

Essays in International Trade

Inaugural-Dissertation
zur Erlangung des akademischen Grades eines Doktors
der Wirtschafts- und Sozialwissenschaften
der Wirtschafts- und Sozialwissenschaftlichen Fakultät
der Christian-Albrechts-Universität zu Kiel

vorgelegt von
Dominik Michel Boddin, M.Sc.
aus Kiel

Kiel, 2019

Gedruckt mit Genehmigung der
Wirtschafts- und Sozialwissenschaftlichen Fakultät
der Christian-Albrechts-Universität zu Kiel

Dekan: Professor Dr. Till Requate
Erstbegutachtung: Professor Horst Raff, Ph.D.
Zweitbegutachtung: Professor Dr. Johannes Bröcker

Tag der Abgabe der Arbeit: 25. Januar 2019
Tag der mündlichen Prüfung: 04. März 2019

Acknowledgements

At the beginning of this dissertation I would like to thank the many people who accompanied and supported me during my doctoral studies. The present thesis has benefited from discussions with professors and fellow students at Kiel University as well as from presentations at various national and international conferences, seminars, and workshops. I am grateful to all who supported my work in that way.

First and foremost, my thanks go to my first advisor, Prof. Horst Raff, Ph.D., who gave me the opportunity to do a doctorate at the Chair of Microeconomics and decisively advanced my work through many fruitful discussions and comments. I am very grateful to Prof. Raff for his advice and support, be it in research or when it comes to visiting conferences or undertaking research stays abroad. He always had an open door for me and I highly appreciate the pleasant and cooperative work environment he creates at his chair.

A very special thanks also goes to my second advisor Prof. Dr. Johannes Bröcker. Prof. Bröcker always supported me with words and deeds and his comments have significantly improved the quality of my work. In addition, I thank Prof. Bröcker for his decisive influence in terms of my professional career in general. On the one hand, working as a research assistant at the Institute for Regional Research, led by Prof. Bröcker, gave me a first insight into research. On the other hand, I owe the deepest gratitude to Prof. Bröcker for his advice after finishing school, without which I would not have studied economics in the first place.

I thank Prof. Holger Görg, Ph.D. for discussing my research and for helpful comments. I would also like to thank my co-authors Dr. Eike Berner, Dr. Laura Birg, Dr. Philipp Henze, Thilo Kroeger, Prof. Alessandro Peri, Ph.D., Dr. Lien Pham-Dao, Prof. Horst Raff, Ph.D., Prof. Dr. Frank Stähler, and Dr. Natalia Trofimenko for the very good and rewarding cooperation. I am grateful for the great collaboration with my colleagues at the Chair of Microeconomics, Anita Hartz, Britta Hasenpusch, Dr. Philipp Henze, Thilo Kroeger, Dr. Zhan (Simon) Qu, and Jenia Sudheimer.

Additionally, I am thankful to Laura Bickel, Christian Bracke, Veronika Harder, Hauke Jelschen, Q. Vera Liao, and Tabea Philipp, who supported and encouraged me. Last but not least, I would like to express my gratitude to my parents who have always supported me throughout my studies.

Contents

List of Figures	v
List of Tables	vii
1 Introduction	1
2 Imports, Exports, and Domestic Innovation	3
2.1 Introduction	4
2.2 Data and Stylized Facts	7
2.2.1 Patenting	8
2.2.2 Trade Exposure	13
2.3 Trade Exposure and Innovation	16
2.3.1 Empirical Specification	17
2.3.2 Results	19
2.4 Further Differentiation and Robustness	25
2.4.1 Further Differentiation	25
2.4.2 Robustness	31
2.5 Conclusion	36
2.6 Bibliography	38
A Appendices	41
A.1 Patenting in Germany	41
A.2 Regional Patenting Structure in Germany	44
A.3 Regional Trade Exposure in Germany	47
A.4 German Trade with Eastern Europe and China	48
A.5 Final and Intermediate Good Trade	48
A.6 Robustness	49
3 The Role of Newly Industrialized Economies in Global Value Chains	53
3.1 Introduction	54
3.2 Data and Calculations	56

3.3	The Position of Newly Industrialized Economies in Global Value Chains	61
3.3.1	Value Added, Trade and Output	62
3.3.2	Foreign and Domestic Value Added in Exports	63
3.3.3	Trade in Value Added - Foreign Consumption of Domestic Value Added	66
3.4	Summary and Conclusion	74
3.5	Bibliography	76
B	Appendix	80
4	Foreign Ownership and the Export and Import Propensities of Developing-Country Firms	89
4.1	Introduction	90
4.2	Theoretical Framework	93
4.2.1	Households	93
4.2.2	Firms	94
4.2.3	Foreign Ownership	95
4.2.4	Equilibrium	96
4.2.5	Implications	99
4.3	Data and Summary Statistics	99
4.4	Empirical Methodology and Results	102
4.4.1	Baseline Model	103
4.4.2	Balancing Test and Alternative Specifications	105
4.5	Comparisons Across Country and Industry Groups	108
4.6	Conclusions	114
4.7	Bibliography	116
5	International Trade and the Occupational Mix in Manufacturing: Evidence from German Micro Data	119
5.1	Introduction	120
5.2	Data	123
5.3	Stylized Facts	124
5.4	Empirical Evidence	127
5.4.1	Matching of Commodity Trade Data	127
5.4.2	Empirical Strategy	129
5.4.3	Results	133
5.5	Conclusion	137
5.6	Bibliography	139
C	Appendices	143
C.1	Structure of Employees by Blossfeld Occupational Groups	143

C.2	Description of Matching Process of Commodity Trade Data . . .	145
C.3	Example: Allocation of Imports of “Leather and Leather Manu- factures” to the Industries of the BHP	149
6	Eidesstattliche Versicherung	155
7	Hilfsmittel	156

List of Figures

2.1	Patenting in Germany: Total Patenting and Subsections	10
2.2	Patenting per 1000 Inhabitants by Municipality of the Inventor	12
2.3	Absolute Change of Patenting per 100.000 Inhabitants by Location of the Inventor; $I\bar{A}_i^{02-04} - I\bar{A}_i^{93-95}$ (Left) and $I\bar{A}_i^{10-12} - I\bar{A}_i^{02-04}$ (Right) .	13
2.4	German Trade with Eastern Europe and China	14
2.5	Absolute Change in Regional Import Exposure $\frac{Imp_i^{East}{}^{10-12}}{Exp_i^{East}{}^{10-12}} - \frac{Imp_i^{East}{}^{93-95}}{Exp_i^{East}{}^{93-95}}$ (Left) and Regional Export Exposure $\frac{Exp_i^{East}{}^{10-12}}{Exp_i^{East}{}^{93-95}}$ (Right) in \$ 1000 per Manufacturing Worker	16
2.6	Coverage of Patenting	41
2.7	Patent Applicants by Type	42
2.8	Distribution of Patents by Applicants	43
2.9	Patenting per 1000 Inhabitants by Location of the Applicant	44
2.10	Total Patenting by Location of the Applicant	45
2.11	Absolute Change of Patenting per 100.000 Inhabitants by Location of the Applicant; $I\bar{A}_i^{93-95} - I\bar{A}_i^{02-04}$ (Left) and $I\bar{A}_i^{02-04} - I\bar{A}_i^{10-12}$ (Right) .	46
2.12	Absolute Change in Regional Import Exposure from Eastern Europe $\frac{Imp_i^{EE}{}^{10-12}}{Imp_i^{EE}{}^{93-95}} - \frac{Imp_i^{EE}{}^{93-95}}{Imp_i^{EE}{}^{93-95}}$ (Left) and China $\frac{Imp_i^{China}{}^{10-12}}{Exp_i^{China}{}^{93-95}} - \frac{Exp_i^{China}{}^{93-95}}{Exp_i^{China}{}^{93-95}}$ (Right) in \$ 1000 per Manufacturing Worker	47
2.13	Absolute Change in Regional Export Exposure from Eastern Europe $\frac{Exp_i^{EE}{}^{10-12}}{Exp_i^{EE}{}^{93-95}} - \frac{Exp_i^{EE}{}^{93-95}}{Exp_i^{EE}{}^{93-95}}$ (Left) and China $\frac{Exp_i^{China}{}^{10-12}}{Exp_i^{China}{}^{93-95}} - \frac{Exp_i^{China}{}^{93-95}}{Exp_i^{China}{}^{93-95}}$ (Right) in \$ 1000 per Manufacturing Worker	47
2.14	Weighted Grubel-Lloyd-Index for German Trade with Eastern Europe and China between 1980 and 2012	48
3.1	Outline of The World Input Output Tables of the WIOD Database	57
3.2	Six NICs and World Average: Foreign Value Added in Gross Exports of NICs (in Percent) from 1995 to 2011	64
3.3	Foreign Value Added in Exports for China and Mexico by Partner Country - 1995 and 2011	67

3.4	Foreign Consumption of Domestic Value Added for China and Mexico by Partner Country - 1995 and 2011	69
3.5	Concentration and Gini of Foreign Consumption of Domestic Value Added - 1995 and 2011	70
3.6	Industry Contribution for Foreign Consumption of China's Domestic Value and for China's Gross Exports in 2011	72
3.7	Six NICs: Foreign Consumption of Domestic Value Added Shares by Industry Category - 1995 to 2011	73
3.8	787 Dreamliner Suppliers; Source: Boeing, Reuters	80
3.9	Output, Exports, Imports, and Value Added for China, India, and Indonesia from 1995 to 2011	82
3.10	Output, Exports, Imports, and Value Added for Mexico, Brazil, and Turkey from 1995 to 2011	83
3.11	Foreign Value Added by Country in Percent of Total Foreign Value Added for Brazil, Indonesia, India, and Turkey - 1995 and 2011	84
3.12	Foreign Consumption of Domestic Value Added for Brazil, Indonesia, India, and Turkey by Partner Country - 1995 and 2011	85
3.13	Five NICs: Industry Contribution for Foreign Consumption of Domestic Value and for Gross Exports in 2011	86
3.14	Six NICs: Foreign Consumption of Domestic Value Added Shares by Industry - 1995 to 2011	87
4.1	Equilibrium Export Modes	97
5.1	Change in the Occupational Mix in Manufacturing	126
5.2	Allocation of Leather Imports to the Industries of the BHP (in 2000) . .	149
5.3	Allocation of Leather Exports to the Industries of the BHP (in 2000) . .	151
5.4	Allocation of Leather Imports and Exports to the Industries of the BHP (in 2000) - "Traditional Approach"	153

List of Tables

2.1	Effect of Periodic Changes in Regional Net Trade Exposures on Periodic Changes in Patenting per 100,000 Inhabitants	20
2.2	Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Changes in Patenting per 100,000 Inhabitants	22
2.3	Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Change in Patenting per 100,000 Inhabitants - Exposure Origin	24
2.4	Final vs. Intermediate Good Trade	26
2.5	Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Changes in Patenting per 100,000 Inhabitants by Exposure Origin and Applicant Type	27
2.6	Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Changes in Patenting per 100,000 Inhabitants by Applicant Categories	29
2.7	Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Changes in Patent Properties	30
2.8	Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Changes in R&D Employment	31
2.9	Effect of Periodic Changes in Regional Import and Export Exposures by Exposure Origin on Periodic Changes in Various Innovation Measures .	49
2.10	Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Changes in Patenting per 100,000 Inhabitants by Exposure Origin - Western and Eastern Germany	50
2.11	Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Changes in Patenting per 100,000 Inhabitants - Commuters and Alternative Administrative Units	51
2.12	Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Changes in Patenting per 100,000 Inhabitants by Exposure Origin - Different Instrument Groups	52

3.1	Six NICs: Total Exports, Imports, Value Added and Output in 2011 (1995=1)	62
3.2	Six NICs: Ratio of Intermediate to Final Exports in 2011	63
3.3	Six NICs Final and Intermediate Imports and Exports in 2011 (1995=1), Base Value 1995 in Brackets (in Million USD)	81
3.4	Six NICs: Foreign Consumption of Domestic Value Added Shares by Industry Category - 2011 and 1995 in Brackets	81
3.5	Industries and Industry Categories	88
4.1	Export Structure by Productivity Level	101
4.2	Import Structure by Productivity Level	101
4.3	Effect of Foreign Ownership on Trade Propensities	104
4.4	Heterogeneous Treatment Effects	106
4.5	Balancing Tests	107
4.6	Alternative Statistical Procedures	109
4.7	Effect of Foreign Ownership on Trade Propensities by Country Income .	110
4.8	Effect of Foreign Ownership by Country's Institutional Quality	112
4.9	Heterogeneous Treatment Effects: Industry Groups	113
5.1	Employment Growth of Occupational Groups in the Manufacturing Sector, 1975-2010	125
5.2	Employment Effects of International Trade (Three-Digit Level)	134
5.3	Employment Effects of International Trade (Establishment-Level)	136
5.4	Matching Process for Intermediate Imports Data	147
5.5	Matching Process for Import Competition and Export Data	148
5.6	Allocation of Leather Imports to the Industries of the BHP (in 2000) . .	150
5.7	Allocation of Leather Exports to the Industries of the BHP (in 2000) . .	152
5.8	Allocation of Leather Imports to the Industries of the BHP (in 2000) - "Traditional Approach"	153
5.9	Comparison of Matched Commodity Trade Flows Before and After Hand Allocation	154

Chapter 1

Introduction

This dissertation consists of four independent papers, each of which is a chapter of the dissertation. The first two papers are single-authored, the last two papers are co-authored.

The first paper titled “Imports, Exports, and Domestic Innovation” identifies the causal effects of trade integration on domestic innovation. For this purpose, I crawl online data to create a new long-term patenting panel dataset for Germany for the period 1993-2012, and exploit the cross-regional variation in the German industry structure to identify the effect of trade integration with the “East” (i.e., Eastern Europe and China) on patenting. I use trade between the East and other advanced economies as instruments for regional import and export exposure. I find that an increase in net trade exposure (defined as import minus export exposure) causes an increase in regional patenting. This effect is purely driven by a positive link between import exposure and innovation, whereas export exposure does not influence innovation. Interestingly, the effects are heterogeneous across exposure origin. The positive link between import exposure and innovation is fully explained by trade integration with Eastern Europe. Increasing integration with China has no effect on innovation. In total, exposure from Eastern Europe accounts for approximately 5.5% of the patenting increase in Germany.

The second chapter contains a paper, for which the work began during a three-month internship at the International Monetary Fund (IMF) in Washington. An earlier edition of the paper titled “The Role of Newly Industrialized Economies in Global Value Chains” is published as “IMF Working Paper No. 16/207”.¹ In this paper, I use the World Input-Output Database (WIOD) to analyze the role of six newly industrialized economies, Brazil, China, India, Indonesia, Mexico, and Turkey, in global value chains. Using WIOD data allows me to compute trade on a value added basis rather than on a

¹Compared to the working paper version, unclear notations have been corrected, Figure 3.2 has been replaced and some parts have been rewritten.

gross output basis, as is done in traditional trade data. To analyze the position of newly industrialized economies in global value chains, the main focus of this paper lies on the origin and share of foreign value added in exports and on the of foreign consumption of domestic value added. The analysis shows that, while all six countries are at a similar stage of development, newly industrialized economies play very different roles in global production and in global value chains. For instance, Mexico's value added trade patterns are marked by a high concentration due to its proximity to the United States, whereas those for Turkey are comparably diverse. India's value added exports focus on services, while China concentrates on manufacturing products. Evidence suggests that Brazil and Indonesia are not integrated as well in global value chains as compared to the other newly industrialized economies.

The third chapter includes a joint paper with Horst Raff and Natalia Trofimenko that has been published in "The World Economy" with the title "Foreign Ownership and the Export and Import Propensities of Developing-Country Firms".² The theoretical part was constructed by Horst Raff, Natalia Trofimenko did the preliminary data preparation, and I was responsible for the empirical part. The paper uses micro data from the World Bank Enterprise Surveys 2002-2006 to investigate how foreign ownership affects the likelihood of manufacturers in developing countries to export and/or import either directly or indirectly. Applying propensity score matching to control for differences across firms in terms of labor productivity and other characteristics, we find that foreign ownership raises the propensity of a firm to export by over 17 and the propensity to import by more than 13 percentage points. The effects are even bigger for countries with the lowest per-capita income and institutional quality.

Finally, the fourth paper is joint work with Philipp Henze with equal contribution in all respects. We use the Establishment History Panel from 1975 to 2010 provided by the German Federal Employment Office to examine the impact of international trade on the occupational structure of the German manufacturing sector. To capture trade, we match the Establishment History Panel with UN Comtrade trade data. For this purpose, we develop a new matching approach that takes the input and output structure of the German manufacturing sector into account. We identify three different trade channels: intermediate imports, import competition, and exports. Using a fixed-effects Poisson regression model, we find diverse occupational effects from trade at the industry-level, while establishment-level estimations show only few significant effects.

²see Boddin, Dominik, Horst Raff, and Natalia Trofimenko (2017), "Foreign ownership and the export and import propensities of developing-country firms", *The World Economy* 40(12), 2543-2563. Note that this version contains very minor changes such as the correction of typos.

Chapter 2

Imports, Exports, and Domestic Innovation

Summary: This paper identifies the causal effects of trade integration on domestic innovation. For this purpose, I crawl online data to create a new long-term patenting panel dataset for Germany for the period 1993-2012, and exploit the cross-regional variation in the German industry structure to identify the effect of trade integration with the “East” (i.e., Eastern Europe and China) on patenting. I use trade between the East and other advanced economies as instruments for regional import and export exposure. I find that an increase in net trade exposure (defined as import minus export exposure) causes an increase in regional patenting. This effect is purely driven by a positive link between import exposure and innovation, whereas export exposure does not influence innovation. Interestingly, the effects are heterogeneous across exposure origin. The positive link between import exposure and innovation is fully explained by trade integration with Eastern Europe. Increasing integration with China has no effect on innovation. In total, exposure from Eastern Europe accounts for approximately 5.5% of the patenting increase in Germany.¹

¹This paper has been presented at the European Trade Study Group meeting in Florence, at the annual conference of the Verein für Socialpolitik in Freiburg, at the workshop on international economic relations in Göttingen, at the Aarhus-Kiel workshop, and at seminars at the University of Colorado Boulder and at Kiel University. I am grateful to the participants and appreciate the helpful comments and suggestions of Johannes Bröcker, Jeronimo Carballo, Robert Gold, Thilo Kroeger, Alessandro Peri, and Horst Raff. I thank Wolfgang Dauth for providing the crosswalk from product classification to (IAB) industry classifications. I am thankful to Q. Vera Liao for supporting the data crawling. I am grateful for excellent research assistance from Sabine Stillger.

2.1 Introduction

The question of how trade affects domestic innovation has been discussed in the literature for a long time. Theoretically, the effect of trade on innovation is ambiguous.² By now, it is a widely held view that the nexus of trade and innovation “remains intrinsically an empirical question” (Autor et al., 2016, p.3). The purpose of this paper is to empirically identify the causal effect of increasing trade integration on innovation. Specifically, I estimate the effects of trade with the “East” (China and Eastern Europe) on innovation in Germany using a regional identification strategy.

To measure innovation, I crawl online patent data from the DPMAregister database of the German Patent and Trademark Office (DPMA). The data cover the period 1993 to 2012 and contain the universe of patent applications (hereafter referred to as “patenting”) in Germany. There are several reasons why these data are well suited to study the effect of trade on innovation. First, the data also include innovation from smaller- and medium-sized firms as well as from private persons, whereas most of the existing literature in this field is biased towards larger firms and only captures a fraction of total patenting. Recent studies have shown that, on average, innovation intensity (share of sales invested in innovation) is higher for small firms (see for instance Itenberg (2013), Akcigit (2010) and Akcigit and Kerr, 2018).³ This suggests that it is important also to consider smaller and medium sized firms when investigating innovation effects, as well as innovation outside of firms such as from suppliers or private entrepreneurs.

Second, the sample period is marked by big changes in patenting in Germany. From the early 1990s, patent applications almost doubled to around 60,000 in the early 2000s. After a peak in 2005, patenting decreased again by two thirds until 2012. Additionally, the period covers two major trade shocks for Germany. The fall of the Iron Curtain in the early 1990s and the opening of China, especially its WTO accession in 2001, increased import competition for Germany, but at the same time, this development created opportunities to tap new export markets. As a result, both German imports from and exports to Eastern Europe and China increased by more than factor 15 and 18, respectively, from 1993 until 2012.

²Increased trade integration will increase competition for domestic firms, which has ambiguous effects on innovation. See for instance Cohen (2010) for a summary of the literature. Autor et al. (2016) provide a summary of the opposing forces of competition on innovation. See Bloom et al. (2016), for a more detailed discussion on various types of innovation and trade models additionally highlighting the ambiguity. Recent theoretical work by Bloom et al. (2013) and Bloom et al. (2014) explain innovation arising from trade by using a “trapped-factor model” of innovation. Production factors can be either used to produce or innovate. Trade with low-wage countries reduces the profitability of producing the same goods as before and the opportunity cost of innovation decreases. For low-wage countries, the economic literature and policy makers often see trade as a potential channel for technology and knowledge access fostering innovation (see UNCTAD (2014), ICTSD (2011) and Goldberg et al., 2010 a, b).

³Previously, this relationship was not observable; firm size did not have effects on innovation intensity. See for instance Cohen et al. (1987) and Cohen and Klepper (1996).

Third, Germany is a big player in global innovation. In 2015, it was the country with the fifth most patent applications worldwide after China, the United States, Japan and Korea, and thus the country with the most patent applications in Europe (WIPO Statistics Database, October 2016).

To make use of the universe of patenting, I apply a regional identification strategy. This is possible, because the patent data allow me to use the zip code of the inventor and the applicant to create a regional exposure measure for Germany. In particular, I measure regional trade exposure using a shift-share approach, for instance applied by Autor et al. (2013), and exploit the cross-regional variation in the German industry structure in combination with industry-specific trade flows to identify regional import competition and export intensity. I then explain changes in the innovation activity of 402 counties (in German: “Landkreise”) between 1993 and 2012 with changes in regional trade exposures. I combine the regional innovation exposure and trade exposure data with regional labor market information from the Establishment History Panel provided by the German Federal Employment Agency. To address concerns of endogeneity, I instrument for German trade flows with trade flows between other similar high-wage countries and Eastern Europe as well as China. Existing literature, especially in the field of regional economics, stresses the role of regional determinants of innovation that my approach allows me to control for.⁴

I find that, on average, an increase in net trade exposure (defined as import exposure minus export exposure) causes an increase in regional patenting. This effect is purely driven by a positive link between import exposure and innovation, whereas export exposure does not influence innovation. Interestingly, the effects are heterogeneous across exposure origin. The positive link between import exposure and innovation is fully explained by trade integration with Eastern Europe. Depending on the specification, I find that a \$1000 increase in Eastern European import exposure per worker in a county increases patenting by 0.044 patents per 100,000 inhabitants in that region. This implies that import exposure from Eastern Europe in Germany accounts for approximately 5.5% of patenting increase in the 1993-2012 period. Increasing integration with China has no effect on innovation.

The results are in line with previous papers that find that Chinese trade exposure, compared to Eastern European exposure, plays only a minor role for Europe, and especially Germany, contrary, for instance, to the United States.⁵ The estimates show that

⁴For instance, Jaffe et al. (1993) show that patent citations are more likely to occur within the state of the cited patent than one would expect based only on the preexisting concentration of related research activity.

