr(>\lvert t\rvert)$	Signif.
(Intercept)	-1.60171	0.11281	-14.198	< 2e-16	***
log_netrz_global	0.37071	0.02334	15.886	< 2e-16	***
romanski_indikator	0.78377	0.13323	5.883	6.4e-09	***
slovanski_indikator	-1.07187	0.12557	-8.536	< 2e-16	***
pirenejski_indikator	-0.74227	0.14198	-5.228	2.3e-07	***
baltski_indikator	-1.67030	0.13370	-12.493	< 2e-16	***
Signif. legenda: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 0					
Std. odklon residualov: 1.033 na 661 stopnjah prostosti					
Večkratni R^2 : 0.6879, $PrirejenR^2$: 0.6855					
F-statistka: 291.4 na 5 in 661 stopnjah prostosti, p-vrednost: < 2.2e-16					

V predstavljenem modelu so vse količine statistično signifikantne, prav tako pa veljajo vse predpostavke linearnih regresijskih modelov. Model je torej veljaven.

Republika Slovenija je nekoliko presenetljivo uvrščena med Avstrijo, Nemčijo in Nizozemsko. Sprva je bila uvrščena med Hrvaško, Češko in Slovaško, glede na podobnost institucionalnih in zgodovinskih faktorjev. Izkaže se, da s svojo močno vključenostjo menjalnih panog na nemško tržišče, Republika Slovenija bolj sodi v skupino držav osredotočenih na *germanski_trg*.

V rezultatih je nekoliko presenetljiv pozitiven koeficient pri državah, osredotočenih na *romanski_trg*. Glede na pregovorno učinkovitost Republike Nemčije in germanskih držav, ki z izjemo Republike Slovenije nastopajo v skupini, osredotočeni na *germanske_trge*, bi pričakovali, da bodo koeficienti ostalih skupin negativni. Situacija, kot jo opazimo, je mogoča ker opazujemo *spremembo oziroma gibanje*. Možno je, da so zelo učinkovite tržne panoge v germanskih gospodarstvih manj odvisne od že učinkovitih nemenjalnih panog, kot v romaskh gospodarstvih, ki morda delujejo v območju učinkovitosti, kjer so te spremembe najbolj izrazite.

C.7 Zaključek

Ekonomski odnos in relativne cene med nemenjalnimi in menjalnimi panogami igrajo pomembno vlogo v vse bolj omejenem naboru orodij, ki so na voljo upravljalcem gospodarske politike v majhnih odprtih gospodarstvih v okviru monetranih unij ter drugih menjalnih in gospodarskih skupnosti. Da bi maksimizirale družbeno blaginjo so države običajno nadzirale inflacijo z nadzorovanjem menjalnih tečajev in obrestnih mer. S članstvom v denarnih unijah se države kot posameznice tema inštrumentoma monetrane politike odpovedo. Edina orodja, ki jih imajo v omejenem obsegu na voljo, sodijo na področje fiskalne politike.

Z upoštevanjem togosti na trgu dela in nominalnih cen v nemenjalnih panogah je možno dosegati povečevanje splošne produktivnosti v gospodarstvu. K temu cilju lahko države stremijo z vplivanjem na povečanje učinkovitosti nemenjalnih panog, torej z osredotočenjem na njihovo *proizvodno vrzel*, ki ni enaka proizvodni vrzeli gospodarstva. S tem je mogoče nadzirati realno inflacijo in splošno blagostanje v državi brez nadzora nad nominalno obrestno mero. Gre za fiskalno politiko, ki ne zajeda blagostanja v drugih državah[67]. Gre torej za politiko v duhu koordiniranega pristopa držav k skupni blaginji.

Rezultati raziskave opisane v tej disertaciji predstvaljajo empirični dokaz odnosa med učinkovitostjo nemenjalnih in menjalnih panog vsakega gospodarstva, glede na globalno učinkovitost. To je mikroekonomska podpora modelom, ki so izpeljani in opisani v makroekonomski literaturi.

Majhno odprto gospodarstvo kot ga ima Republika Slovenija bi moralo stremeti k povečanju učinkovitosti nemenjalnih panog. Ker tržne panoge že poslujejo bolj učinkovito, lahko ta osredotočenost na pravi del gospodarstva popravi amplitudo nekaterih neprimernih signalov, ki jih EU uporablja za ocenjevanja stanja v posameznih gospodarstvih. Zaradi napačnih ocen lahko centralne evropske institucije od držav zahtevajo omejitve s potencialno katastrofalnimi posledicami v prihodnjih letih.

[67] *angl.* Beggar-thy-neighbor