⁵Pierce and Schott (2016), for instance, show that China’s WTO accession caused a decrease in the manufacturing employment in the United States. For the EU, there is no similar effect. The US labor market effects from trade with China estimated by Autor et al. (2013) are much larger than those of Dauth et al. (2014).

the effect of import exposure from Eastern Europe on patenting is largest for the most patent-intensive firms. However, the effect also holds for low-patent applicants. I find that there is still a considerable amount of innovation originating from smaller firms or private persons.⁶ In general, these applicants are neglected in previous publications, although they make up a significant proportion of total patenting. The results hold for a wide range of robustness checks.

The current paper is most closely related to Bloom et al. (2016) (hereafter referred to as “BDR”).⁷ They match patent data from the European Patent Office with firm-level data from the Bureau Van Dijk’s Amadeus database. For twelve European countries, including Germany, they find that Chinese import competition accounts for approximately 15% of technology upgrading between 2000 and 2007. They argue that import competition led to a reallocation of employment towards innovative firms and an increase in information technology (IT), total factor productivity (TFP), R&D and patenting for exposed firms. In this current paper, I also find a positive effect of import exposure on innovation. Contrary to BDR, I find that this effect is caused by exposure from Eastern Europe, whereas Chinese exposure has no effect on patenting in Germany.

There may be several reasons for why the findings differ. First, the estimation strategy in this paper differs. Using a regional estimation strategy has the advantage that I cover the universe of patenting in Germany - including smaller firms and private applicants. BDR cover on average around 24% of firm patenting and around 20% of total patenting in Germany. Section A.1 in the Appendix provides more details on this comparison and discusses the patent composition in Germany. Second, my sample period covers a longer time span that is marked by major changes in patenting, whereas during the 2000 to 2007 period, studied by BDR, patenting in Germany was at a steady all-time high. Third, BDR use a group of twelve European countries, and results may be driven by countries other than Germany. The industry structure is diverse across different European countries.

Another related paper is by Autor et al. (2016) who match U.S. patents with data for publicly held firms listed in Compustat and find, contrary to my paper, a strong negative effect of import exposure on patenting. It does not come as a surprise that Chinese trade exposure may have different effects for Germany compared to the United States. As discussed previously, the economic literature suggests that the China shock is of much greater importance for the United States.⁸ Additionally, as before, differences

⁶Low patent applicants account for a smaller share of total patenting. As compared to firms they usually only hold one or at most a few patents per applicant.

⁷To my knowledge, their paper is the only other paper that examines the impact of trade exposure on innovation for Germany, albeit only as part of an aggregated group of 12 European countries.

⁸See Pierce and Schott (2016) and the difference in the results of Autor et al. (2013) and Dauth et al. (2014).

in results may be explained by the fact that I use a different estimation strategy and include the universe of patents. Similar to BDR, the focus on publicly listed firms in Autor et al. (2016) suggests that their sample is restricted to large firms.

More generally, my paper is also related to studies that link trade liberalization to firm productivity. Shu and Steinwender (2018) provide an excellent summary of the empirical findings for trade impacts on both firm productivity and innovation.⁹ Despite the fact that the majority of papers seems to find a positive link between trade and productivity as well as between trade and innovation, different results show that the effects may vary across countries depending on characteristics such as industry and employment structure, competition intensity, exposure origin, sample period, etc. It is all the more surprising that the main focus so far has been on trade exposure from China. More than 70% of the studies published after 2010 listed in Shu and Steinwender (2018) focus on trade exposure from China. Given that exposure from Eastern Europe played a much greater role for Europe, and Germany in particular, I deviate from this practice and also include the exposure from Eastern Europe in this paper.

The remainder of the paper is organized as follows. In the next Section 2.2, I describe the data and stylized facts about regional innovation and trade exposure in Germany. Section 2.3 discusses the empirical methodology and presents the baseline results. Section 2.4 presents further differentiated results and various robustness checks. Conclusions follow in Section 2.5.

2.2 Data and Stylized Facts

I combine crawled patent data from the DPMAregister database of the German Patent and Trademark Office and trade data from the UN Comtrade database with the Establishment History Panel (in German: Betriebs-Historik-Panel (BHP)) provided by the Research Data Centre of the German Federal Employment Office (IAB).¹⁰ The Establishment History Panel is a detailed micro-level dataset that covers a representative 50% sample of all establishments in Germany from 1975 to 2014 (for the 1975-1990 period, it includes only establishments in Western Germany) with at least one employee subject to social insurance contributions. Information on the location of the establish-

⁹Additionally, a number of case studies exist on the issue. See for instance Freeman and Kleiner (2005), who investigate how large US shoe manufacturers respond to import competition from low wage countries or Bartel et al. (2007) and Bugamelli et al. (2008) who look at US valve manufactures and Italian manufacturers, respectively, with similar questions. For the cases under investigation, an increase in innovation to avoid increasing competition from low wage countries seems to be a prominent strategy.

¹⁰This study uses the weakly anonymous Establishment History Panel (Years 1975 - 2014). Data access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and via remote data access (Project Number: fdz1043). For further information concerning the BHP see also Gruhl et al. (2012) (German version) or Hethy-Maier and Seth (2010) (English version).

ment allows aggregating establishment level variables to the county level. I thus obtain local labor market controls providing information on education (employment shares by skill category), the industry structure (employment shares at the three-digit industry level) and employment (share of foreign workers, male/female worker ratio, age structure and occupational structure by Blossfeld categories). The Blossfeld categories contain information on the number of engineers and scientists, which I use as a proxy for R&D employment. The combined dataset covers the years 1993-2012. Reliable data on establishments and trade in Eastern Germany, as well as patent data based on the current five-digit postal code system, is available from 1993 onwards, determining the first year of observation. The time frame coincides with the rapid increase in trade with Eastern Europe shortly after the fall of the Iron Curtain and with China after its WTO accession in 2001. In the following, I will refer to the combined trade with Eastern Europe and China as trade with the “East”.

2.2.1 Patenting

To measure innovation, I crawl patent data from the DPMAregister database of the German Patent and Trademark Office (DPMA). The data cover the years 1993 to 2012.¹¹ Patents are a widely accepted and common proxy for innovation despite its well-known drawbacks.¹² The data contain the universe of patent applications from applicants and inventors located in Germany.¹³ Applicants can be either natural persons (e.g., private entrepreneurs) or legal persons (e.g., corporations). The data provide rich information on every patent and contain details on the applicants (name, zip code, (legal) type), inventors (name, zip code), patent content (title, description and classification as well as subclassifications according to the International Patent Classification, “IPC”) and patent history (changes in ownership, different steps in the application process). Using a zip code-municipality crosswalk provided by the German postal service (“Deutsche Post Di-

¹¹Patent data is also available from 1980 to 1992. For this time period, however, zip codes are primarily based on the former four-digit system. After the introduction of the current five-digit system the number of zip codes in Germany increased by factor six to around 30,000 allowing for a much more precise allocation of innovation based on the zip code of the inventor or applicant to administrative units.

¹²Deyle and Grupp (2005) provide a brief summary of main drawbacks including 1) limited distinguishability of novelty, 2) limitation to innovation that is subject to patent protection, 3) differing value and quality of patents, 4) limited distinguishability in terms of innovation types such as process or product innovation.

¹³Note: In this paper, “Patenting” (and “Patents”) always refer to patent applications. Patent applications are a well suited proxy for underlying innovation activity, as they capture any innovation process that is deemed successful by the applicant. Additionally, the procedure until a patent is eventually granted oftentimes takes several years (and might even be revoked later on) such that patent applications rather than granted patents are the more feasible and immediate measure. Crawling of the dataset began in 2013, such that information on the grant is insufficient. On average, around 42% of total patent applications are eventually granted. This share remains rather constant over the years.

rekt”), I use the zip code information of the applicants and inventors to create measures for patent intensity at the regional administrative level.¹⁴ The smallest administrative unit for which I calculate regional patenting intensities is the municipality level. For the empirical analysis, however, the data are aggregated to the county level to match the regional aggregation level of the trade exposures. The baseline index for innovation intensity in administrative region i at time t , IA_{it} , is given by:

$$IA_{it} = \frac{\sum_{n=1}^N \frac{1}{k^z} \frac{1}{s_n} PAT_{nt}^z}{E_{it}}, \quad z \subset i, \quad (2.1)$$

where PAT_{nt}^z refers to patent n that was filed at time t in zip code area z , which (at least partly) has to be located inside the administrative region i . If the zip code area crosses administrative lines, each administrative unit accounts for fraction $\frac{1}{k^z}$ of the patent, where k^z is the number of administrative regions that are part of the zip code area.¹⁵ Regional innovation is measured either based on the zip code of the inventor or of the applicant (i.e., the owner). Each patent is weighted with $\frac{1}{s_n}$, where s_n is the number of inventors / applicants of patent n .¹⁶ To obtain an innovation measure that takes regional population into account, the absolute number of regionally allocated patents (in the numerator) is divided by the population size of this region E_{it} . To deal with the reorganization of municipality boundaries over time, I use municipality crosswalks provided by the German Federal Office for Building and Regional Planning (“Bundesamt für Bauwesen und Raumordnung”) to convert regional data to the territorial borders of 2014. This is necessary, since, without territorial reallocation, there would be cases, for which the county of the inventors or applicants changes without the inventors or applicants having actually moved. Additionally, the Establishment History Panel is also based on the territorial borders of 2014.

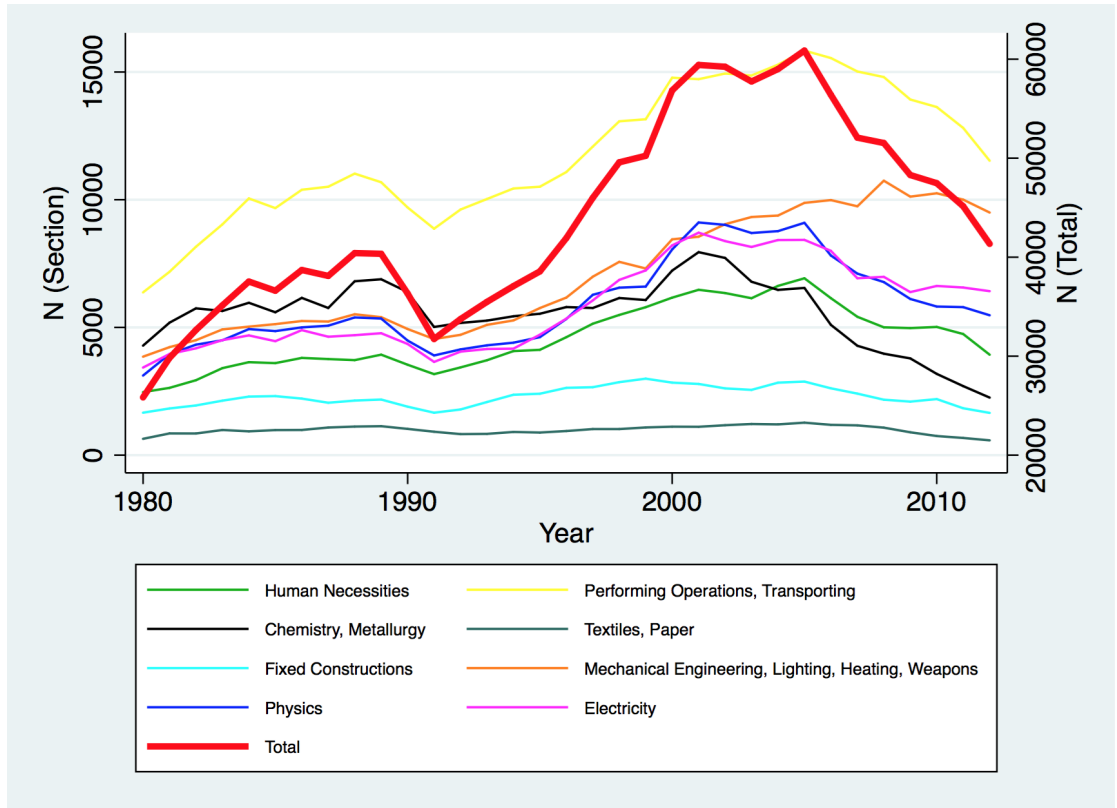
Figure 2.1 shows the yearly numbers of patent applications in Germany (also including East Germany before German reunification) both in total (right axis) and also broken down by the one-digit level of IPC categories (left axis) from 1980 to 2012. In the

¹⁴The regional approach is used to establish a link between trade and patenting. Another link, e.g., via the industry to which a patent can be assigned to is not directly accessible. The patents are only classified according to IPC and crosswalks to industry classification have a questionable quality due to the very different nature of the classifications. An industry allocation based on the patent description, for instance, by using machine learning techniques, would also be extremely time-consuming and error-prone.

¹⁵In Germany, zip codes label areas that are defined for postal delivery which do not always adhere to geopolitical administrative boundaries. However, for 81.55% of the observations zip code areas are municipality-sharp, which means that the zip code area lies within one municipality only. Aggregation to the county level (the preferred aggregation level for the empirical analysis) increases the number of cases, for which the zip code area corresponds to only one administrative region to 99.11%. Accordingly, concerns that inaccurate zip code to administrative unit allocations might bias results can be precluded.

¹⁶In 2012, the average number of inventors per patent was 2.3 and the average number of applicants per patent was 1.1.

Figure 2.1: Patenting in Germany: Total Patenting and Subsections



1980s, yearly patenting increased continuously from around 25,000 in 1980 to slightly more than 40,000 in 1989, before a sharp drop around the time of German reunification occurred.¹⁷ This trend is similar for all of the eight categories. After 1991, patenting increased quickly throughout the 1990s and the first half of the 2000s to peak at more than 60,000. In the second half of the 2000s, the number of patent applications dropped continuously to a level of around 41,000 applications in 2012. With around 28%, “Performing Operations, Transporting” accounted for the largest share of patenting, followed by “Mechanical Engineering, Lighting, Heating, Weapons” with a share of about 23%. “Textiles, Paper” (about 1%), “Fixed Constructions” (about 4%) and “Chemistry, Metallurgy” (about 6%) only play a minor role in patenting. Over time, patent growth within the categories roughly follows the growth pattern of total patenting described above. This means that category shares of patenting remain largely unchanged. One interesting exception are the shares of “Mechanical Engineering, Lighting, Heating, Weapons” and “Chemistry, Metallurgy”. In 2001, both sections accounted for almost

¹⁷Before reunification, the data includes patents filed both at the “German Patent Office” in West Germany and at the “Office of Inventions and Patents” in East Germany. After reunification, both patent offices merged and patenting in Eastern Germany dropped tremendously.

identical shares of 14.4% and 13.4%, respectively. Since then, the share of “Mechanical Engineering, Lighting, Heating, Weapons” has increased to about 23% and the one of “Chemistry, Metallurgy” has decreased to only 5.5% in 2012. For all other sections, shares remain within a 5 percentage point range during the 33 years of observation.

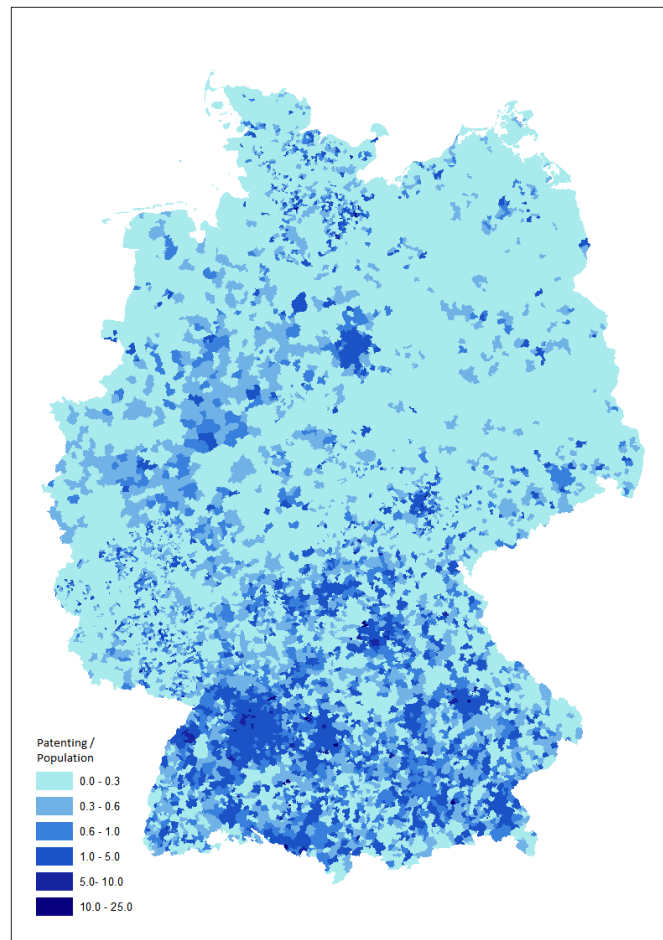
Innovation activity in Germany is very heterogeneous across regions. Figure 2.2 depicts the number of patent applications in 2012 by the inventor’s location for every 1000 inhabitants at the municipality level based on Equation 2.1. The map shows both a distinct North-South and West-East divide. In the southern states of Baden-Wuerttemberg and Bavaria, patent intensity is much higher than in states that are located further north. At the same time, we can find much more innovation in Western Germany compared to Eastern Germany (including Berlin). Despite the fact that per capita patenting is comparatively low in some of the largest German cities like Berlin or Hamburg, agglomeration generally seems to favor innovation. Patenting is highest in densely populated areas: In Western Germany, especially the corridor reaching from the Rhine-Ruhr metropolitan area up to the metropolitan area of Hannover, Wolfsburg and Braunschweig in the southern part of Lower Saxony shows the highest per capita innovation. In South Germany, a stretch reaching from Würzburg down to the area around Lake Constance and including the metropolitan regions of Nuremberg, Stuttgart and Munich is patent intensive. Consider that here the inventor’s rather than the applicant’s location is taken as the origin of innovation. Inventors may live in commuting distance from the firm’s location, and thus innovation patterns are regionally more dispersed. Indeed, regional innovation activity is more centralized, when patent applications for every 1000 inhabitants are calculated by the applicant’s location (see Figure 2.9 in the Appendix). Now cities in general, and the centers of metropolitan regions in particular, show relatively high per capita patenting. It is here, where oftentimes the firms or at least the branches that are responsible for the patent applications are located. However, the general picture does not change: The North-South and West-East divide persists and per capita innovation is still relatively high in densely populated areas.¹⁸

The regional intensity of innovation shows considerable variation over the years. Figure 2.3 presents the absolute change of patenting per 100,000 inhabitants measured by the location of the inventor at the county level.¹⁹ The map on the left shows the change between the period averages of 1993 to 1995 and 2002 to 2004, $\bar{I}A_i^{02-04} - \bar{I}A_i^{93-95}$, whereas the map on the right depicts the change between the period averages from 2002 to 2004 and from 2010 to 2012, $\bar{I}A_i^{10-12} - \bar{I}A_i^{02-04}$. One immediate observation is

¹⁸Unsurprisingly, the picture changes slightly when looking at total patenting rather than per capita patenting (see Figure 2.10 in the Appendix). Now, the largest German cities like Berlin, Hamburg or Dresden also show high numbers of patent applications.

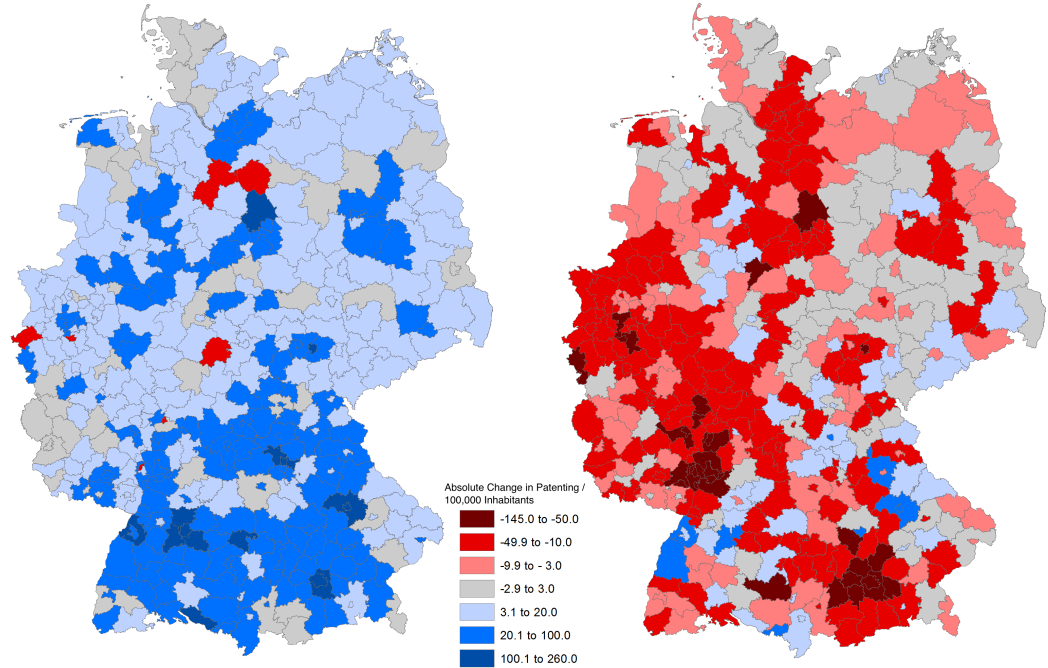
¹⁹The following observations remain largely unchanged when the location of the applicant rather than the location of the inventor is used to calculate regional patenting (see Figure 2.11 in the Appendix).

Figure 2.2: Patenting per 1000 Inhabitants by Municipality of the Inventor



that regional growth of patenting differs considerably between the two periods. During the first period, patenting increases in almost all counties with larger growth in the South than in the North and stable values for Eastern Germany. For the second period, the picture is more diverse: Patenting decreases in about 60% of the counties, remains stable in about 20% of the counties and increases in about 20% of the counties as well. Again, most of the regions with increased patenting are located in the South, whereas the Eastern German regions face a decrease in patenting. Regional changes in patenting are a reflection of the diverse regional industry structure in Germany. Previously, it was shown that the numbers of yearly patent applications develop heterogeneously across different IPC categories. This will result in dispersed patterns of regional innovation, as the applicants of patents with certain IPC categories tend to be regionally concentrated. In the second period, for instance, patenting decreases strongly in the Ruhr area - a region characterized by traditional manufacturing industries likely to file patents in the field of “Chemistry and Metallurgy” that showed a patenting decrease of more than

Figure 2.3: Absolute Change of Patenting per 100.000 Inhabitants by Location of the Inventor; $I\bar{A}_i^{02-04} - I\bar{A}_i^{93-95}$ (Left) and $I\bar{A}_i^{10-12} - I\bar{A}_i^{02-04}$ (Right)



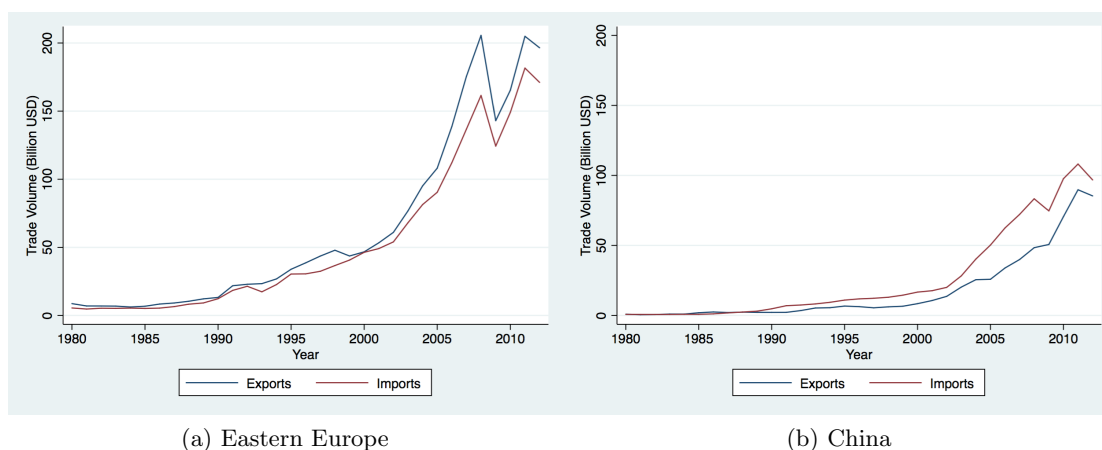
50% during that period (cf. Figure 2.1). Another observation is that regional patenting shows both elements of a clustered and dispersed pattern. On the one hand, we can observe general North-South and East-West patterns and partly also clustering at the more local level such as for the Ruhr area example above. On the other hand, innovation patterns within states are still quite dispersed as patenting intensities vary considerably at the county level within a state.

2.2.2 Trade Exposure

The fall of the Iron Curtain and the opening of China increased import competition for Germany. At the same time, however, this development created opportunities to tap new export markets. German trade relations during the 1993-2012 period are marked by a strong intensification of trade with China and Eastern Europe. Figure 2.4 shows the increase in German exports to and imports from Eastern Europe (left) and China (right) (measured in billion USD). During the 1980s and early 1990s, trade with either of the two regions was almost non-existent.²⁰ After the fall of the Iron Curtain in the early 1990s, trade with Eastern Europe picked up pace. Also, trade with China started

²⁰This observation supports the previous claim that the industry structure in the early 1990s is well suited to allocate trade flows, as it will be unaffected by Eastern trade at that point in time.

to increase slowly. However, it was not until its WTO accession in 2001 that the trade increase with China became eminent. Accordingly, the import and export exposure in the 1990s primarily originated from trade with Eastern Europe, whereas it was both Eastern Europe and China that contributed to increasing exposures in the 2000s. Overall, German imports from and exports to Eastern Europe and China increased by more than factor 15 and 18, respectively, from the early 1990s until 2012. The nature of the German trade relations with Eastern Europe and China differs substantially. Trade with Eastern Europe is primarily intra-industry, implying that product categories of German export goods are similar to those of the goods imported from Eastern Europe. By contrast, trade with China is primarily inter-industry. Section A.4 in the Appendix discusses the differences in the nature of German-Eastern European and German-Chinese trade in more detail and shows that the weighted Grubel-Lloyd-Index (cf. Figure 2.14) is much larger for German-Eastern European than for German-Chinese trade.



(a) Eastern Europe

(b) China

Figure 2.4: German Trade with Eastern Europe and China

To compute regional trade exposures, I use a shift-share approach, for instance applied by Autor et al. (2013), and exploit the cross-regional variation in the German industry structure to regionally allocate trade flows.²¹ For this purpose, I obtain trade flows between Germany and Eastern Europe, as well as between Germany and China at the four-digit product level (in SITC 2/3 classification) from the UN Comtrade database. I harmonize trade and IAB employment data using a crosswalk that reclassifies trade flows into the three-digit industry-level classification used in the IAB data.²² Here, Eastern Europe is defined as the countries of the former Soviet Union plus the member

²¹For Germany, this identification strategy was, for instance, used by Dauth et al. (2014) and by Dippel et al. (2015) who measure the effect of trade exposure on voting behavior.

²²Establishments in the IAB data are classified according to the WZ93 classification (“Industrial Classification of Economic Activities for the Statistical Office of the Federal Employment Agency, 1993 Edition”), which is based on the NACE classification.

states of the Warsaw Pact and its predecessor states, except Albania, East Germany, and Slovakia.²³ Using a product-industry crosswalk, the trade flows are converted into the industry classifications of the Establishment History Panel. To obtain the change in regional import exposure ΔImp_{it}^{East} in region i at time t from trade with the East, the following expression is calculated:

$$\Delta Imp_{it}^{East} = \sum_j \frac{E_{ijt}}{E_{jt}} * \frac{\Delta Imp_{jt}^{Ger-East}}{E_{it}}, \quad (2.2)$$

where the change in imports ΔImp of industry j is allocated to county i according to the share of total employment in industry j that can be found in county i , $\frac{E_{ijt}}{E_{jt}}$. Additionally, the import flows are weighted with the total county employment E_{it} , such that the exposure for a region is, ceteris paribus, larger if overall employment in that region is lower. Taking the sum over all industries then yields the regional import exposure. Likewise, the change in regional export exposure ΔExp_{it}^{East} in region i at time t is calculated as:

$$\Delta Exp_{it}^{East} = \sum_j \frac{E_{ijt}}{E_{jt}} * \frac{\Delta Exp_{jt}^{Ger-East}}{E_{it}} \quad (2.3)$$

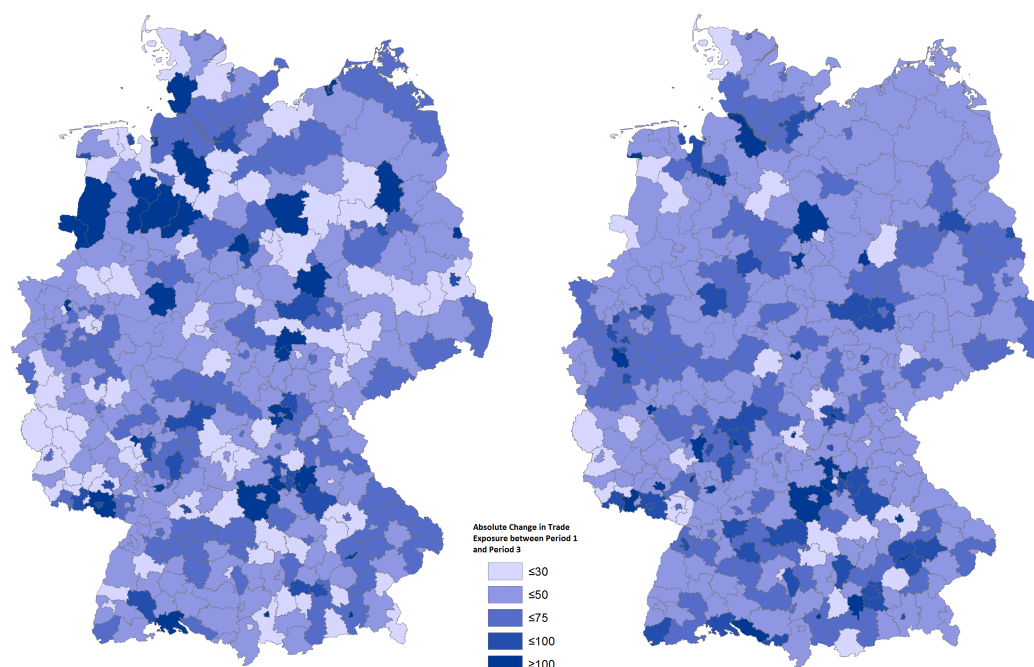
Figure 2.5 depicts the change in the computed trade exposure measure separately for import exposure ΔImp_{it}^{East} (left) and export exposure ΔExp_{it}^{East} (right) between the period averages of 2010 to 2012 and 1993 to 1995. As can be seen, the trade shock is spatially rather diverse meaning there is no clear, broad clustering within certain regions. However, certain patterns become visible. First, Eastern Germany is affected less compared to Western Germany. Second, the regions exhibit different import and export exposure, meaning that regions with high import exposure do not necessarily exhibit a high export exposure as well (and vice versa). Third, not only counties that are well-known for their manufacturing industry, such as Wolfsburg (car manufacturing) or Nuremberg-Erlangen (machinery and plant engineering), show relatively high import exposure, but also areas that are not particularly known for their high importance of manufacturing (e.g., certain counties in Lower Saxony). One reason for this pattern might be that the exposures are weighted by the number of manufacturing employees.²⁴

²³To be precise, “Eastern Europe” includes Armenia, Azerbaijan, Belarus, Bulgaria, Czech Republic, Estonia, Georgia, Hungary, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Moldova, Poland, Romania, Russia, Tajikistan, Turkmenistan, Ukraine, and Uzbekistan.

²⁴Note: Compared to Dauth et al. (2014), the figure shows a larger exposure for counties in Eastern Germany. The reason for the difference lies in the different time of observation. I also include Eastern Germany in the first period for the baseline estimation. Shortly after the German reunification,

Figure 2.12 and Figure 2.13 in Section A.3 in the Appendix depict the changes in import and export exposure between the period averages of 2010 to 2012 and 1993 to 1995 separately for both origins, Eastern Europe and China. The graphics show that the exposure differs regionally according to the origin, reflecting both the diverse industry structure in Germany but also the differences between the goods traded between Germany and Eastern Europe and between Germany and China.²⁵

Figure 2.5: Absolute Change in Regional Import Exposure $\overline{Imp}_t^{East}{}^{10-12} - \overline{Imp}_t^{East}{}^{93-95}$ (Left) and Regional Export Exposure $\overline{Exp}_t^{East}{}^{10-12} - \overline{Exp}_t^{East}{}^{93-95}$ (Right) in \$ 1000 per Manufacturing Worker



2.3 Trade Exposure and Innovation

The next subsection contains the baseline estimations for the effects of trade on innovation. I first describe the empirical specification, and then estimate the effect of net exposure on innovation. I break down this effect further into import and export exposure. Finally, I present coefficient estimates separately depending on the origin of

manufacturing in Eastern Germany was hardly existent, explaining why in this paper the change in the exposure in Eastern Germany is larger.

²⁵Furthermore, the change in the trade shocks also differs between observation periods (not displayed in this paper), meaning that the change in trade exposure between the period averages of 2010 to 2012 and 2002 to 2014 differs from that between the period averages of 2002 to 2004 and 1993 to 1995.

the exposure (Eastern Europe and China).

2.3.1 Empirical Specification

In the baseline specification, I first estimate the effect of changes in the three-year averages of regional net trade exposures on changes in three-year averages in patenting per 100,000 inhabitants with the following equation:

$$\Delta \overline{IA}_{it} = \alpha + \beta \Delta \overline{NetX}_{it}^{East} + \gamma \overline{X}'_{it} + \sigma_i + \kappa_t + u_{it}, \quad (2.4)$$

with

$$\Delta \overline{NetX}_{it}^{East} = \Delta \overline{Imp}_{it}^{East} - \Delta \overline{Exp}_{it}^{East} \quad (2.5)$$

where $\Delta \overline{IA}_{it}$ is the change in the three year average of innovation activity, i.e., patenting per 100,000 inhabitants in region i at time t from Equation (2.1), and $\Delta \overline{NetX}_{it}^{East}$ is the change in the three year average of net trade exposure. The change in net trade exposure is defined as the difference between the change in three year average of import exposure $\Delta \overline{Imp}_{it}^{East}$ and the change in three year average of export exposure $\Delta \overline{Exp}_{it}^{East}$ (cf. Equation (2.2) and Equation (2.3)). I deflate the trade flows using the German CPI to the base year 2010. X'_{it} is a vector of regional control variables. Region fixed effects σ_i are implemented at the disaggregated county-level.²⁶ κ_t are time fixed effects. The standard error u_{it} is clustered at the level of the 402 counties. Note that the estimation approach will generate very conservative estimations for the effects of trade on innovation. The only effects that count here are deviations from the trend, i.e., effects are measured only to the extent that the variation in trade causes a deviation from the linear time trend.

To overcome concerns that shocks that affect German trade and regional innovation simultaneously might drive the results, I follow Autor et al. (2013) and instrument for the trade exposures $\Delta \overline{NetX}_{it}^{East}$, $\Delta \overline{Imp}_{jt}^{Ger-East}$ and $\Delta \overline{Exp}_{jt}^{Ger-East}$ using trade flows between other advanced economies and the East. This way, the effect that drives the empirical results originates purely from the exogenous rise in Eastern supply. The selection of the group of countries used for instrumentation for the baseline estimations closely follows Dauth et al. (2014) and includes Canada, Japan, New Zealand, Norway,

²⁶Results remain qualitatively unchanged when I implement region fixed effects at more aggregated regional levels of labor market regions, regional planning regions, states and four larger regions (South, North, East and West). This latter regional fixed effects specification follows Dauth et al. (2014); region North covers the states of Schleswig-Holstein, Hamburg, Bremen and Lower Saxony. Region West includes Rhineland-Palatinate, Hessa and Saarland. South contains Bavaria and Baden-Wuerttemberg, and East covers the new eastern states of Germany plus Berlin.

Singapore, Sweden, and the UK.²⁷

I estimate differences between periods that consist of three year averages, as patenting is comparatively volatile, contrary, for instance, to labor market outcomes such as manufacturing employment (e.g., Autor et al., 2013). Taking averages over several years thus prevents that outliers in yearly patenting, i.e., years in which patenting is exceptionally high or low, drive the results.

I study changes between averages of the years 1993, 1994, 1995 (period one) and the averages of the years 2002, 2003, 2004 (period two) and between the averages of the years 2002, 2003, 2004 and the averages of the years 2010, 2011, 2012 (period three). This time frame fits well the patenting time trend in Germany (cf. Figure 2.1): From period one to period two, patenting in Germany rises to an all time high that persists during the years of period two. The following years from period two to period three are then marked by a steady decline in patenting. Additionally, reliable patent data based on the current five-digit postal code system and establishment data for Eastern Germany is not available before 1993.

Patenting per 100,000 inhabitants based on the home address of the inventor is the preferred baseline measure of regional innovation. Patenting based on the inventor's location is a frequently used innovation measure in the literature and has been proven to reliably determine the regional origin of innovation.²⁸ Since inventors will most likely live in close proximity to their workplace, which is the location marking the regional origin of trade exposure, a geographic link between innovation and trade exposure can be established. Patenting based on the applicant's address is less suited to build this link. Firms oftentimes use just one address (generally that of the firm's headquarter) to file patent applications. However, large companies (especially MNEs), which are also responsible for a big share of patent applications, often have multiple locations, holdings, affiliations or subsidiaries, so this procedure could be geographically misleading (see for instance Blind and Grupp, 1999).²⁹

In the second baseline estimation (Equation (2.6)), I then disentangle the net exposure effect and separately include changes in three-year averages of regional import and

²⁷The rationale for the selection of this instrument group, in particular, is well described in their paper. The only difference to Dauth et al. (2014) is that I exclude Australia from the baseline instrument group, as I find Australia negatively affecting the performance of the instruments for German-Chinese trade. As a robustness check, I additionally alter the instrument group by adding other countries and conducting the regressions with various compositions of the instrument group. Results remain unaffected by choice of the instrument group. See Section 2.4.2.

²⁸See, for instance, Paci and Usai (2000), Paci and Pigliaru (2002) and Mancusi (2008).

²⁹Also see Jaffe et al. (1993) and Jaffe and Trajtenberg (2002) for a profound discussion on the suitable geographical measure of patenting.

export exposure:

$$\Delta \overline{IA}_{it} = \alpha + \beta_1 \Delta \overline{Exp}_{it}^{East} + \beta_2 \Delta \overline{Imp}_{it}^{East} + \gamma \overline{X}_{it}^I + \sigma_i + \kappa_t + u_{it}, \quad (2.6)$$

Finally, in a third estimation, I re-estimate Equation (2.6) again distinguishing between trade flows from Eastern Europe and China.

2.3.2 Results

Net Exposure, Import Exposure, and Export Exposure

Table 2.1 presents the baseline results from Equation (2.4). Every column pair includes one specification. The first column of the pair always contains the OLS estimates, and the second one the IV results, where I instrument for the trade flows between Germany and the East by using trade flows between other advanced economies and the East. The least conservative specification in the first two columns only includes basic labor market controls, such as the employment shares of skilled workers (“% Skill”), foreigners (“% Foreigner”), women (“% Women”), and workers performing routine tasks (“% Routine”). Additionally, I control for the manufacturing share (“% Manufacturing”). On the one hand, the share of manufacturing drives the trade exposures, and on the other hand, manufacturing accounts for a large proportion of corporate patenting such that regions with larger manufacturing shares are expected to be more patenting intensive. The second specification adds time fixed effects and region fixed effects at the county level. This controls for any unobserved county or period characteristics. Thus, the only remaining identifying variation originates from the county-time dimension. The preferred and most conservative third specification additionally adds controls for the relative importance of specific industries in a given region. These controls account for the fact that patenting in Germany is biased towards larger firms. For the time of observation, the 20 biggest applicants account for almost 25% of total patenting in Germany. Primarily, these firms are part of the automobile (9 out of 20 of these firms) or chemical industry (5 out of 20 of these firms). Accordingly, I add controls for the employment share in these three-digit industries (“% Chemistry” and “% Automobile”) as well as a control for the share of the largest industry (“% Largest Industry”) in a region.

The effect of changes in regional net trade exposure on changes in patenting (“ Δ Net Exposure”) is insignificant for the estimations with only basic labor market controls, but turns statistically significant and is positive when adding fixed effects and industry information. IV estimates are similar to the OLS results. As the change in net exposure is defined in units of \$1000 per worker, the coefficient of 45.77 in the preferred 2SLS estimation implies that a \$1000 increase in the net exposure per worker in a county increases

Table 2.1: Effect of Periodic Changes in Regional Net Trade Exposures on Periodic Changes in Patenting per 100,000 Inhabitants

Estimation	Baseline Labor Market		+Region / Time FE		+Industry Information	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
$\Delta NetExposure$	7.813 (10.122)	6.594 (9.142)	54.367* (31.429)	36.202* (19.204)	63.713* (32.581)	45.766** (19.157)
% Manufacturing	93.053*** (14.545)	92.957*** (14.417)	206.701*** (59.940)	207.843*** (41.914)	216.185*** (69.548)	216.784*** (48.531)
% Skill	-311.130*** (64.277)	-311.358*** (64.226)	-742.855* (437.419)	-744.803** (306.706)	-828.788** (420.316)	-827.581*** (293.291)
% Foreigner	-51.324*** (18.426)	-51.327*** (18.334)	387.435*** (133.436)	388.539*** (93.563)	379.984*** (131.776)	381.352*** (92.108)
% Women	191.403*** (43.801)	191.506*** (43.641)	74.693 (218.777)	69.093 (154.085)	96.769 (198.563)	90.624 (139.089)
% Routine	-207.899*** (25.366)	-207.839*** (25.190)	-272.927* (145.235)	-273.941*** (102.062)	-276.528* (150.768)	-277.451*** (105.577)
% Chemistry					-3.885 (192.465)	- 2.984 (134.354)
% Automobile					-237.868 (223.421)	-228.359 (154.515)
% Largest Industry					91.148 (139.744)	87.669 (97.071)
County FE	No	No	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	Yes	Yes

2SLS First Stage Estimates, Dependent Variable: Net Exposure			
$\Delta NetExposure$	0.913***	0.693***	0.692***
(Other Countries)	(0.116)	(0.035)	(0.037)
F-Test excl. Instr.	25.52	59.22	39.74

Note: N=804; Clustered standard errors (by county) in parentheses; *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level; All regressions include a constant; First stage estimates also include the same control variables that are indicated in the columns for the second stage estimates.

patenting by 45.77 patents per 100,000 inhabitants in that county. The coefficient for the IV estimation is slightly smaller and indicates greater significance compared to the OLS estimate consistent with an upward bias of the OLS estimate. Additionally, the results show that an increase in the share of foreigners is positively linked to innovation and that - as expected - patenting increases with the share of manufacturing. Patenting is smaller when the number of routine workers increases. Innovation requires complex tasks that are generally conducted by non-routine occupations. Surprisingly, patenting

is also negatively related to the share of skilled workers. A probable explanation is that a large proportion of high-skilled workers is employed in the service sector, which, in turn, is significantly less patent intensive than manufacturing. The first stage estimations are displayed at the bottom of the table and indicate strong and fitting instruments. The F-tests show that the hypotheses that instruments are excluded can be rejected, and the instruments are strongly correlated with the endogenous explanatory variable.

To identify whether the positive coefficients are either explained by changes in import exposures or by changes in export exposures, estimating Equation (2.6) disentangles the effects. The results are displayed in Table 2.2. As before, I apply the three specifications “baseline labor market”, “fixed effects” and “industry controls”. Again, the first column for every specification shows the OLS estimate, whereas the second column shows the IV results.

The results show that the positive effect on changes in innovation from increasing net exposure is completely driven by import exposure effects. $\overline{\Delta Exp_{it}^{East}}$ (“ Δ Export Exposure”) is insignificant for all specifications, whereas $\overline{\Delta Imp_{it}^{East}}$ (“ Δ Import Exposure”) is statistically significant and positive for specification 2 and 3. The coefficient of 0.051 in the preferred 2SLS estimation implies that a \$1000 increase in the import exposure per worker in a county increases patenting by 0.051 patents per 100,000 inhabitants in that county.³⁰ Again, first stage estimations displayed at the bottom of the table show strong and fitting instruments. The results for the control variables are in similar ranges as in the previous estimate.

Heterogeneity between Eastern Europe and China

To disentangle the findings, I now break down the effects by further distinguishing between the origin of trade exposure, and estimate Equation (2.6) separately for both Eastern European and Chinese exposure. This distinction is well justified, as exposures from Eastern Europe and China are rather diverse. First, trade exposure from Eastern Europe kicked in much earlier after the fall of the Iron Curtain in the early 1990s, whereas the exposure from China primarily began to increase after its WTO accession in 2001. Second, exposure from Eastern Europe is much higher compared to China. Both imports from and exports to Eastern Europe are approximately 10 times larger in the 1990s and still twice as high in 2012. Third, the nature of trade differs: As shown

³⁰Compared to estimation (2.4) coefficients might seem small in magnitude at first glance. However, it has to be considered that the values of net exposure $\overline{NetX_{it}^{East}} = \overline{\Delta Imp_{it}^{East}} - \overline{\Delta Exp_{it}^{East}}$ are much smaller compared to the values for the import or export exposure. The values for the import exposure are only slightly larger than those for the export exposure during the years of observation (cf. Figure 2.4). Additionally, the figures for average patenting per county are not large either. For the observation period, total yearly average patenting in Germany reached a number of 49,712. Taking into account that there are 402 counties in Germany, average yearly patenting per county amounts to a number of around 124.

Table 2.2: Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Changes in Patenting per 100,000 Inhabitants

Estimation	Baseline Labor Market		+Region / Time FE		+Industry Information	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
$\Delta Import Exposure$	0.004 (0.007)	0.002 (0.007)	0.059* (0.034)	0.042** (0.018)	0.067* (0.035)	0.051*** (0.018)
$\Delta Export Exposure$	-0.178** (0.080)	-0.201* (0.114)	0.060 (0.194)	0.142 (0.242)	0.029 (0.237)	0.122 (0.302)
% Manufacturing	95.378*** (14.582)	95.583*** (14.423)	219.624*** (60.871)	227.962*** (44.126)	225.475*** (69.989)	233.606*** (50.893)
% Skill	-262.803*** (76.293)	-255.979*** (81.187)	-724.646 (440.874)	-716.577** (307.585)	-818.569* (421.272)	-809.073*** (289.373)
% Foreigner	-42.202** (17.988)	-40.856** (18.234)	389.015*** (133.510)	391.031*** (94.093)	382.315*** (133.052)	385.580*** (94.255)
% Women	175.785*** (45.810)	173.622*** (45.862)	54.987 (223.020)	38.285 (169.619)	87.432 (201.849)	73.690 (146.414)
% Routine	-195.450*** (26.727)	-193.520*** (27.932)	-258.712* (142.725)	-251.890*** (93.250)	-267.113* (145.210)	-260.409*** (94.195)
% Chemistry					-8.736 (192.454)	-11.762 (134.219)
% Automobile					-202.735 (247.574)	-164.705 (195.777)
% Largest Industry					99.438 (149.750)	102.661 (112.006)
County FE	No	No	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	Yes	Yes

2SLS First Stage Estimates, Dependent Variable: Import Exposure

$\Delta Import Exposure$ (Other Countries)	0.878*** (0.072)	0.652*** (0.021)	0.650*** (0.021)
F-Test excl. Instr.	169.98	151.47	151.48

2SLS First Stage Estimates, Dependent Variable: Export Exposure

$\Delta Export Exposure$ (Other Countries)	0.551*** (0.091)	0.591*** (0.119)	0.559*** (0.106)
F-Test excl. Instr.	180.71	161.75	131.63

Note: N=804; Clustered standard errors (by county) in parentheses; *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level; All regressions include a constant; First stage estimates also include the same control variables that are indicated in the columns for the second stage estimates.

previously, trade between Germany and Eastern Europe is primarily intra-industry (cf. Section A.4 in the Appendix), whereas for China, the inter-industry component is much larger.

Table 2.3 shows the OLS and IV estimations for both Eastern Europe and China, using again the three specifications from above. Unsurprisingly, changes in export exposure remain widely insignificant for both Eastern Europe and China. Interestingly, the results show that the import exposure effect is purely driven by Eastern Europe: For all specifications including fixed effects, the effect is positive and significant, whereas exposure from China is largely insignificant. The coefficient of 0.044 in the preferred IV estimation implies that a \$1000 increase in Eastern European import exposure per worker in a county increases patenting by 0.044 patents per 100,000 inhabitants in that county. A simple calculation reveals that import exposure from Eastern Europe in Germany accounts for approximately 5.5% of the patenting increase in the 1993-2012 period.³¹ This corresponds to the average annual number of 1,215 patent applications.

The result that trade with Eastern Europe affects Germany more than trade with China is in line with previous findings in the literature. Dauth et al. (2014), for instance, show that imports from Eastern Europe affect manufacturing employment in Germany way more than Chinese imports. Effects from trade with China on labor market outcomes for the United States estimated by Autor et al. (2013) are much larger than those estimated by Dauth et al. (2014) for German labor markets - presumably due to Germany's different industry structure that is characterized by a large share of skill-intensive manufacturing. Pierce and Schott (2016) show that China's WTO accession caused a decrease in the manufacturing employment in the United States. For the EU, there is no similar effect.

³¹The exposure per worker in \$ 1000 increased by a factor of 33.36. The calculated coefficient results in an increase of approximately 1.5 patents per 100,000 inhabitants. The actual increase of patenting per 100,000 inhabitants in this period was 27.4, so the import exposure from Eastern Europe accounts for about 5.5% of the patenting increase.

Table 2.3: Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Change in Patenting per 100,000 Inhabitants - Exposure Origin

Estimation	Baseline Labor Market						+Region / Time FE				+Industry Information			
	Eastern Europe		China		China		Eastern Europe		China		Eastern Europe		China	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
$\Delta Import Exposure$	0.004 (0.007)	0.003 (0.005)	-0.015 (0.041)	-0.090 (0.077)	0.044* (0.024)	0.036** (0.016)	0.155** (0.079)	0.163 (0.203)	0.049** (0.022)	0.044*** (0.015)	0.177** (0.077)	0.242 (0.230)		
$\Delta Export Exposure$	-0.271** (0.126)	-0.093 (0.213)	-0.277* (0.144)	-0.525* (0.302)	0.261 (0.414)	0.707 (0.890)	0.002 (0.277)	0.150 (0.506)	0.278 (0.465)	0.546 (1.105)	-0.091 (0.320)	0.089 (0.620)		
% Manufacturing	95.385*** (14.412)	93.535*** (14.469)	93.851*** (14.598)	94.953*** (14.541)	224.901*** (62.433)	252.120*** (61.581)	221.470*** (60.736)	229.470*** (45.343)	233.233*** (72.093)	249.218*** (73.626)	231.951*** (70.543)	245.295*** (54.383)		
% Skill	-274.510*** (73.401)	-299.463*** (81.397)	-272.019*** (74.528)	-230.086*** (86.148)	-707.472 (439.765)	-650.111** (314.483)	-733.180* (438.993)	-729.752** (311.195)	-796.688* (418.766)	-768.755*** (291.501)	-813.282* (422.446)	-808.103*** (296.382)		
% Foreigner	-39.962** (18.005)	-47.400*** (17.984)	-47.436** (18.571)	-40.004** (19.607)	384.403*** (131.197)	374.559*** (93.599)	385.582*** (133.826)	390.911*** (99.985)	378.525*** (129.249)	373.148*** (90.477)	374.083*** (134.384)	380.226*** (103.994)		
% Women	185.419*** (44.258)	189.835*** (45.126)	174.255*** (46.788)	160.889*** (49.837)	49.321 (218.565)	27.707 (163.152)	65.042 (225.331)	46.197 (187.175)	76.768 (197.579)	69.452 (140.932)	93.461 (203.547)	82.231 (157.676)		
% Routine	-196.954*** (26.687)	-204.001*** (27.762)	-198.889*** (26.139)	-189.811*** (29.552)	-252.281* (139.253)	-220.095** (105.158)	-264.423* (144.603)	-257.394*** (94.593)	-257.497* (142.234)	-239.831** (104.543)	-268.801* (148.766)	-258.448*** (97.553)		
% Chemistry														
% Automobile														
% Largest Industry														
Region FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		
Time FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		
2SLS First Stage Estimates, Dependent Variable: Import Exposure														
$\Delta Import Exposure$	1.005*** (0.022)	1.005*** (0.022)	0.343*** (0.027)	0.343*** (0.027)	0.76*** (0.032)	0.76*** (0.032)	0.39*** (0.111)	0.39*** (0.111)	0.761*** (0.034)	0.761*** (0.034)	0.376*** (0.106)	0.376*** (0.106)		
F-Test excl. Instr.	11858.01	11858.01	68.03	68.03	48.75	48.75	3.38	3.38	36.66	36.66	5.76	5.76		
2SLS First Stage Estimates, Dependent Variable: Export Exposure														
$\Delta Export Exposure$	0.505*** (0.111)	0.505*** (0.111)	0.278*** (0.07)	0.278*** (0.07)	0.354*** (0.1)	0.354*** (0.1)	0.357*** (0.125)	0.357*** (0.125)	0.344*** (0.094)	0.344*** (0.094)	0.32*** (0.1)	0.32*** (0.1)		
F-Test excl. Instr.	102.03	102.03	90.12	90.12	48.7	48.7	62.3	62.3	36.89	36.89	36.88	36.88		

Note: N=804; Clustered standard errors (by county) in parentheses; *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level; All regressions include a constant; First stage estimates also include the same control variables that are indicated in the columns for the second stage estimates.

The fact that trade exposure from Eastern Europe is much larger in magnitude may be an explanation for the findings. Furthermore, results are in line with the observed trend in patenting (cf. Figure 2.1). During the time of increasing import exposure from Eastern Europe in the 1990s, patenting in Germany increases tremendously. However, during the second wave of import exposure during the 2000s, when trade from China was picking up pace, patenting in Germany was on the decline. One potential explanation is that during the first exposure wave, Germany adapted its product mix to avoid competition with low-wage countries in Eastern Europe resulting in an increase of patenting. When China, almost a decade later, entered the world market (at the beginning with low quality goods that were partly similar to the initial Eastern European product mix), Germany did not face immediate competition anymore as it already had adjusted. Lastly, and probably most importantly, the fact that German-Eastern European trade (contrary to German-Chinese trade) is primarily intra-industry (cf. Section A.4 in the Appendix) is likely to imply that German firms face much larger import competition from Eastern Europe. Increased competition decreases the opportunity costs of innovation as existing products become less profitable.

2.4 Further Differentiation and Robustness

Following the identification of Eastern Europe as the driving force behind positive trade effects on German innovation, I will now use the breakdown by import and export exposure and exposure origin to differentiate the baseline results further and to conduct a wide range of sensitivity checks to validate the robustness of the results. The findings are all based on the most sophisticated specification (3) that includes labor market and industry controls as well as time and county fixed effects.³²

2.4.1 Further Differentiation

Final and Intermediate Good Trade

The explanation that import exposure from Eastern Europe and not from China causes innovation due to the higher proportion of intra-industry trade, and thus higher competition, implies that the effects are caused by trading final goods. Intra-industry imports can either be final products that are directly consumed by German consumers, and thus stand in competition with German products, or intermediate goods that are

³²Note, however, that the results of the robustness check also confirm the results of the other specifications and also those of Equation (2.4) and Equation (2.6) (in all specifications). These results are not published in this paper but are available upon request. The same applies to first-stage results. The results indicate strong and fitting instruments for all differentiation (unless stated otherwise) and are also available upon request.

used as inputs by German industries. If the latter was the case, the imports would not imply competition, but instead offshoring of upstream production to Eastern Europe. In this case, German firms will receive a larger share of intermediate goods for assembly from abroad. Thus they may specialize in high-skilled tasks and allocate more production factors to R&D activities. To examine the effect of final goods trade on innovation, I use the import matrix from the input-output tables provided by the Federal Statistical Office to compute industry specific final good shares. Using these shares, I adjust the trade flows and re-estimate the baseline equation. See Section A.5 in the Appendix for more details. The results are presented in Table 2.4 and confirm the explanation that competition causes an increase in patenting: Still, the effect for import exposure from Eastern Europe is positive, statistically significant, and even larger compared to total trade. The effects on innovation from Chinese import exposure, as well as from Chinese and Eastern European export exposure, remain insignificant.

Table 2.4: Final vs. Intermediate Good Trade

Estimation	Final Good Trade
Eastern Europe	
$\Delta Import Exposure$	0.435*** (0.168)
$\Delta Export Exposure$	0.417 (1.113)
China	
$\Delta Import Exposure$	0.268 (0.243)
$\Delta Export Exposure$	0.187 (0.58)

Note: N=804; Clustered standard errors (by county) in parentheses; *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level; All regressions include a constant; First stage estimates also include the same control variables that are indicated in the columns for the second stage estimates.

Patent Applicants

The results presented so far are based on the universe of patenting in Germany. This, of course, does not only include firms, but also private persons, research institutions, foundations, government institutions, etc. Using the name of the patent applicant allows me to distinguish between certain types of applicants (see Section A.1 in the Appendix for more details). To control which type of applicant drives the results, I identify five

different applicant categories (“firms”, “research”, “foundation / club”, “government” and “not classified”) and re-estimate the baseline equation for each category separately. The “not classified” category primarily consists of private persons. The results are presented in Table 2.5. As expected, it is primarily firms that are affected by Eastern trade exposure. However, innovation in research institutions also increases. One potential explanation is that firms may collaborate with research institutes in order to innovate. Indeed, around 24% of patents from research institutions are commonly filed together with a firm. Again, it is only trade exposure from Eastern Europe driving the results. Import exposure from China and export exposure do not affect innovation for any of the applicant types significantly.

Table 2.5: Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Changes in Patenting per 100,000 Inhabitants by Exposure Origin and Applicant Type

Estimation	Company	NC	Research	Foundation/ Club	Government
Eastern Europe					
$\Delta Import Exposure$	0.041*** (0.014)	0.001 (0.002)	0.002** (0.001)	0.001 (0.000)	-0.000 (0.000)
$\Delta Export Exposure$	0.807 (1.022)	-0.142 (0.101)	-0.096 (0.105)	-0.024 (0.029)	0.000 (0.004)
China					
$\Delta Import Exposure$	0.231 (0.212)	0.025 (0.038)	-0.027 (0.025)	0.016 (0.019)	-0.002 (0.003)
$\Delta Export Exposure$	0.144 (0.517)	0.021 (0.095)	-0.060 (0.070)	-0.018 (0.027)	0.001 (0.003)

Note: N=804; Clustered standard errors (by county) in parentheses; *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level; All regressions include a constant; First stage estimates also include the same control variables that are indicated in the columns for the second stage estimates.

Patenting by firm’s innovation activity

Patenting in Germany is highly concentrated. Very few firms - mostly MNEs - account for the lion’s share of patenting (see Section A.1 in the Appendix). One advantage of the regional identification strategy in this paper is that it allows me to cover all patents and not only patenting by larger firms.³³ Focusing on larger firms, as commonly

³³Note: The data do not contain any firm level information except the firm’s name. The number of patent applications, however, seems to be closely related to common size definition such as the number

done in the literature, may cover the majority of patents, but will fail in covering the majority of innovating companies. To disentangle the effects by patent intensity of the firm, I subdivide the data into three categories depending on the number of patents by applicant. Each category accordingly includes approximately the same number of patent applications.³⁴ Table 2.6 shows the properties of each category and presents the results for separately re-estimating the baseline equation for each category. The first category consists of 94,337 different applicants. This corresponds to a share of 97.7% of all applicants, and thus the majority of applicants. On average, these applicants file approximately 0.18 patents per year (or 1 patent every five years). The 2,154 applicants in the second category file on average 7.85 patents per year. The 64 most patent intensive firms in the third category account for the same share of total patenting as the 94,337 least patent intensive applicants in the first category and file approximately 273 patents every year. The estimates show that the effects of import exposure from Eastern Europe on patenting is largest for the patent-intensive firms. However, also for the less patent-intensive firms, the coefficients are positive and significant. The size of the effect doubles approximately from the first to the second category and again from the second to the third category. The third category accounts for slightly more than 50% of the total estimated effect from Eastern European import exposure on patenting. Focusing on larger firms only, would thus only capture part of the total trade effect on innovation.

of employees or turnover. The firms with the largest amount of patenting are well-known multinationals (cf. Section A.1 in the Appendix). On the contrary, a random check of the names of firms with only a small number of patent applications largely reveals unknown small- and medium sized firms.

³⁴Note: The categories do not include exactly the same amounts of patents, as the same applicants are attributed to one category only.

Table 2.6: Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Changes in Patenting per 100,000 Inhabitants by Applicant Categories

Estimation	1. Category	2. Category	3. Category
Eastern Europe			
$\Delta Import Exposure$	0.006* (0.000)	0.013* (0.007)	0.025*** (0.01)
$\Delta Export Exposure$	-0.058 (0.187)	0.458 (0.637)	0.146 (0.841)
China			
$\Delta Import Exposure$	-0.033 (0.053)	0.173 (0.126)	0.102 (0.196)
$\Delta Export Exposure$	0.037 (0.118)	-0.096 (0.41)	0.149 (0.333)
Applicants	94337	2154	64
Avg. Patents / Year	0.18	7.854	273.025

Note: N=804; Clustered standard errors (by county) in parentheses; *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level; All regressions include a constant; First stage estimates also include the same control variables that are indicated in the columns for the second stage estimates.

Patent Properties

In this section, I check if trade exposure has any effect on patent properties. The patent data contain information on the number of foreign and domestic inventors as well as the number of foreign and domestic applicants per patent. Furthermore, the number of countries for which protection has been requested is known. In the absence of other patent quality measures such as patent citations, this measure is the best proxy for patent quality available. When applying for a patent, firms have to decide on the countries the patent should grant protection for. Adding countries entails additional costs both in terms of application fees as well as information costs (e.g., knowledge about the local patent law). Acknowledging other factors that may influence the number of protection countries³⁵, this figure could be seen as the firm's self-evaluation of the patent quality. If applicants deem the patent to be valuable, they might be willing

³⁵One likely alternative factor influencing this measure is company size. Larger companies are potentially more likely to apply for a larger number of countries as they may operate internationally and thus have lower information costs. To control for this potential explanation, I re-estimate the following estimation by the firms innovation category. For every category, the results are identical to results for the whole sample.

to bear additional costs and add countries of protection. They might, however, decide for protection in fewer countries if the patent is believed to be less valuable. The results in Table 2.7 show that the number of countries for which protection has been requested is unaffected by trade exposure. I thus conclude that the patent quality remains unchanged. Also, the number of inventors per patent is unaffected. This holds true for both the number of domestic and foreign inventors (partition not displayed in the table). Import exposure from Eastern Europe increases, however, the number of applicants per patent. This is caused by an increase in the number of domestic applicants, whereas the number of foreign applicants is unaffected. One potential explanation is that domestic companies form cooperations to jointly innovate to avoid competition.

Table 2.7: Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Changes in Patent Properties

Estimation	# Inventors	# Applicants	# Foreign Applicants	# Domestic Applicants	# Protected Countries
Eastern Europe					
$\Delta Import Exposure$	-0.000 (0.000)	0.000*** (0.000)	0.000 (0.000)	0.000*** (0.000)	-0.001 (0.006)
$\Delta Export Exposure$	0.011 (0.013)	0.000 (0.002)	0.000 (0.001)	0.000 (0.002)	0.012 (0.140)
China					
$\Delta Import Exposure$	-0.003 (0.003)	0.001 (0.001)	-0.000 (0.000)	0.001 (0.001)	-0.025 (0.037)
$\Delta Export Exposure$	0.011 (0.007)	0.003 (0.002)	0.000 (0.000)	0.003 (0.002)	-0.033 (0.060)

Note: N=804; Clustered standard errors (by county) in parentheses; *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level; All regressions include a constant; First stage estimates also include the same control variables that are indicated in the columns for the second stage estimates.

R&D Employment

I now deviate from patenting as the dependent variable and estimate the effect of trade exposure on R&D employment instead. For this purpose, I again differentiate between Eastern European and Chinese exposure and estimate the following equation:

$$\overline{\Delta R\&D}_{it} = \alpha + \beta_1 \overline{\Delta Exp}_{it}^{East} + \beta_2 \overline{\Delta Imp}_{it}^{East} + \gamma \overline{X}_{it}^T + \sigma_i + \kappa_t + u_{it}, \quad (2.7)$$

The estimation approach and all controls are identical to Equation (2.6), except that now R&D is the left hand side variable. R&D employment $R\&D_{it}$ is defined as the total number of engineers and natural scientists in region i at time t . The measure is provided by the Establishment History Panel and serves as a “proxy to measure establishment’s R&D” according to the data description. Table 2.8 displays the results. In line with the previous findings, import exposure from Eastern Europe significantly increases absolute R&D employment. Companies are increasing R&D employment as a result of import competition from Eastern Europe, allowing them to innovate more. Import exposure from China, as well as export exposure, does not show significant effects. The result implies that for every \$2000 increase in Eastern European import exposure per worker in a county, one additional R&D job is created in that county.

Table 2.8: Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Changes in R&D Employment

Estimation	# R&D workers
Eastern Europe	
$\Delta Import Exposure$	0.505** (0.227)
$\Delta Export Exposure$	-19.383 (15.147)
China	
$\Delta Import Exposure$	-2.109 (3.128)
$\Delta Export Exposure$	3.56 (4.118)

Note: N=804; Clustered standard errors (by county) in parentheses; *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level; All regressions include a constant; First stage estimates also include the same control variables that are indicated in the columns for the second stage estimates.

2.4.2 Robustness

Alternative Innovation Measures

In this section, I deviate from the previous innovation measure of patenting per 100,000 inhabitants based on the home address of the inventor. Table 2.9 in Section A.6 in the Appendix shows the results, when, instead, various other regional innovation measures are used. In column one, innovation is measured as the absolute number of patents based on the home address of the inventor instead of the population weighted number.

In columns two and three, I use the zip code of the applicant instead of that of the inventor in order to regionally compute both population weighted patenting (column two) and total patenting (column three). Using land size as weight is common in the regional economics literature (see for instance Nordhaus, 2006). Accordingly, I use patenting per hectare based on the home address of the inventor (column four) and based on the address of the applicant (column five) as additional alternative innovation measures. So far, I computed regional patent exposures based on the five-digit zip code system. There are a few observations (less than 1%), for which the inventor's or the applicant's zip code is based on the old four-digit zip code system (from before the 1993 reform). Correspondence tables between former four-digit postal codes and administrative units are rather inaccurate, such that I did not take these observations into account before. Instead of dropping these observations as before, I now use correspondence tables to reclassify the origin of the innovation and re-estimate the regressions, also taking former four-digit zip codes into account. Results are displayed in column six (patenting per 100,000 inhabitants based on the inventor's home address) and seven (total patenting based on the inventor's home address). All alternative measures confirm the previous findings and show that only import exposure from Eastern Europe has positive and significant effects on patenting.

Regional Sensitivity

Using a regional identification strategy, it is crucial to check the robustness of the results with respect to regional sensitivity. The following section discusses the robustness with respect to the distinction between Western and Eastern Germany, the aggregation level of the administrative units and the consideration of commuter flows.

Western and Eastern Germany

As a robustness check, I re-estimate Equation (2.6) differentiated by Eastern European and Chinese trade exposure for Western Germany and Eastern Germany separately. One concern could be that the inclusion of Eastern Germany distorts the results. Especially during the first observation period shortly after German reunification, extensive restructuring processes make it difficult to identify the effects. After reunification, much of the manufacturing industry collapsed in Eastern Germany. Accordingly, the calculation of import exposures could be misleading for Eastern Germany and instrumentation could be difficult, bearing in mind that there were only a few companies still importing or exporting. Still today, large fractions of the patent intensive manufacturing sector are located in Western Germany, whereas manufacturing in Eastern Germany is comparatively scarce. Thus it does not come as a surprise to find the results in Table 2.10

in Section A.6 in the Appendix confirming the hypothesis that the effects discussed so far mainly originate in Western Germany. Although the Eastern German regions also show a significant positive effect of import competition from Eastern Europe on innovation, the effect is almost twice as large for Western Germany only and also approximately twice as large as the baseline estimates for Western and Eastern Germany combined (see Table 2.3). Furthermore, almost all previously discussed control variables are insignificant for Eastern Germany.³⁶

Commuter Flows and Aggregation of Local Labor Markets

I use patenting per 100,000 inhabitants based on the home address of the inventor as the preferred baseline measure of regional innovation. Even though this regional innovation measure is commonly accepted, widely used, and has been proven to reliably determine the regional origin of innovations, one concern may be that the geographic link between innovation and trade exposure fails to hold for commuters. The regional trade exposure is based on the industry structure and thus on the location of the firm. My measure for regional innovation, however, is based on the home address of the inventor. If the county of the inventor's workplace deviates from the county of his home address (and he thus commutes across county borders for work), the geographic link between innovation and trade exposure fails to hold. First and foremost, this may imply underestimating patenting in larger cities compared to the surrounding area as the commuting balance is generally positive for cities and negative for the hinterland. Commuter flows provided by the German Federal Employment Office show that in 2013 around 13.9% of the population in Germany commuted across county borders.³⁷

To control for the potential commuter bias, I adjust regional patenting using the commuter flows between counties in 2013. For each of the 402 counties, I compute the share of commuters to the 401 other counties relative to the county's labor force and to the county's population, and adjust county based patenting according to these shares.³⁸ The results for the commuter adjusted estimations are displayed in column one to column four of Table 2.11 in Section A.6 in the Appendix and confirm the previous results. Results remain in a very similar range as before, independent of the innovation

³⁶Note additionally that the IV estimation for Eastern Germany only shows weak instruments. The F-tests show that the hypotheses that instruments are excluded can be rejected. However, the instruments are not significantly correlated with the endogenous explanatory variable. This finding does not come as a surprise, given the fact that after German reunification the manufacturing industry collapsed and trade was almost non-existent. For Western Germany, instruments are strong and fitting.

³⁷2013 is the first year for which commuter flows are available at the county level.

³⁸Note: This procedure is based on the assumption that the share of commuters among the inventors is equal to that of the total labor force. I use commuters relative to the county's population as one measure, since the inventors and applicants may be private persons that do not necessarily belong to the working population.

measure both for patenting per population (column one and two) and total patenting (column three and four) and independent from the measure of the commuter share both when measured as commuters relative to the county's workforce (column one and three) and commuters relative to the county's population (column two and four).

The choice of the regional aggregation level is crucial, especially in light of the innovation measure used in this paper. To establish a geographic link between innovation and trade exposure, it is important that workplace and place of residence of the inventor are located within the same regional unit. Thus, one concern could be that counties are too small to capture this link. The smaller the geographic entities, the higher the chance that inventors commute across county borders. Accordingly, I additionally repeat the estimation at the level of 258 labor market regions (in German: "Arbeitsmarktregionen") and at the level of 96 regional planning regions (in German: "Raumordnungsregionen"). Labor market regions cover the center of functional labor markets and its surroundings. Its boundaries are formed under the condition that commuting flows across regions are minimized. Regional planning regions are even more aggregated and represent the observation and analysis grid of the federal spatial order. Naturally, the share of commuters decreases as the spatial units become more aggregated. Approximately 9.37% of the population commutes across the borders of the labor market regions and around 7.2% commutes across the borders of the regional planning regions. Results for the estimation at the level of labor market regions (column five) and for the estimation at the level of regional planning regions (column six) are shown in Table 2.11 in Section A.6 in the Appendix. Regression results for both spatial units do not differ qualitatively from the results at the county level.

Instrument Group

As another robustness check, I vary the selection of the country group that I use to instrument the trade flows between Eastern Europe / China and Germany. Table 2.12 in Section A.6 in the Appendix exemplarily shows three alternative instrument groups.³⁹ For the first reported alternative specification, I delete the UK, Sweden, and Norway from the sample and add Korea and the United States instead (column one). This specification deals with concerns that other European countries are too much integrated with Germany (common market, member of the Schengen Area, no tariffs, etc.). Next,

³⁹Note: The reported results represent only a small part of the performed robustness check variations in the group of instruments. In general, no deviations were found in any of the alternative instrument groups. This also holds true for the over-identification case, in which I include the trade flows of all countries in the instrument group as separate instruments instead of the aggregate. The list of countries whose trade flows I use in different combinations for instrumentation is limited to advanced economies and includes Australia, Canada, France, Italy, Japan, Korea, the Netherlands, New Zealand, Norway, Singapore, Sweden, the UK, and the United States.

I include only countries that are member of the European Union (France, the Netherlands, and Italy, see column two).⁴⁰ Finally, column three shows the results when the instrument group consists of all countries previously mentioned. As can be seen, the results remain largely unaffected by choice of the instrument group. The instruments generally perform well for all specifications, except for the last specification, where contrary to the baseline specification the instruments are not significantly correlated with the endogenous explanatory variable for German-Chinese trade.

Time Framing

Finally, I alter the time framing to check the robustness of the results. First, I do not use value changes between three year averages, but conduct estimations based on single year data instead. I use all 27 three-year combinations from the years that are covered in the baseline scenario.⁴¹ Results remain qualitatively unchanged and are not driven by choice of the years.

The time frame also matters for the computation of the regional trade exposures. In the baseline estimation, the start-of-period industry composition is used to regionally allocate industry-level trade flows. Even though Eastern trade is still very limited during the first period, I additionally use the industry composition ten years prior to the start-of-period to compute regional exposures.⁴² Both approaches generate qualitatively identical results. Using the start-of-period industry composition or the pre-start-of-period industry composition guarantees that the industry structure is unaffected by Eastern trade. This should help alleviate concerns about reverse causality. However, it is also well established that changes in trade exposure affect the regional industry structure (see for instance Dauth et al. (2014)). Thus over time, regional exposures will, in fact, also vary, because the industry structure changes. To account for this fact, I replicate the estimations using trade exposures based on time varying industry structures. Again results are qualitatively unaffected.

In summary, the robustness checks show that neither alternative innovation measures, nor the choice of regional units and consideration of commuter flows, nor the choice of instruments, nor the time frame, influence the results. These findings reinforce

⁴⁰Naturally, this way the instrumental variable is most likely not independent from the left hand side variable as trade integration is very high among the countries. This, in turn leads to a high and significant correlation between instrument variable and endogenous explanatory variable.

⁴¹In detail, this means that changes between the following year-year-year combinations are estimated: 1993-2002-2010, 1994-2002-2010, 1995-2002-2010, 1993-2003-2010, 1994-2003-2010, 1995-2003-2010, 1993-2004-2010, 1994-2004-2010, 1995-2004-2010, 1993-2002-2011, 1994-2002-2011, 1995-2002-2011, 1993-2003-2011, 1994-2003-2011, 1995-2003-2011, 1993-2004-2011, 1994-2004-2011, 1995-2004-2011, 1993-2002-2012, 1994-2002-2012, 1995-2002-2012, 1993-2003-2012, 1994-2003-2012, 1995-2003-2012, 1993-2004-2012, 1994-2004-2012, 1995-2004-2012

⁴²Note: This specification only includes West Germany, as data for the East German industry structure is not available for that time period.

the observation that trade with Eastern Europe drives innovation in Germany.

2.5 Conclusion

So far, we have little systematic empirical evidence on the effect of increasing trade integration on innovation. The purpose of this paper is to shed some light on the issue and identify the causal effect of increasing trade integration of Germany with Eastern Europe and China on innovation. For this purpose, I create a regional measure of innovation activity by crawling online patent data and apply different regional trade exposure measures. The findings show that, on average, an increase in net trade exposure (defined as import minus export exposure) causes innovation to increase. Disentangling the effect further, I find that it is purely driven by a positive link between import exposure and innovation, whereas export exposure does not influence innovation. Contrary to existing studies, this paper also shows that exposure effects are heterogeneous across exposure origins. The positive link between import exposure and innovation is fully explained by trade integration with Eastern Europe. Increasing integration with China has no effect on innovation.

I find that trade induced innovation primarily affects firms, but interestingly also the innovation activity of research institutions increases as a result of increased Eastern European trade exposure. The regional identification approach of this paper allows me to cover the universe of patenting, unlike most other papers in this field. This makes it possible to subdivide the effects according to the applicant's patent intensity. Patenting is highly concentrated, meaning that few firms account for the majority of patenting. Although the estimates show that the effects are greatest for the most patent intensive applicants, I also find a positive effect on innovation originating from applicants with low patent intensity. These low patent applicants represent the majority of the applicants, contribute in their entirety significantly to total patenting and are generally excluded from previous publications. The estimated effects are robust for a wide range of sensitivity checks and remain largely unchanged by choice of instruments, the time framing, and the choice of regional units and controls.

The findings on the relation between trade and innovation have important policy implications: First, it is an interesting insight that innovation effects are heterogeneous with respect to the country of exposure origin. One potential explanation for the finding that exposure from Eastern Europe but not from China drives innovation is that German-Eastern European trade (contrary to German-Chinese trade) is primarily intra-industry. This likely implies that German firms face much larger import competition from Eastern Europe. Additionally, trade exposure from Eastern Europe is much larger in magnitude. Another potential explanation is that during the first exposure wave in

the 1990s, Germany adapted its product mix to avoid competition with low-wage countries in Eastern Europe resulting in an increase of patenting. When China, almost a decade later, entered the world market, Germany did not face immediate competition anymore as it already had adjusted. Second, and more generally, the results show that arguments that trade with low wage countries is bad for innovation have to be rejected. The fear that trade with low-wage countries might block innovation is unfounded. In fact, for Germany increasing trade integration on average even fosters innovation.

2.6 Bibliography

- (1) Akcigit, Ufuk (2010), “Firm Size, Innovation Dynamics and Growth”, Working Paper, University of Pennsylvania.
- (2) Akcigit, Ufuk and William R. Kerr (2018), “Growth through heterogeneous innovations”, *Journal of Political Economy* 126(4), 1374-1443.
- (3) Autor, David, David Dorn and Gordon Hanson (2013), “The China Syndrome: Local Labor Market Effects of Import Competition in the United States”, *American Economic Review* 103(6), 2121-68.
- (4) Autor, David, David Dorn, Gordon Hanson, Gary Pisano and Pian Shu (2016), “Foreign Competition and Domestic Innovation: Evidence from US Patents”, Working Paper.
- (5) Bartel, Ann, Casey Ichinowski and Kathryn Shaw (2007), “How Does Information Technology Really Affect Productivity? Plant-level Comparisons of Product Innovation, Process Improvement and Worker Skills”, *Quarterly Journal of Economics* 122(4), 1721-1758.
- (6) Blind, Knut and Hariolf Grupp (1999), “Interdependencies between the science and technology infrastructure and innovation activities in German regions: empirical findings and policy consequences”, *Research Policy* 28(5), 451-468.
- (7) Bloom, Nicholas, Mirko Draca and John Van Reenen (2016), “Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity”, *The Review of Economic Studies* 83(1), 87-117.
- (8) Bloom, Nicholas, Paul M. Romer, Stephen J. Terry and John Van Reenen (2013), “A Trapped-Factors Model of Innovation”, *American Economic Review* 103(3), 208-13.
- (9) Bloom, Nicholas, Paul M. Romer, Stephen J. Terry and John Van Reenen (2014), “Trapped Factors and China’s Impact on Global Growth”, NBER Working Paper 19951.
- (10) Bugamelli, Matteo, Fabiano Schivardi and Roberto Zizza (2008), “The Euro and Firm Restructuring”, NBER Working Paper 14454.
- (11) Cohen, Wesley M, Richard C. Levin and David C. Mowery (1987), “Firm Size and R&D Intensity: A Re-examination”, *Journal of Industrial Economics* 35(4), 543-65.

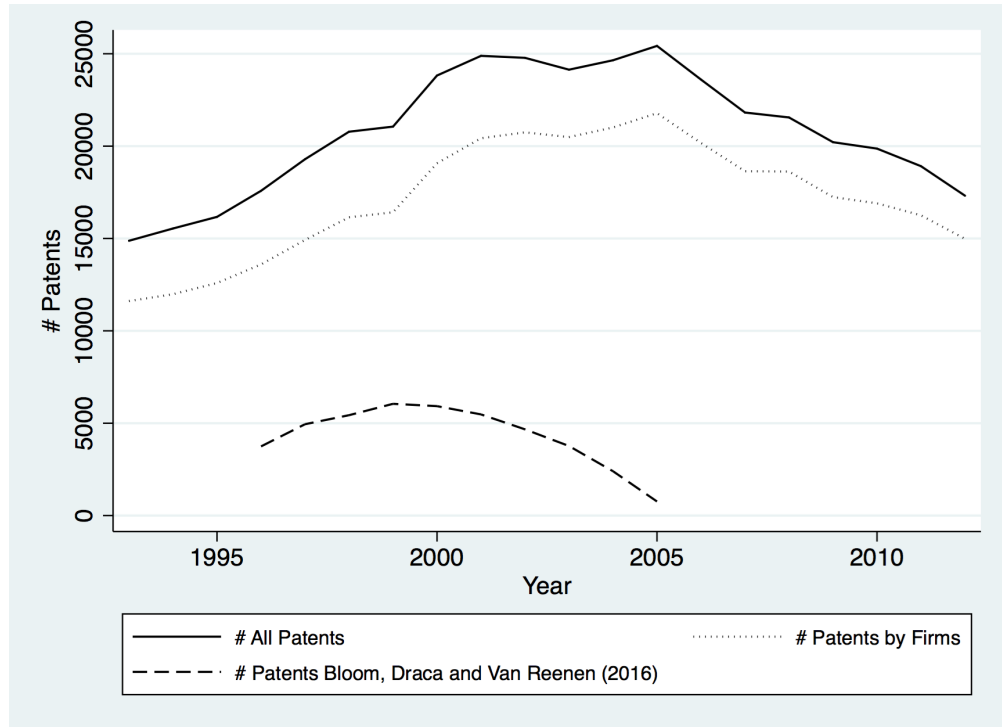
- (12) Cohen, Wesley M. and Steven Klepper (1996), “A reprise of size and R&D”, *The Economic Journal* 106, 925-951.
- (13) Cohen, Wesley M. (2010), “Fifty years of empirical studies of innovative activity and performance”, *Handbook of the Economics of Innovation* 1, edited by Bronwyn H. Hall and Nathan Rosenberg, 129-213.
- (14) Dauth, Wolfgang, Sebastian Findeisen and Jens Südekum (2014), “The Rise Of The East And The Far East: German Labor Markets And Trade Integration”, *Journal of the European Economic Association* 12(6), 1643-1675.
- (15) Deyle, Hanno-G. and Hariolf Grupp (2005), “Commuters and the regional assignment of innovative activities: A methodological patent study of German districts”, *Research Policy* 34(2), 221-234.
- (16) Dippel, Christian, Robert Gold and Stephan Heblich (2015) “Globalization and its (dis-) content: Trade shocks and voting behavior”, NBER Working Paper 21812.
- (17) Freeman, Richard and Morris Kleiner (2005), “The Last American Shoe Manufacturers”, *Industrial Relations* 44, 307-342.
- (18) Goldberg, Pinelopi K., Amit K. Khandelwal, Nina Pavcnik and Petia Topalova (2010a), “Multiproduct firms and product turnover in the developing world: Evidence from India”, *Review of Economics and Statistics* 92(4), 1042-1049.
- (19) Goldberg, Pinelopi, Amit Khandelwal, Nina Pavcnik and Petia Topalova (2010b) “Imported Intermediate Inputs and Domestic Product Growth: Evidence from India”, *Quarterly Journal of Economics* 125(4), 1727-1767.
- (20) Gruhl, Anja, Alexandra Schmucker and Stefan Seth (2012), “Das Betriebs-Historik-Panel 1975-2010, Handbuch Version 2.1.1, FDZ Datenreport 04/2012, Dokumentation zu Arbeitsmarktdaten”, Forschungsdatenzentrum (FDZ) der Bundesagentur für Arbeit (BA) im Institut für Arbeitsmarkt- und Berufsforschung (IAB).
- (21) Hethey-Maier, Tanja and Stefan Seth (2010), “The Establishment History Panel (BHP), Handbook Version 1.0.2, FDZ Methodenreport 04/2010, Documentation of Labour Market Data”, Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB).
- (22) ICTSD (2011), “Meaningful Technology Transfer to the LDCs: A Proposal for a Monitoring Mechanism for TRIPS Article 66”, by Suerie Moon, Policy Brief Number 9.

- (23) Itenberg, Olga (2013), “Firm Size, Equity Financing and Innovation Activity”, Working Paper.
- (24) Jaffe, Adam B., Manuel Trajtenberg and Rebecca Henderson (1993), “Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations”, *Quarterly Journal of Economics* 108(3), 577-598.
- (25) Jaffe, Adam B. and Manuel Trajtenberg (2002), “Patents, Citations and Innovations”, The MIT Press, Cambridge, MA.
- (26) Mancusi, Maria Luisa (2008), “International spillovers and absorptive capacity: A cross-country cross-sector analysis based on patents and citations”, *Journal of International Economics* 76(2), 155-165.
- (27) Nordhaus, William D. (2006), “Geography and macroeconomics: New data and new findings”, *Proceedings of the National Academy of Sciences* 103(10), 3510-3517.
- (28) Paci, Raffaele and Stefano Usai (2000), “Technological Enclaves and Industrial Districts: An Analysis of the Regional Distribution of Innovative Activity in Europe”, *Regional Studies* 34(2), 97-114.
- (29) Paci, Raffaele and Francesco Pigliaru (2002), “Technological Diffusion, Spatial Spillovers and Regional Convergence in Europe”, In: Cuadrado-Roura, Juan R., and Marti Parellada (eds.), *Regional Convergence in the European Union. Advances in Spatial Science*. Springer, Berlin, Heidelberg.
- (30) Pierce, Justin and Peter Schott (2016), “The Surprisingly Swift Decline of U.S. Manufacturing Employment”, *American Economic Review* 106(7), 1632-1662.
- (31) Shu, Pian, and Claudia Steinwender (2018), “The Impact of Trade Liberalization on Firm Productivity and Innovation”, *Innovation Policy and the Economy* No 19, University of Chicago Press.
- (32) UNCTAD (2014), “Transfer of technology and knowledge-sharing for development: Science, technology and innovation issues for developing countries” - UNCTAD Current Studies on Science, Technology and Innovation, No 8 (UNCTAD/DTL/STICT/2013/8)

A Appendices

A.1 Patenting in Germany

Figure 2.6: Coverage of Patenting



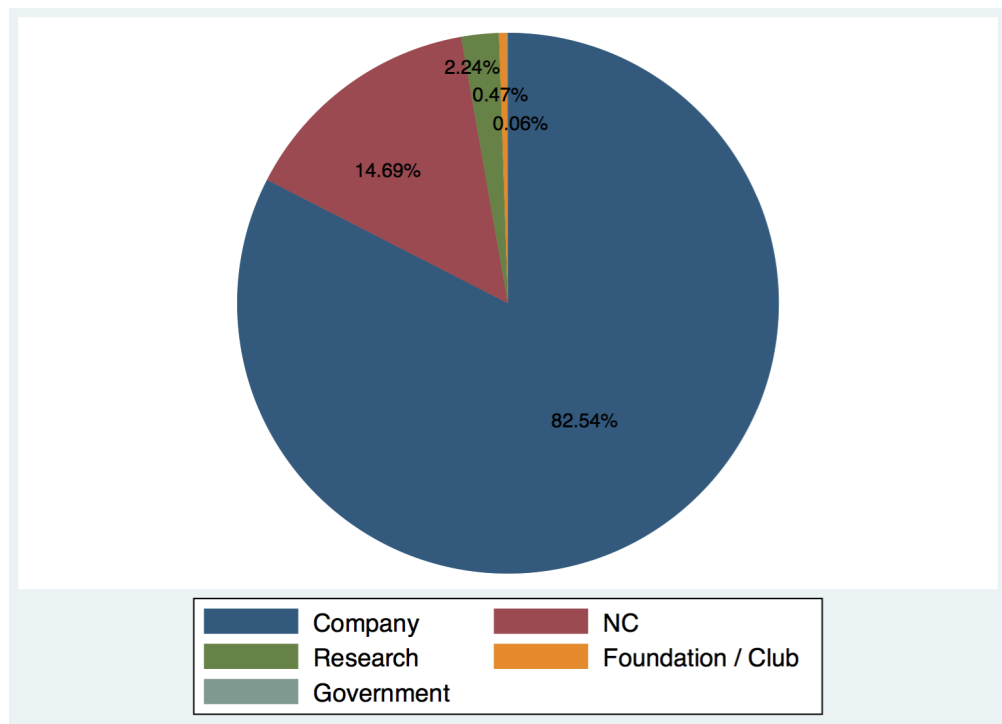
Note: Bloom et al. (2016) use granted patents, whereas in this paper I use patent applications as a proxy for innovation. To conduct a simple comparison, I multiply the total number of patent applications (cf. Figure 2.1) with the average number of granted patents during the time of observation.

Figure 2.6 compares the number of patents covered in this paper with that of Bloom et al. (2016). In their study, Bloom et al. (2016) combine Bureau Van Dijk's Amadeus data with patent data from the European Patent Office for twelve European countries, one of which is Germany. The advantage of obtaining firm level data comes at the expense of only capturing a fraction of total patenting. Using a regional approach addresses this disadvantage and allows considering the universe of patenting in Germany. The solid black line shows a proxy for the total number of granted patents and the dotted line shows a proxy for the total number of patents applied by firms in Germany covered in this study. The dashed line shows the number of patents covered by Bloom et al. (2016), which, on average, accounts for approximately 24% of firm patenting and around 20% of total patenting.⁴³

⁴³Bloom et al. (2016) use granted patents, whereas in this paper I use patent applications. To conduct a simple comparison, I multiply the total number of patent applications (cf. Figure 2.1) with the average number of granted patents during the time of observation.

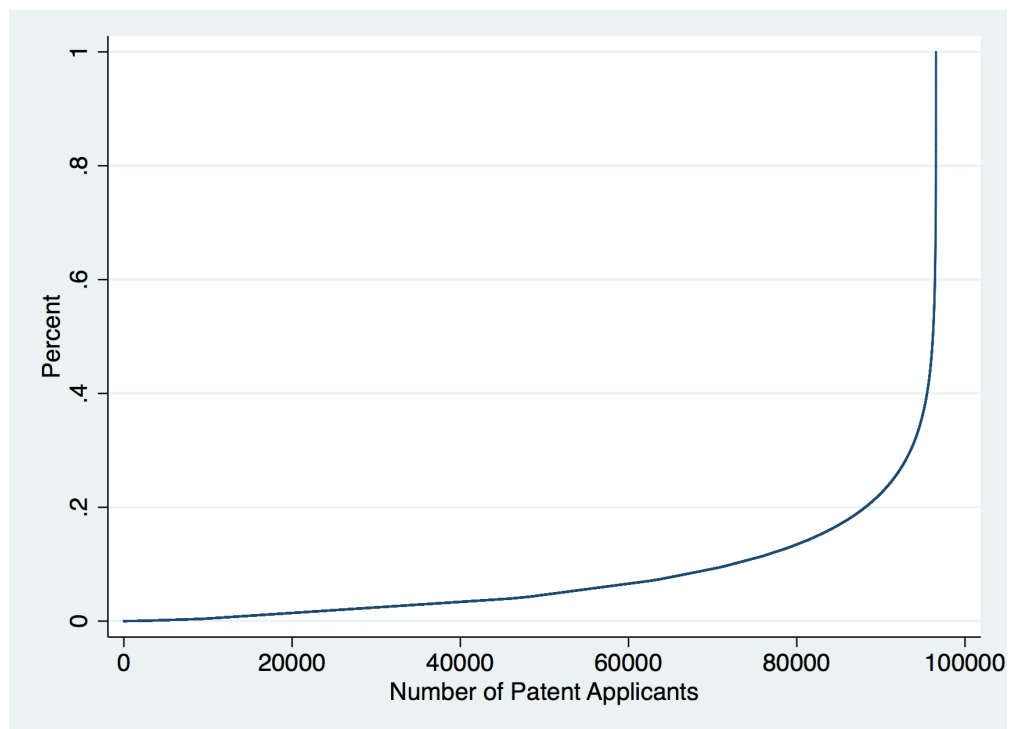
As can be seen, firms account for the vast majority of patenting in Germany. Since the data does not contain any further information about the applicant, I use the applicant's name in the patent document to distinguish between certain types of applicants. Companies must use the name with which they are officially registered in the commercial register. In Germany, the official firm name contains an abbreviation identifying the legal structure of the firm (e.g., "AG" and "GmbH" for corporations). This abbreviation allows uniquely identifying firms. Additionally, I classify three other applicant types using different key words. These types are "research", using key words such as "Universität" (= university) or "Fachhochschule" (= university of applied sciences), "foundation / club", using key words such as "Stiftung" (= foundation) or "e.V." (= abbreviation for registered society) and "government", using key words such as "Bundesrepublik" (= federal republic) or "Ministerium" (= ministry). I label any applicant that cannot be uniquely defined as "not classified". Most of these applicants are private persons (as can be seen by the fact that the applicant's name is the name of a person). Figure 2.7 gives an overview of the type composition of patent applicants between 1993 and 2012. With more than 82%, firms account for the vast majority of patenting in Germany. "Not classified" types (mostly consisting of private persons) represent the second largest share with around 15%. Patenting shares of research institutions (2%), foundations and clubs (0.5%) and government entities (0.05%) are negligible.

Figure 2.7: Patent Applicants by Type



Patenting in Germany is very unequally distributed across the applicants. This means that a small number of different applicants accounts for a large share of patent applications. Figure 2.8 shows the Lorenz Curve for the distribution of patenting between the years 1993 and 2012 with the cumulative number of patent applicants on the x-axis and the percentage share of applied patents on the y-axis. The figure suggests that patenting is highly concentrated. This impression is confirmed by the Gini coefficient of 0.849. The 10 applicants with the highest number of applications account for approximately 20% of total patenting in Germany. The top applicants are all well known multinationals such as “Robert Bosch GmbH” (with a patenting share of 5.5%), Siemens AG (with a patenting share of 5.4%), BASF AG (with a patenting share of 1.6%), BMW AG (with a patenting share of 1.2%) or DaimlerChrysler AG (with a patenting share of 1.2%). At the same time, a share of 47.5% of the patent applicants, applied for not more than 1 patent during the sample period. These 47.5% of applicants account for merely 3.9% of total patenting in Germany.

Figure 2.8: Distribution of Patents by Applicants



A.2 Regional Patenting Structure in Germany

Figure 2.9: Patenting per 1000 Inhabitants by Location of the Applicant

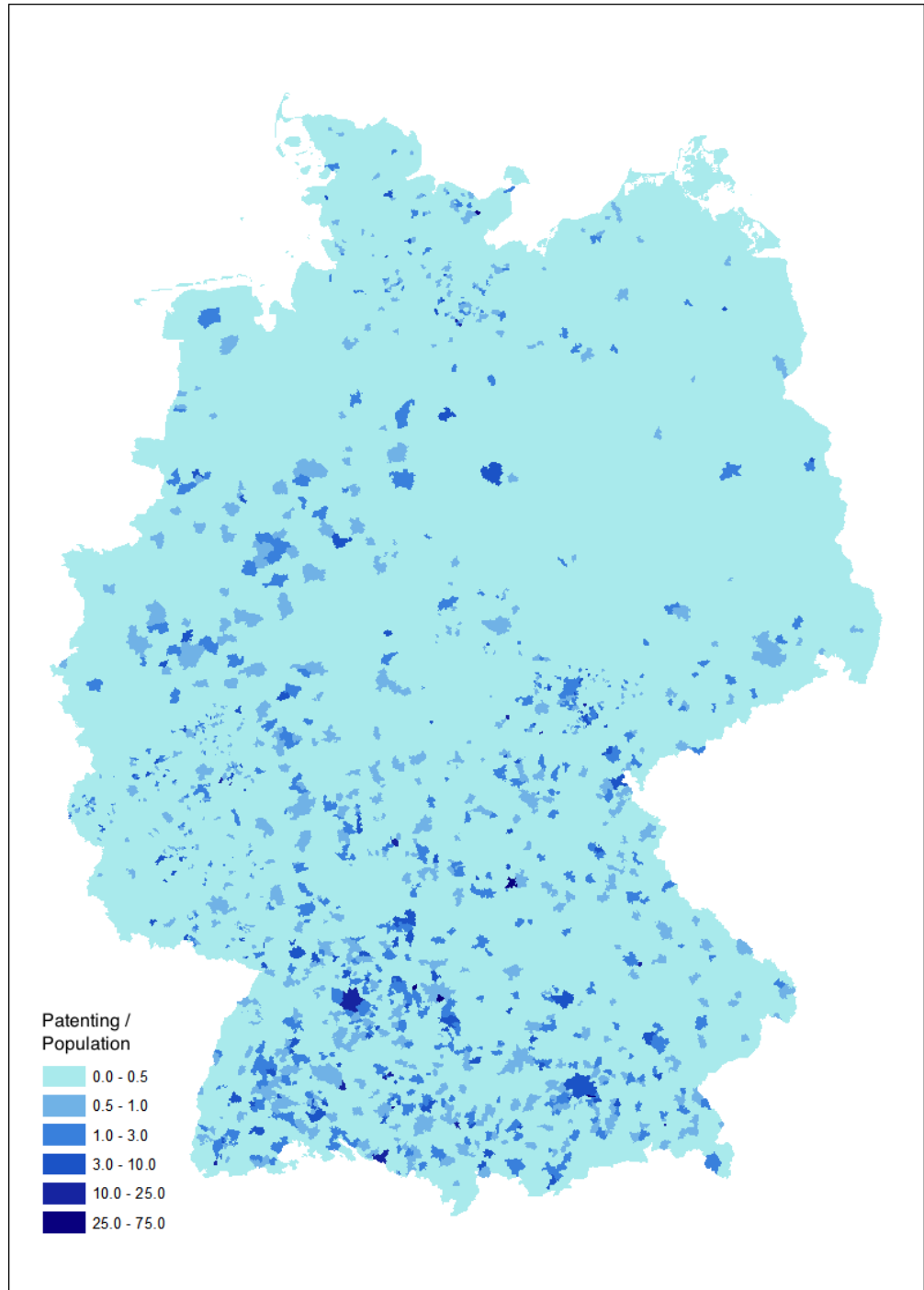


Figure 2.10: Total Patenting by Location of the Applicant

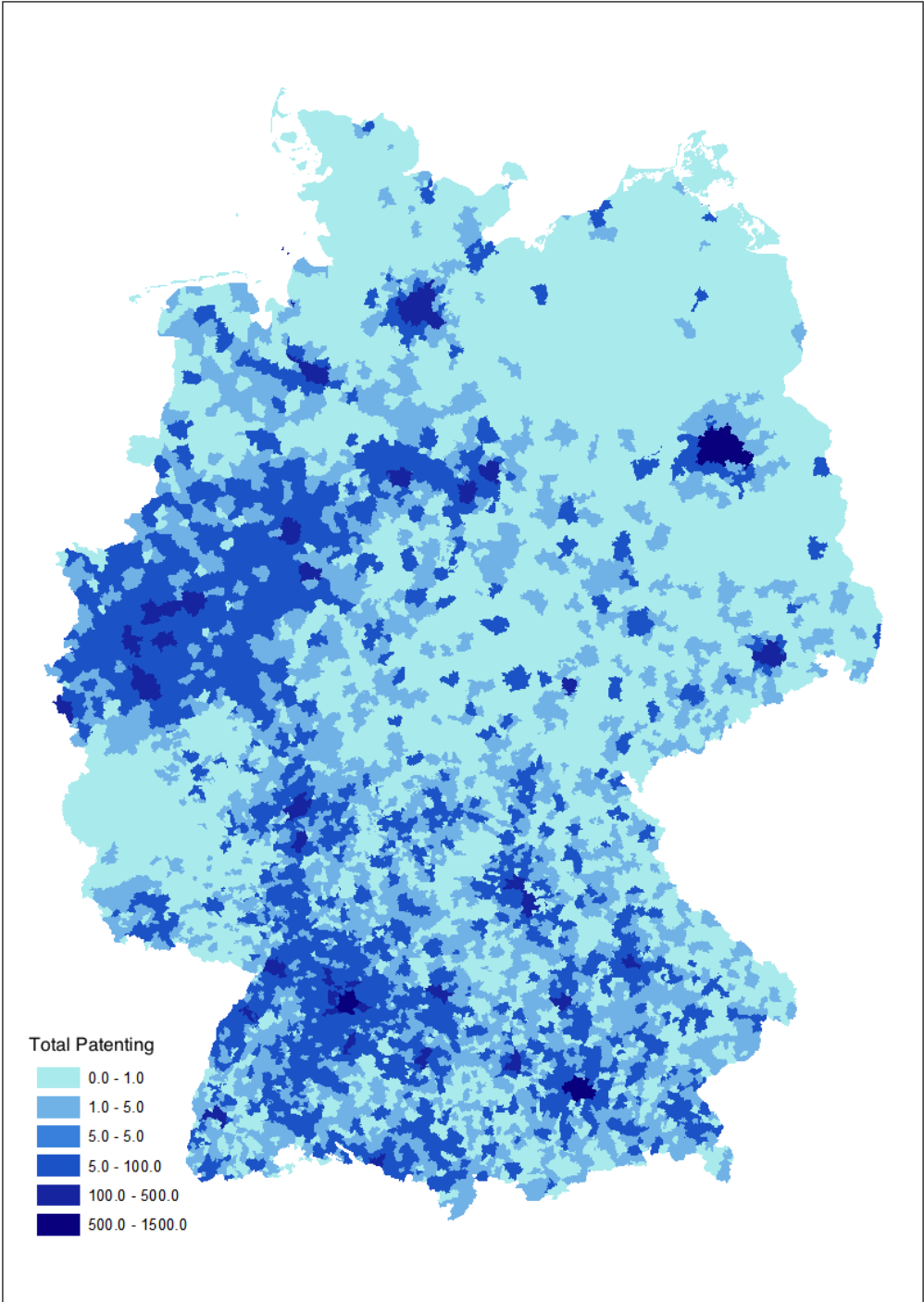
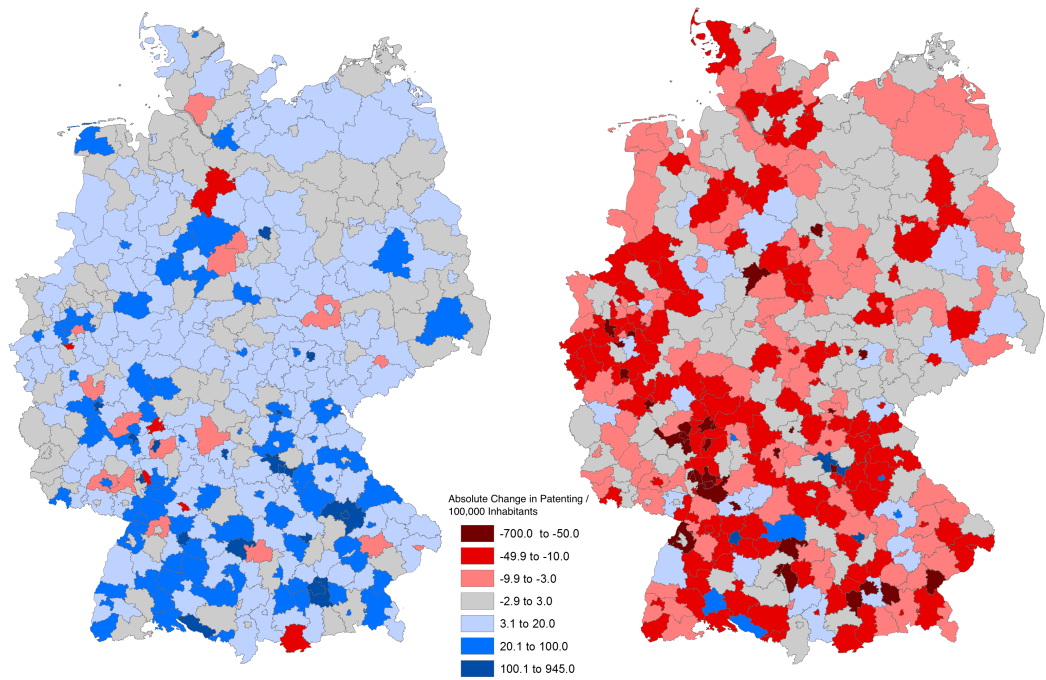


Figure 2.11: Absolute Change of Patenting per 100.000 Inhabitants by Location of the Applicant; $I\bar{A}_i^{93-95} - I\bar{A}_i^{02-04}$ (Left) and $I\bar{A}_i^{02-04} - I\bar{A}_i^{10-12}$ (Right)



A.3 Regional Trade Exposure in Germany

Figure 2.12: Absolute Change in Regional Import Exposure from Eastern Europe $\frac{Imp_i^{EE}}{Imp_i^{EE}}{}^{10-12} - \frac{Imp_i^{EE}}{Imp_i^{EE}}{}^{93-95}$ (Left) and China $\frac{Imp_i^{China}}{Imp_i^{China}}{}^{10-12} - \frac{Exp_i^{China}}{Exp_i^{China}}{}^{93-95}$ (Right) in \$ 1000 per Manufacturing Worker

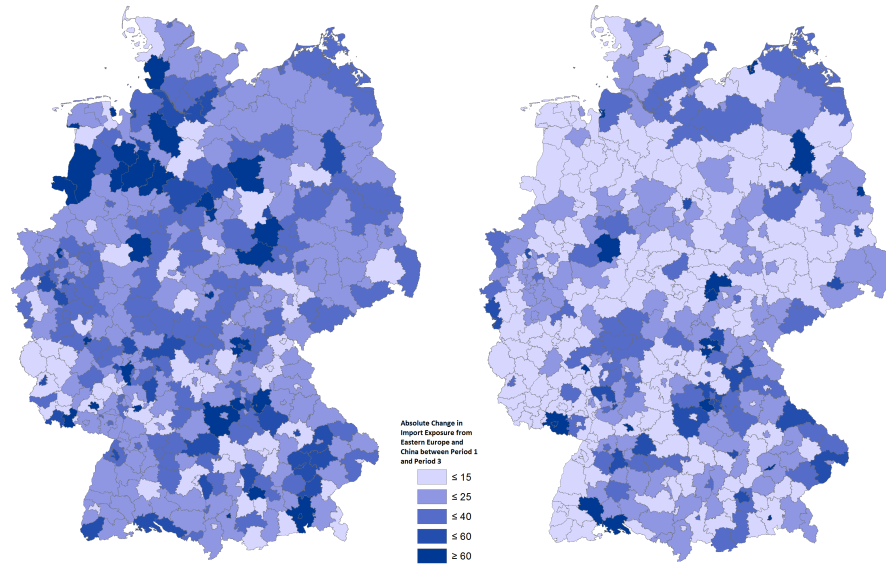
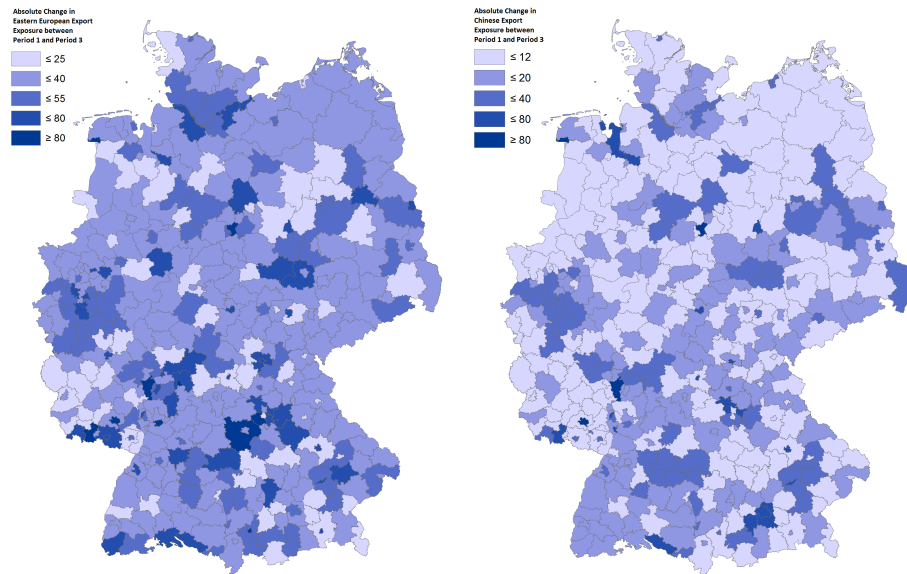


Figure 2.13: Absolute Change in Regional Export Exposure from Eastern Europe $\frac{Exp_i^{EE}}{Exp_i^{EE}}{}^{10-12} - \frac{Imp_i^{EE}}{Imp_i^{EE}}{}^{93-95}$ (Left) and China $\frac{Exp_i^{China}}{Exp_i^{China}}{}^{10-12} - \frac{Exp_i^{China}}{Exp_i^{China}}{}^{93-95}$ (Right) in \$ 1000 per Manufacturing Worker



A.4 German Trade with Eastern Europe and China

Figure 2.14: Weighted Grubel-Lloyd-Index for German Trade with Eastern Europe and China between 1980 and 2012

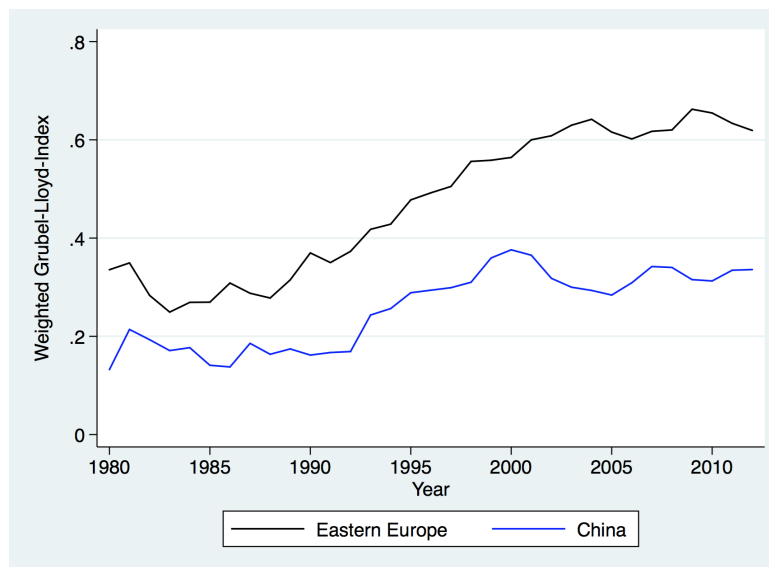


Figure 2.14 depicts the weighted Grubel-Lloyd-Indices for trade between Germany and Eastern Europe as well as between Germany and China computed as

$$GL_{jt} = \sum_j w_{jt} \frac{|Exp_{jt}^{Ger-East} - Imp_{jt}^{Ger-East}|}{Exp_{jt}^{Ger-East} + Imp_{jt}^{Ger-East}}, \quad (2.8)$$

$$\text{with } w_{jt} = \frac{Exp_{jt}^{Ger-East} + Imp_{jt}^{Ger-East}}{\sum_j Exp_{jt}^{Ger-East} + Imp_{jt}^{Ger-East}}$$

A.5 Final and Intermediate Good Trade

Similar to Autor et al. (2013) and Dauth et al. (2014), I use the input-output table for the year 2002 provided by the Federal Statistical Office to compute industry specific final good shares. To be precise, I use the share of imports that is used for final consumption or investment (rather than for inputs) to calculate the final good shares at the two-digit or three-digit industry level. The classification of the input-output tables can be easily transferred into the industry classification of the IAB. The choice of the year is driven by data limitations. For the years of the first period, input-output tables are not available, for the years of the third period the industry classification cannot be transferred into that of the IAB. As a robustness check, I additionally use the years 2000 and 2001 to calculate final trade shares, but results remain unchanged.

A.6 Robustness

Table 2.9: Effect of Periodic Changes in Regional Import and Export Exposures by Exposure Origin on Periodic Changes in Various Innovation Measures

Innovation Measure	Total Pat. by Inventor	Pat. / Pop by Applicant	Total Pat. by Applicant	Pat./ Area by Inventor	Pat. / Area by Applicant	Pat. / Pop by Inventor zip codes II	Total Pat by Inventor zip codes II
Eastern Europe							
$\Delta ImportExposure$	0.071** (0.036)	0.077*** (0.028)	0.227* (0.129)	0.000*** (0.000)	0.001** (0.000)	0.036*** (0.012)	0.063* (0.034)
$\Delta ExportExposure$	1.412 (3.101)	-3.591* (1.963)	-13.564 (10.081)	-0.011 (0.014)	-0.052 (0.036)	0.256 (1.067)	0.737 (2.955)
China							
$\Delta ImportExposure$	-1.139 (0.760)	-0.099 (0.357)	-1.780 (1.099)	-0.004 (0.003)	-0.010 (0.007)	0.121 (0.214)	-1.210 (0.736)
$\Delta ExportExposure$	0.928 (1.094)	-1.430 (1.120)	-1.113 (1.769)	-0.004 (0.007)	-0.017 (0.014)	0.016 (0.599)	0.759 (1.053)

Note: N=804; Clustered standard errors (by county) in parentheses; *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level; All regressions include a constant; First stage estimates also include the same control variables that are indicated in the columns for the second stage estimates.

Table 2.10: Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Changes in Patenting per 100,000 Inhabitants by Exposure Origin - Western and Eastern Germany

Estimation	Only Western Germany		Only Eastern Germany	
	Eastern Europe	China	Eastern Europe	China
Δ ImportExposure	0.070** (0.032)	0.007 (0.282)	0.046* (0.026)	1.919 (1.762)
Δ ExportExposure	1.142 (1.173)	0.525 (0.477)	-4.781 (3.917)	-4.126 (6.876)
% Manufacturing	204.354* (113.617)	125.639 (89.063)	-215.688 (487.091)	563.728 (528.182)
% Skill	-917.912 (618.718)	-997.312* (593.031)	298.762 (389.029)	-305.369 (512.601)
% Foreigner	429.197*** (136.080)	467.945*** (143.499)	292.147 (211.984)	-168.899 (461.890)
% Women	12.677 (183.054)	9.326 (194.324)	247.956 (276.925)	403.291 (446.359)
% Routine	-338.164** (140.624)	-362.672*** (128.046)	139.311 (263.661)	-30.021 (438.585)
% Chemistry	20.125 (157.437)	22.174 (161.084)	-561.713** (281.886)	-818.521 (592.712)
% Automobile	-160.061 (198.273)	-41.047 (234.719)	-754.837 (512.334)	-393.867 (501.720)
% Largest Industry	229.191 (151.724)	235.814 (156.598)	9.028 (141.659)	291.938 (428.238)
County FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Note: N=650 for Western Germany, N=154 for Eastern Germany; Clustered standard errors (by county) in parentheses; *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level; All regressions include a constant; First stage estimates also include the same control variables that are indicated in the columns for the second stage estimates.

Table 2.11: Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Changes in Patenting per 100,000 Inhabitants - Commuters and Alternative Administrative Units

Innovation Measure	Pat. / Pop by Inventor com. adj. I	Pat. / Pop by Inventor com. adj. II	Total Pat. by Inventor com. adj. I	Total Pat. by Inventor com. adj. II	Pat. / Pop by Inventor AMR aggr.	Pat. / Pop by Inventor ROR aggr.
Eastern Europe						
$\Delta Import Exposure$	0.047*** (0.014)	0.049*** (0.013)	0.079** (0.037)	0.084** (0.039)	0.097*** (0.036)	0.357* (0.194)
$\Delta Export Exposure$	-0.000 (1.080)	-0.275 (1.081)	0.200 (3.204)	-0.439 (3.296)	-3.970 (3.448)	9.024 (12.913)
China						
$\Delta Import Exposure$	0.156 (0.220)	0.110 (0.219)	-1.410* (0.825)	-1.558* (0.867)	-1.483 (1.352)	0.687 (2.257)
$\Delta Export Exposure$	-0.102 (0.609)	-0.190 (0.606)	0.723 (1.138)	0.629 (1.171)	-1.691 (1.717)	4.221 5.757

Note: N=804 for commuter adjusted estimations in column one to four. N=516 for AMR, N=192 for ROR; Clustered standard errors (by county) in parentheses; *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level; All regressions include a constant; First stage estimates also include the same control variables that are indicated in the columns for the second stage estimates.

Table 2.12: Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Changes in Patenting per 100,000 Inhabitants by Exposure Origin - Different Instrument Groups

Estimation	Instr. Group 1	Instr. Group 2	Instr. Group 3
Eastern Europe			
$\Delta Import Exposure$	0.064*** (0.021)	0.046*** (0.015)	0.062*** (0.021)
$\Delta Export Exposure$	-1.467 (1.745)	0.802 (0.666)	-1.232 (1.846)
2SLS First Stage Estimates; Dependent Variable: Import Exposure			
$\Delta Import Exposure$ (Other Countries)	0.636*** (0.025)	0.477*** (0.01)	0.358*** (0.014)
F-Test excl. Instr.	32.19	25.40	38.72
2SLS First Stage Estimates; Dependent Variable: Export Exposure			
$\Delta Export Exposure$ (Other Countries)	0.297*** (0.074)	0.724*** (0.181)	0.14*** (0.032)
F-Test excl. Instr.	31.28	66.15	32.25
China			
$\Delta Import Exposure$	-1.886 (2.68)	0.089 (0.093)	0.166 (0.198)
$\Delta Export Exposure$	0.079 (0.259)	-0.165 (1.127)	-3.046 (2.967)
2SLS First Stage Estimates; Dependent Variable: Import Exposure			
$\Delta Import Exposure$ (Other Countries)	0.215*** (0.078)	1.24*** (0.315)	0.0223 (0.087)
F-Test excl. Instr.	5.85	4.40	2.94
2SLS First Stage Estimates; Dependent Variable: Export Exposure			
$\Delta Export Exposure$ (Other Countries)	0.099* (0.03)	0.524*** (0.156)	0.029 (0.018)
F-Test excl. Instr.	24.57	12.26	26.2

Note: N=804; Clustered standard errors (by county) in parentheses; Instrument group 1 includes: Canada, Japan, Korea, New Zealand, Singapore, the United States; Instrument Group 2 includes: France, Italy, the Netherlands; Instrument Group 3 includes: Australia, Canada, France, Italy, Japan, Korea, the Netherlands, New Zealand, Norway, Singapore, Sweden, the UK, the United States; *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level; All regressions include a constant; First stage estimates also include the same control variables that are indicated in the columns for the second stage estimates.

Chapter 3

The Role of Newly Industrialized Economies in Global Value Chains

Summary: In this paper, I use the World Input-Output Database (WIOD) to analyze the role of six newly industrialized economies, Brazil, China, India, Indonesia, Mexico, and Turkey, in global value chains. Using WIOD data allows me to compute trade on a value added basis rather than on a gross output basis, as is done in traditional trade data. To analyze the position of newly industrialized economies in global value chains, the main focus of this paper lies on the origin and share of foreign value added in exports and on the of foreign consumption of domestic value added. The analysis shows that, while all six countries are at a similar stage of development, newly industrialized economies play very different roles in global production and in global value chains. For instance, Mexico's value added trade patterns are marked by a high concentration due to its proximity to the United States, whereas those for Turkey are comparably diverse. India's value added exports focus on services, while China concentrates on manufacturing products. Evidence suggests that Brazil and Indonesia are not integrated as well in global value chains as compared to the other newly industrialized economies.¹

¹I am grateful to Thomas Alexander, Paul Austin, Johannes Bröcker, Paul Cashin, Claudia Dziobek, Cornelia Hammer, Chris Hinchcliffe, Joji Ishikawa, Gary Jones, Silvia Matei, Kenji Moriyama, Horst Raff, Luca Ricci, Mika Saito, Piyaporn Sodsriwiboon and seminar participants at the IMF Statistics Department for their helpful comments.

3.1 Introduction

International trade over the last 20-25 years is characterized by an ever more flattening of the world (Antras, 2015). In the 1990s, unbundling their production became profitable for many firms.² The opening of China, particularly due to its accession to the World Trade Organization (WTO) in 2001, and the fall of the Iron Curtain provided a large new workforce for international production at comparatively low wages. This coincided with both liberal trade policies adopted in many countries that fostered globalization and decreasing transportation costs. The Uruguay Round created the WTO in 1995. Mean tariff rates decreased dramatically from 34% in 1996 to 2.9% in 2012 (World Development Indicators). The number of regional trade agreements more than quadrupled from the mid 1990s until today (WTO Secretariat). Improvements in information, communication, and other technologies further decreased transport costs. Inventions such as the Internet made it possible to communicate instantaneously with people on the other side of the globe at almost zero cost. As a result of these developments, trade in intermediate goods has largely replaced traditional final goods trade (Ricardo’s world of “clothes against wine”). Trade in intermediate goods today accounts for approximately two thirds of world trade.

Prominent examples that document vertical specialization are the production of Apple’s iPod (Dedrick et al., 2010) and Boeing’s Dreamliner 787 (Tang et al., 2009). In both cases, a great proportion of the component production is outsourced and a sizeable proportion of the product’s value added is generated abroad. Figure 3.8 in the Appendix shows the Dreamliner’s suppliers. More than 70% of the plane’s value is not generated by Boeing. The literature on offshoring (see for instance Feenstra and Hanson (1996), and Feenstra, 2010) and later the trade in task literature (see Grossman and Rossi-Hansberg (2006) and Baldwin and Robert-Nicoud, 2014) also documented the relocation of jobs and slicing up of the value chain. Evidence from the 2011 Tohoku earthquake in Japan highlights the international fragmentation of production and documents the transmission of shocks along global value chains (see Boehm et al., 2018): Shortly after the earthquake and tsunami hit Japan, US production for goods that required components from the affected Japanese areas dropped.

The rapid increase in vertical specialization poses challenges to economists, policy makers and international institutions. First, traditional measurements of international trade flows might not be well suited to capture these new developments calling for new measures. Gross trade fails to allocate value added along global value chains across countries and cannot account for the fact that an increasing share of export value is generated by imported intermediates.³ A number of newly available world input output

²Also tax incentives can be a reason for multinationals to slice up their production.

³Relocation of production can also have large impacts on national accounts, especially for small

tables allow the identification of value added flows.⁴ Recent studies that make use of these newly available data highlight some policy implications of measuring trade on a value added basis. For instance, Koopman et al. (2014) calculate value added trade and revise the comparative advantage of countries. Johnson and Noguera (2012a) recalculate bilateral trade deficits and show that the US trade deficit with China is much lower when measured in value added terms.⁵

Second, identifying the role that countries play in global production is important: Policy advice for upstream producers may differ from the set of policies that is suited for downstream producers. Additionally, slicing up the value chain across borders creates spillovers across countries. Given these inter-country linkages, it is also essential to understand the position of countries in global value chains in order to assess the vulnerability to the transmission of shocks.⁶ Recently, a growing number of studies have been concerned with the role of individual countries in global value chains, but there is need for additional individual country studies as Stehrer and Stöllinger (2013) point out. Existing individual country studies on Austria's (Stehrer and Stöllinger, 2013) and Denmark's (Andersen et al., 2015) position in the global economy focus on small open economies.⁷

This study contributes to the economic literature by performing a similar analysis for the position of newly industrialized economies in global value chains, including Brazil, China, India, Indonesia, Mexico, and Turkey. The analysis shows that, while all are outsourcing locations,⁸ and at a similar stage of development, newly industrialized economies (see for instance Ireland).

⁴If data quality and coverage for value added data increases, trade in value added might be a more accurate measure to determine the openness parameter for the IMF quota calculation as double counting is avoided. The current quota formula is (among others) relevant for the voting power and access to financing for countries and is calculated as a weighted average of GDP (50%), openness (30%), economic variability (15%), and international reserves (5%). Openness is calculated based on gross exports and imports. At the current stage, available trade in value added data does not allow for robust adjustment of the openness quota (see <http://www.imf.org/external/np/pp/eng/2012/110812a.pdf>). The topic of trade in value added is of significant interest to international institutions and policy makers. An expert group comprised of members from the IMF, OECD, UN, World Bank, and WTO is currently working on a "Handbook on a System of Extended International Global Accounts". For further information, see for instance UNECE (2015) and OECD (2015).

⁵Other papers in this field include Daudin et al. (2011) and Johnson and Noguera (2012b). See Saito et al. (2013) for macroeconomic policy implications.

⁶An analysis of global value chains supports the Fund's policy advice and the UN sustainable development goals (SDGs). Access to world markets is one necessary condition for sustained economic growth and poverty reduction (WTO, 2001), and global value chains provide key measures. Recent work by the World Bank (Taglioni and Winkler, 2016) highlights the importance of identifying countries' positions in GVC to adjust policies in three steps: attracting foreign direct investment (FDI), expanding and strengthening GVC participation and turning GVC participation into sustainable growth.

⁷See also short trade in value added country profiles provided by the OECD-WTO: <http://www.oecd.org/sti/ind/measuringtradeinvalue-addedanoecd-wtojointinitiative.htm>.

⁸See for instance Autor et al. (2013) and Dauth et al. (2014) on China, Hummels et al. (2001) and Bergin et al. (2009) on Mexican Maquiladoras, and Liu and Treffer (2008) on outsourcing to India (and China).

economies play very different roles in global production and in global value chains.

The paper is organized as follows: Section 3.2 introduces the data and shows the computation to derive information on value added trade. Section 3.3 shows and compares the results for the newly industrialized economies and the final Section 3.4 concludes and discusses some policy implications.

3.2 Data and Calculations

Traditional trade data on a gross output basis do not allow us to quantify the geography of global production and to answer questions about the origin and destination of value added in value chains. This paper, therefore, uses the World Input Output Database (WIOD) to calculate a number of indicators to determine the role of newly industrialized economies in global value chains.⁹

The WIOD is arguably the most suited dataset among a number of recently available world input output datasets.¹⁰ The data are provided for the 1995 to 2011 period and include 35 industries comprising primary-, durable-, nondurable-, service-, and financial industries. The WIOD covers 41 countries¹¹, the 41st country is the “Rest of the World” modeled as one economy. The majority of the countries are members of the European Union (EU 27), but the data also include the newly industrialized economies of Brazil, China, India, Indonesia, Mexico, and Turkey. These countries account for more than 90% of GDP generated by newly industrialized countries.¹² World input output data cannot be measured directly, but are compiled from data provided by national statistics (national account statistics, supply and use tables) and international trade data in goods and services. Consequently, the data quality depends on the data quality of the national statistics (which is one of the reasons for the European country bias in the WIOD). See Dietzenbacher et al. (2013) for a detailed description of the WIOD construction.

Even though the availability of world input output data is a step towards a better understanding of global value chains, the need for further improvement of the data should be highlighted. The fact that the data quality of world input output tables depends on the reliability of national statistics creates a trade-off between data coverage

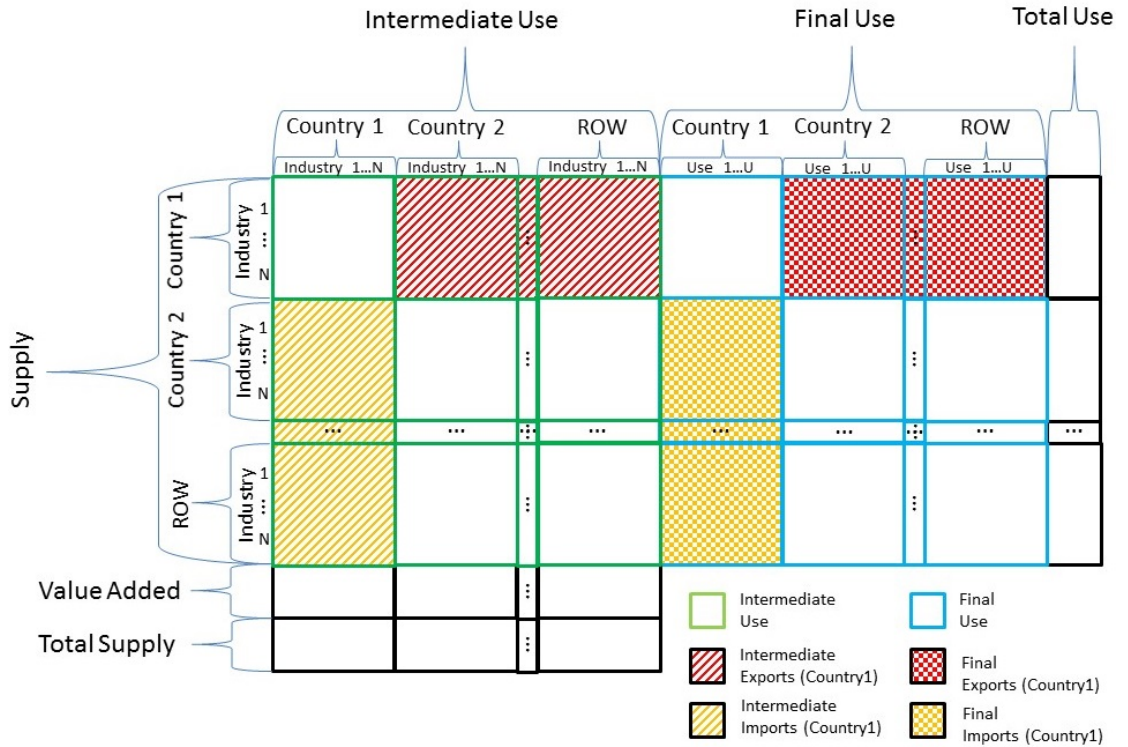
⁹The WIOD project is funded by the European Commission, comprises of a number of partners and is coordinated by the University of Groningen. See <http://www.wiod.org/home.htm> for further information.

¹⁰Other datasets include GTAP, TiVa, EORA, IDE-JETRO.

¹¹Countries include Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovak Republic, Slovenia, Spain, Sweden, United Kingdom, Canada, United States, Brazil, Mexico, China, India, Japan, South Korea, Australia, Taiwan, Turkey, Indonesia, Russia, and “Rest of the World”.

¹²The remaining newly industrialized countries that are not covered by the data are South Africa, Malaysia, the Philippines, and Thailand.

Figure 3.1: Outline of The World Input Output Tables of the WIOD Database



and data quality. The better the data quality, the fewer countries can be covered. For instance, IDE-JETRO arguably is the data with the highest quality, but covers only a few Asian countries. Other data such as EORA cover almost all the countries in the world, but the data quality is comparatively low. A first step to improve world input output tables therefore has to be the improvement of national data such as supply and use tables. At that, the IMF takes on an important role by providing assistance, especially to countries with lower data quality. Additionally, attempts should be undertaken to generate more disaggregated data. The WIOD covers 35 industries, which is much more aggregated than traditional trade data as, for instance, provided by the UN Comtrade database. The fact that national country data is needed to capture the development of vertical specialization also raises the need for standardizing methods of measurements, compilation of data, and data classification.

Despite the need for further improvement, world input output tables are the best data source to determine the role of newly industrialized economies in global value chains. Figure 3.1 shows the outline of the world input output tables of the WIOD database (for one year). The green area highlights the intermediate use matrix (later on defined as A) of dimension 1435×1435 (41 countries \times 35 industries).

This matrix shows the production (rows) for all industries ($n=1, \dots, N$, $N=35$) in all

origin countries ($o=1,\dots,O$, $O=41$) that is used as intermediate inputs (columns) by all industries n in all destination countries ($d=1,\dots,D$, $D=41$). The $35*35$ squares on the main diagonal accordingly show intermediate domestic use of domestic production. In this case the country of origin o equals the country of destination d . Squares off the main diagonal show imports and exports of intermediate products. For instance, for country 1 the red dashed squares show intermediate exports, whereas the yellow dashed squares show intermediate imports. The blue matrix shows the final use matrix (later on defined as F). This matrix shows the production for all industries in all countries that go to final use in all countries. Final use contains five different categories ($j=1,\dots,J$, $J=5$) such as capital formation, household or government consumption, etc. As before, squares on the main diagonal represent domestic final use of domestically produced goods, whereas squares off the main diagonal show final use of foreign production. Again, for country one the red squared squares show final exports, whereas the yellow squared squares show final imports. The total use and total supply have to be identical in equilibrium.

To analyze the position of newly industrialized economies in global value chains, the main focus of this paper lies on the origin and share of foreign value added in exports and the destination of foreign consumption of domestic value added. To compute the required indicators, this paper follows Miller and Blair (2009) and Foster-McGregor and Stehrer (2013).¹³ The starting point is Equation 3.1 that states that the total gross output y^t equals the total intermediate use $\tilde{A}^t y^t$ plus the total final use f^t at time t in equilibrium.¹⁴

$$y^t = \tilde{A}^t y^t + f^t \quad (3.1)$$

The total output vector y^t shows total output for all industries in all origin countries:

$$y^t = \begin{bmatrix} y_{11}^t \\ y_{12}^t \\ \vdots \\ y_{ON}^t \end{bmatrix}_{1435*1}$$

Matrix \tilde{A}^t shows the intermediate input coefficients for all industries in all destination countries, i.e., the matrix contains for every industry n in every destination country d the share of inputs that originates from every industry in every origin country o per

¹³As mentioned previously, this computation also follows closely the work of Stehrer and Stöllinger (2013) for Austria and Andersen et al. (2015) for Denmark.

¹⁴As shown above, the WIOD contains 35 industries ($N = 35$), 41 origin and destination countries ($O, D = 41$) and five final use categories ($J = 5$).

unit of total gross output of that industry (in that destination country). To obtain \tilde{A}^t , the matrix A^t of intermediate inputs (in absolute values) is “divided” (\oslash) by the total output vector TO^t : Here “divided” (\oslash) means that every element in a given column of matrix A^t (i.e., all the inputs for an industry in a destination country) is divided by the same element of the total output vector TO^t (which shows the total output of that particular industry in that country):¹⁵

$$\tilde{A}^t = A^t \oslash TO^t,$$

where

$$A^t = \begin{bmatrix} A_{11-11}^t & A_{11-12}^t & \cdots & A_{11-DN}^t \\ A_{12-11}^t & A_{12-12}^t & \cdots & A_{12-DN}^t \\ \vdots & \vdots & \ddots & \vdots \\ A_{ON-11}^t & A_{ON-12}^t & \cdots & A_{ON-DN}^t \end{bmatrix}_{1435 \times 1435}$$

and

$$TO^t = \begin{bmatrix} TO_{11}^t & TO_{12}^t & \cdots & TO_{DN}^t \end{bmatrix}_{1 \times 1435}$$

f^t is the total final demand vector. Total final demand for products produced by industry n in origin country o is obtained by summing up the consumption of that industry’s products in all final demand categories ($J = 5$) in all destination countries:¹⁶

$$f^t = \begin{bmatrix} \sum_{d=1}^D \sum_{j=1}^J F_{11-dj}^t \\ \sum_{d=1}^D \sum_{j=1}^J F_{12-dj}^t \\ \vdots \\ \sum_{d=1}^D \sum_{j=1}^J F_{ON-dj}^t \end{bmatrix}_{1435 \times 1}$$

Rearranging Equation 3.1 yields:

$$y^t = (I - \tilde{A}^t)^{-1} f^t \tag{3.2}$$

Let $L^t = (I - \tilde{A}^t)^{-1}$ be the Leontief Inverse that shows how much production from each industry in each country is required given a vector of final use. Using the Leontief

¹⁵For instance, A_{ax-bz}^t is the amount of intermediate inputs produced by origin country a ’s industry x and consumed by destination country b ’s industry z . Dividing A_{ax-bz}^t by TO_{bz}^t , the total output of country b ’s industry z , yields the share of intermediate inputs produced by origin country a ’s industry x in total output of destination country b ’s industry z .

¹⁶For example, $\sum_{d=1}^D \sum_{j=1}^J F_{ax-dj}^t$ is the total final demand of destination country 1 to D and category 1 to J for goods produced by origin country a ’s industry x .

Inverse allows us to compute the foreign value added component embodied in the exports of a certain country k . The foreign value added component FVA_k^t in the export of origin country k is the product of the foreign value added coefficients vector $fvac_k^t$ with the Leontief Inverse L^t and the export vector x_k^t :

$$FVA_k^t = fvac_k^t L^t x_k^t, \quad (3.3)$$

The value added coefficient for a given industry in a given country is the share of value added generated within that industry VA_{dn}^t relative to the total output TO_{dn}^t of that industry. Thus the value added coefficients vector vac_k^t is the element wise division ($\cdot /$) of the value added vector and the total output vector. To compute the foreign value added component in exports for country k , $fvac_k^t$ includes value added coefficients for all industries in all countries except for the 35 industries in country k , where the coefficients are set equal to 0:

$$fvac_k^t = \left[VA_{11}^t \quad VA_{12}^t \quad \cdots \quad VA_{DN}^t \right]_{1*1435} \cdot / \left[TO_{11}^t \quad TO_{12}^t \quad \cdots \quad TO_{DN}^t \right]_{1*1435},$$

with

$$VA_{dn} = 0 \text{ if } d = k.$$

x_k^t , the export vector for a given origin country k , is retrieved from general export vector \tilde{x}^t by only keeping the elements that show country k 's exports and setting all other elements showing the exports of the other 40 countries equal to 0. The general export vector \tilde{x}^t contains export information for all industries in all origin countries. To generate the general export vector, I aggregate the foreign intermediate use (displayed in matrix A^t) and the foreign final use (displayed in matrix F^t) of output from every industry in every origin country.¹⁷ To exclude the domestic use of output, summation of final and intermediate use in the destination country is restricted to the cases where the destination country is not the country of origin, i.e., $d \neq o$:

$$\tilde{x}^t = \begin{bmatrix} \sum_{d=1; d \neq o}^D \sum_{n=1}^N A_{11-dn}^t + \sum_{d=1; d \neq o}^D \sum_{j=1}^J F_{11-dj}^t \\ \sum_{d=1; d \neq o}^D \sum_{n=1}^N A_{12-dn}^t + \sum_{d=1; d \neq o}^D \sum_{j=1}^J F_{12-dj}^t \\ \vdots \\ \sum_{d=1; d \neq o}^D \sum_{n=1}^N A_{ON-dn}^t + \sum_{d=1; d \neq o}^D \sum_{j=1}^J F_{ON-dj}^t \end{bmatrix}_{1435*1}$$

¹⁷For instance, the exports of industry x in country a consist of foreign intermediate use in all destination countries across all industries $\sum_{d=1; d \neq o}^D \sum_{n=1}^N A_{ax-dn}^t$ and foreign final use across all destination countries and all final use categories $\sum_{d=1; d \neq o}^D \sum_{j=1}^J F_{ax-dj}^t$.

To compute the foreign consumption of domestic value added (FCDVA) the diagonalized value added coefficient matrix VAC^t is multiplied with the product of Leontief Inverse L^t and final use matrix \tilde{F}^t :

$$FCDVA^t = VAC^t L^t \tilde{F}^t, \quad (3.4)$$

with the final use matrix

$$\tilde{F}^t = \begin{bmatrix} \tilde{F}_{11-1}^t & \tilde{F}_{11-2}^t & \cdots & \tilde{F}_{11-D}^t \\ \tilde{F}_{12-1}^t & \tilde{F}_{12-2}^t & \cdots & \tilde{F}_{12-D}^t \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{F}_{ON-1}^t & \tilde{F}_{ON-2}^t & \cdots & \tilde{F}_{ON-D}^t \end{bmatrix}_{1435 \times 41},$$

where for every industry n in every destination country d the final use categories 1 to J have been aggregated to obtain total final use such that \tilde{F}^t displays the final use of every countries' industry output in every country.¹⁸ VAC^t is the diagonalized value added coefficient matrix, where the value added coefficients for all industries in all countries are located on the main diagonal and values off the main diagonal are 0. Equation 3.4 yields $FCDVA^t$ of dimension 1435×41 , which shows how much value added generated by industry n in a given country is consumed by all other countries.¹⁹

3.3 The Position of Newly Industrialized Economies in Global Value Chains

When firms slice up their production, they have to determine which stage of the production should take place in which country.²⁰ Countries at the beginning of the value chain (“upstream producer”) typically use capital and labor to produce raw materials which, further down the value chain, are combined with other production factors and raw materials into intermediate inputs. Each production step adds value, and intermediate inputs are getting more and more sophisticated. At the end of the global value chain, the “downstream producer” assembles the finalized intermediate inputs to a final product.

¹⁸For instance, \tilde{F}_{ax-b}^t shows the final use of goods produced by country a 's industry x in country b . The difference between final use matrix F^t and final use matrix \tilde{F}^t is that for the latter all five final use categories j have been aggregated such that for every destination country only one category displaying total final use exist.

¹⁹To be precise, the final use matrix also includes final use of domestic goods. Accordingly, FCDVA also includes domestic consumption of domestic value added, which needs to be ignored when only focusing on the foreign consumption of domestic value added.

²⁰A number of studies explain how firms organize global value chains; see for instance Antras and Chor (2013) and Antras and de Gortari (2016).

3.3.1 Value Added, Trade and Output

Table 3.1 shows the increase in total exports and imports from 1995 to 2011 (1995=1) for Brazil, China, India, Indonesia, Mexico, and Turkey. For instance, Chinese gross exports in 2011 were 12.41 times larger than in 1995. From all countries, China showed the largest increase for all four indicators over the time of observation followed by India, suggesting that these two countries are among the major drivers of worldwide trade and economic growth in the past three decades (see for instance Srinivasan, 2006). Additionally, the countries also played an important role for the recovery after the financial crisis in 2008. For all of the six newly industrialized economies, all indicators reached pre-crisis levels already in 2010, whereas recovery of the industrialized economies took much longer. In Denmark, for instance, all indicators were still below pre-crisis level in 2011 (Andersen et al., 2015). Figure 3.9 and 3.10 in the Appendix show the detailed development of trade, output and value added over the years 1995 to 2011. Another observation is that for all countries value added and output grew less than exports and imports. The fact that the domestic economy grew less than trade points to an increase in specialization.

Table 3.1: Six NICs: Total Exports, Imports, Value Added and Output in 2011 (1995=1)

	Brazil	China	India	Indonesia	Mexico	Turkey
Total Exports	5.27	12.41	8.01	4.04	4.26	5.53
Total Imports	4.7	12.6	8.61	3.71	4.77	6.43
Value Added	3.11	10.06	5.08	3.51	3.6	3.28
Output	3.17	11.79	4.96	3.59	3.48	3.71

Notes: Source: WIOD, author's calculations.

Table 3.2 sheds light on the relative importance of intermediate and final products. In 2011, all countries exported more intermediate products than final products. For instance, Indonesia exported almost four times more intermediate than final products. The figures are similar for the ratio of intermediate to final imports. All countries imported a higher number of intermediate products except Turkey, which imported more final than intermediate products. Over the period from 1995 to 2011 the relative importance of intermediate products increased for the majority of NICs (see Table 3.3 in the Appendix). India and Mexico pose an exception, as for the two countries both trade in final imports and exports grew faster than trade in intermediate imports and exports. For Brazil, the increase in final exports was slightly larger than the increase in intermediate exports. The dominance of intermediate goods trade reflects the major role that global value chains play in international trade. The figures additionally give an idea about a country's upstream-/ downstreamness. China's much higher ratio of

intermediate to final imports, as compared to the ratio of intermediate to final exports, suggests a rather downstream position of China. This is in line with the idea of China being a main assembler in global value chains. As, for instance, documented for the iPod (Dedrick et al., 2010), components are produced in several countries and then being shipped to China for final assembly.

Table 3.2: Six NICs: Ratio of Intermediate to Final Exports in 2011

	Brazil	China	India	Indonesia	Mexico	Turkey
Intermediate- / Fi- nal Exports	2.69	1.22	1.11	4.02	1.63	1.4
Intermediate- / Fi- nal Imports	7.98	4.69	2.52	3.05	1.97	0.94

Notes: Source: WIOD, author's calculations.

3.3.2 Foreign and Domestic Value Added in Exports

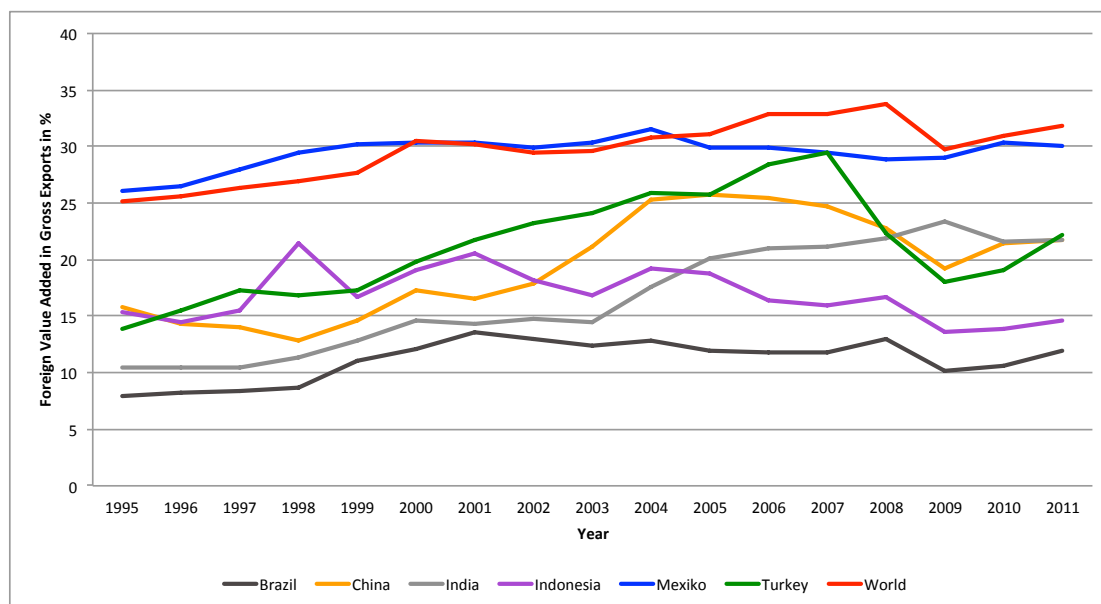
Using Equation 3.3 yields the foreign value added component embodied in exports FVA_k^t . Figure 3.2 shows the foreign value added share in gross exports for all six NICs and for the world average²¹ from 1995 until 2011.²² The foreign value added share in 2011 was higher for all countries except Indonesia compared to 1995, confirming the increasing importance of global value chains in international trade. The largest increase of about 11.2 percentage points can be observed for India, whose foreign value added share in gross exports increased from around 10.5% in 1995 to around 21.7% in 2011. China shows the second largest increase. The foreign value added share increased by around 8.4 percentage points and also reached a share of around 21.7% in 2011. Consequently, in 2011, around 21.7% of India's and China's export value was not generated in India or China, respectively, itself, but already previously imported for the production of export goods.

The trend of increasing foreign value added shares was interrupted by the 2008 financial crisis. On average, the foreign value added share in NICs decreased by about 2.1 percentage points from 2008 to 2009. Even before the reverse development during the financial crisis, a slowdown of the rise in foreign value added in exports can be observed for countries like China, Mexico, Indonesia, and Turkey. Accordingly, it is an

²¹Note: Here "world average" refers to the average share of foreign value added in gross exports across all 41 countries.

²²Note that the shares of foreign value added is also potentially influenced by price changes that cannot be captured here. Consider a country whose foreign value added is mostly generated by natural resources: Especially if the resource prices show a high volatility (e.g., oil or gas), frequent decreases (increases) in the prices of natural resources will decrease (increase) the share of foreign value added.

Figure 3.2: Six NICs and World Average: Foreign Value Added in Gross Exports of NICs (in Percent) from 1995 to 2011



Notes: Source: WIOD, author's calculations.

open question, whether with the further recovery from the financial crisis, the trend of the late 1990s and early 2000s continues, or whether shares remain at a rather stable pre-crisis level or even decrease. A potential explanation for constant or decreasing foreign value added shares could be changes in the comparative advantage, for example, as a result of learning from GVC participation (see Cattaneo et al. (2013), and Humphrey and Schmitz, 2002). Starting as an assembling destination, firms, for instance in China, learn (by doing) over time, gradually take over more skill intensive steps of production and upgrade their industrial production. Some intermediate inputs that were imported previously can now be produced domestically.

Mexico has the highest share of foreign value added in gross exports among the six NICs with slightly more than 30% in 2011. The reason for this figure is Mexico's role as an assembly location for US intermediate products. Maquiladoras located close to the US border receive intermediate inputs from the United States that are assembled and shipped back (see for instance Hummels et al. (2001), Bergin et al., 2009).

With about 11.9% in 2011, Brazil has the lowest share of foreign value added in gross exports. Brazil's tariff regime, which is more protectionist than the average Latin American country (see Cardoso, 2009), may be the reason. This finding also supports the observations in the economic literature that the term "global" value chains might need to be changed to "local" value chains, as the phenomenon is restricted to "Factory North

America”, “Factory Europe” and “Factory Asia” - see Baldwin and Lopez-Gonzalez (2015) who present interesting stylized facts, which show that within and across these continents trade relationships are strongest. For instance, the most intensive supply-chain relationship is found in North America and the biggest producers and consumers of intermediates are the United States, China, and Germany. Africa and Latin America (and thus Brazil) are largely excluded from the international production network. However, Indonesia also does not play a major role in international production.²³

All NICs show a lower share of foreign value added in gross exports than the world average (except Mexico in the 1990s and early 2000s). Considering that most of world trade takes place between highly industrialized countries, this is not surprising. For trade between highly industrialized economies, distance is often smaller (e.g., Intra-EU-Trade) and border effects can also be expected to be smaller (better quality of institutions, lower non-tariff barriers, better information, similar culture, legal security, etc.).²⁴ During the 1995 to 2011 period, only India and Turkey showed an absolute increase in the share of foreign value added in gross exports that was above that of the world’s average. India’s foreign value added share increased by about 11 percentage points (from around 10.5% to 21.5%) and Turkey’s value added share increased by about 8 percentage points (from around 14% to 22%), contrary to an increase of around 7 percentage points for the world average (from around 25% to 32%).

To address the question of where the foreign value added in exports originates from, an altered version of Equation 3.3 yields foreign value added shares in exports by partner country. Figure 3.3 depicts the foreign value added in exports by partner country in percentage of total foreign value added in exports for China and Mexico for the years 2011 (in blue) and 1995 (in orange) and Figure 3.11 in the Appendix shows the same graphs for Brazil, Indonesia, India, and Turkey. China’s foreign value added share was about 22% in 2011 (see previous figure). The data show that the share from the “Rest of the World” as the largest contributor accounts for more than 30% of this foreign value added share - ergo for a value of around 6.6% in China’s total exports. The “Rest of the World” consists of all countries that are not directly covered by the WIOD. This includes many Asian countries such as Bangladesh, Malaysia, the Philippines, and Singapore, major producers of intermediates imported by China (see for instance Antras

²³Another explanation may be that Brazil (and Indonesia) produce less skill intensive goods than other NICs. Those goods usually show less vertical specialization or are goods that are at the first stages of the value chain (and thus do not require as much intermediate inputs).

²⁴See for instance Anderson and van Wincoop (2003), who show that borders reduce trade between industrialized countries by only 20 to 50% or Head and Mayer (2000), who document a decrease of the border impact over time for European countries. Applying the same estimation method to China, Poncet (2003) yields much higher estimates for border effects than those observed for Europe or North America (e.g., McCallum, 1995 and Helliwell, 2000). See Head and Mayer (2013) for an overview of sources of resistance to cross-border trade.

and de Gortari, 2016). Generally, many countries with high shares in foreign value added in Chinese exports show close geographic proximity to China. Apart from the “Rest of the World”, Japan (10%), Korea (6%) and Taiwan (6%) are among the six largest foreign value added contributors.

This result is similar for the other NICs (except Mexico): The “Rest of the World” always accounts for the largest share in foreign value added. Apart from physical proximity also economic size, the other classic gravity parameter, seems to play a role as a determinant for foreign value added shares. For most NICs, at least three, often four of the five largest contributors in value added shares of exports consist of the four largest economies (Japan, China, Germany, and the United States). An exception is Turkey, for which, for instance, the United States plays less of a role, presumably because of its proximity to the EU and Russia.

The importance of intermediate inputs from countries close to China in China’s production of export goods is in line with its role as a major assembly location. Many intermediate components, especially in the field of “Electrical and Optical Equipment” (see Figure 3.6), are produced by other Asian countries (particularly by the Tiger states) and then shipped to China for final assembly. Mexico differs from the other NICs in the sense that the origin of foreign value added embodied in its export is very concentrated. In 1995, more than 60% of foreign value added in Mexican exports originated from the United States. This share dropped to around 37% in 2011 which is still more than twice as high as the second largest share of 17% from China. In 1995, China accounted for only around 1.13% of foreign value added in Mexican exports. This means that the Chinese share in 2011 was more than 15 times higher than in 1995.

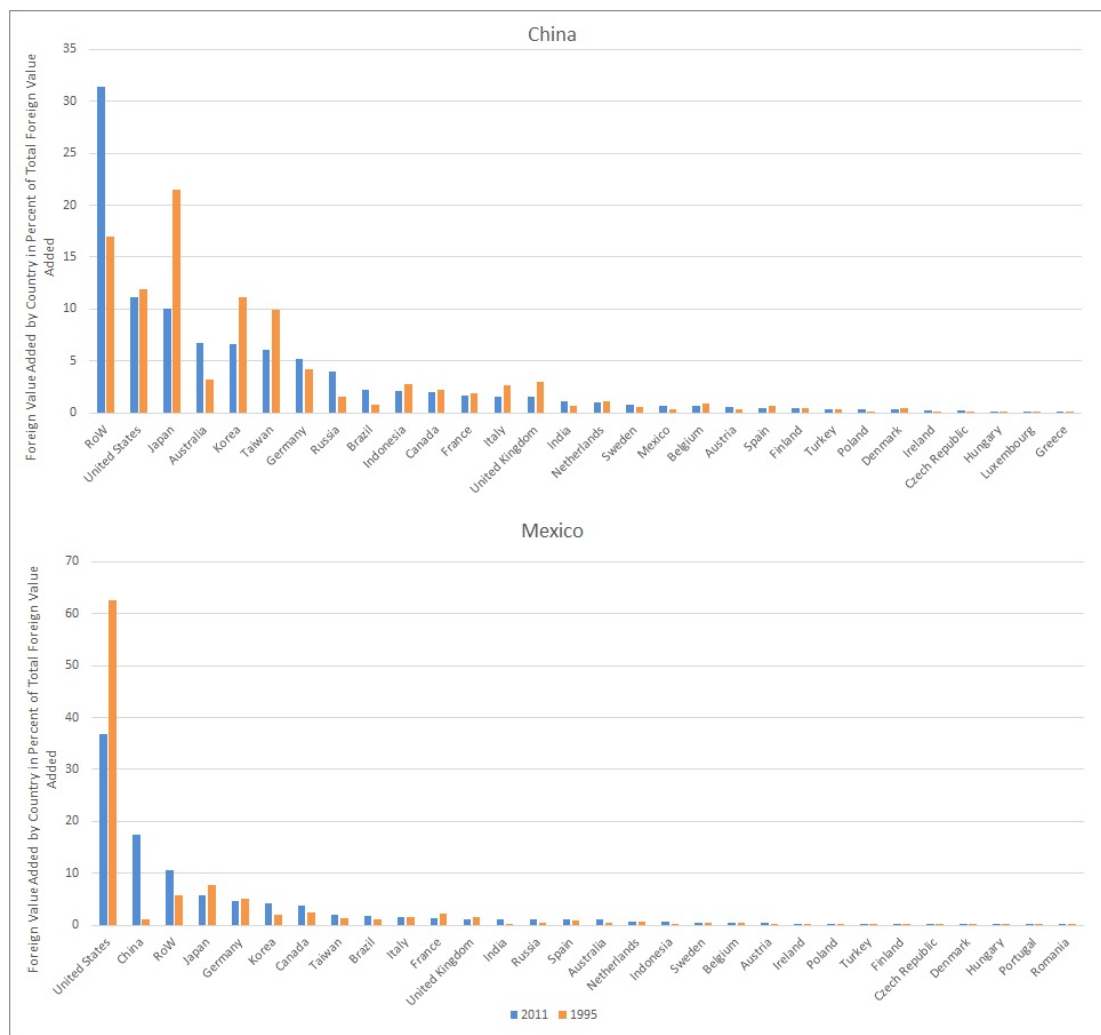
An increase of China’s contribution to value added exports can also be observed for Brazil (increase by factor seven), Indonesia (increase by factor four), India (increase by factor five) and Turkey (increase by factor three). This observation indicates that China’s role in global production is not only that of a final assembler. It obviously also produces intermediates that are then further used along global value chains. The share of foreign value added from the other five NICs only increased slightly since 1995 and remained at fairly low levels.

3.3.3 Trade in Value Added - Foreign Consumption of Domestic Value Added

Tracking foreign consumption of domestic value added²⁵ is key to determining country interdependencies, for instance, when it comes to evaluating the risk of spillovers after a shock. Measuring trade in value-added-terms implies that not only direct trade

²⁵In the following, “value added exports” will be defined as “foreign consumption of domestic value added” and both terms will be used interchangeably.

Figure 3.3: Foreign Value Added in Exports for China and Mexico by Partner Country - 1995 and 2011



Notes: Source: WIOD, author's calculations.

linkage, but also indirect trade relationships are taken into account. Consider the Boeing 787 Dreamliner example from the introduction: Jet engines for the Dreamliner are produced in the UK. If, after assembly in the United States, the plane is exported to Australia, then traditional trade measures would not reflect the indirect link between the UK and Australia, even though Australia is the destination of final consumption of UK's value added. A recession in Australia may affect the engine production in the UK, even though traditional measures would not show a trade relationship between the two countries. To disentangle intermediate and direct trade relationships simultaneously, Equation 3.4 is used to compute the foreign consumption of domestic value added

(FCDVA).

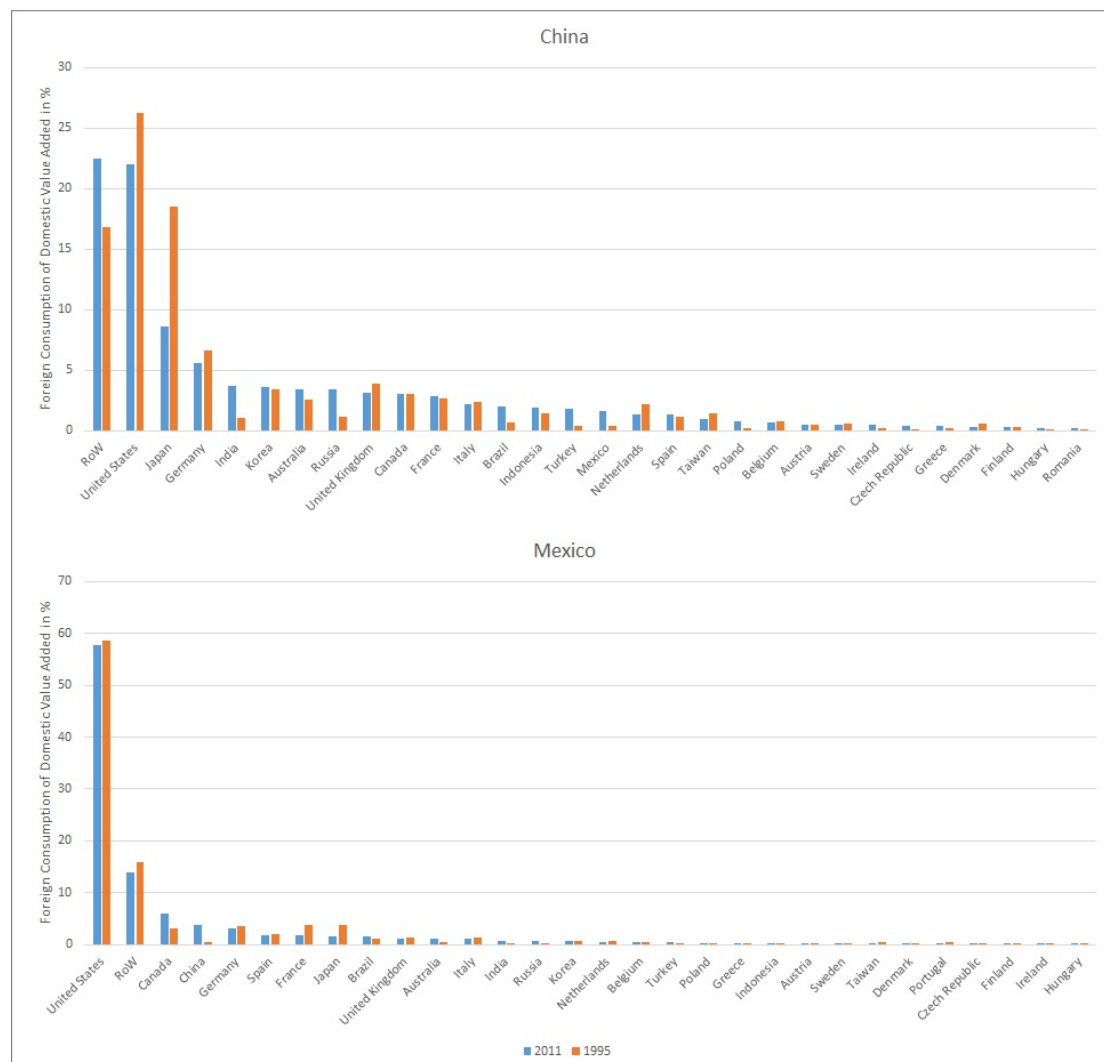
Figure 3.4 shows the destination of foreign domestic value added consumption for China and Mexico, arranged according to the destination's importance in 2011. The graphs for the other four NICs can be found in the Appendix (see Figure 3.12). The blue bars show the country-specific foreign consumption shares of value added generated in China and Mexico in relation to the total foreign consumption of value added generated in China and Mexico in 2011. The orange bars show the same information for 1995.

For instance, in 2011, the "Rest of the World" was the largest consumer of Chinese value added with a share of 22.5% in total foreign consumption followed by the United States (22%) and Japan (8.6%). The importance of foreign countries for the consumption of domestic value added seems to be largely driven by the classic gravity parameters size and distance. The three largest economies (except China) - the United States, Germany and Japan - are among the top four foreign consumers of Chinese value added, emphasizing the role of economic size as a determinant for trade patterns. The fourth consumer is the "Rest of the World".

Even though still concentrated, the foreign consumption of Chinese value added is more dispersed across countries in 2011 than in 1995. The patterns are similar for the other NICs: Consumption destinations generally were more dispersed in 2011 than in 1995. During that time span, the share in the foreign consumption of value added generated by NICs increased for most of the other NICs, whereas the share for highly industrialized economies often decreased. The largest economies (particularly the United States, China, Germany and Japan) absorb the largest shares of value added generated by NICs, but also countries with geographic proximity are among the major consumers like Korea for China. Again, Mexico is an extreme case. Almost 60% of foreign consumption of Mexico's value added takes place in the United States. The common border, size of the countries, NAFTA membership, and the Maquiladora system reinforce the United States' position as Mexico's primary trading partner. Interestingly, from 1995 to 2011 the United States' consumption share did not drop, contrary to its share of foreign value added in Mexican exports. One explanation for this observation may be that production of intermediates that Mexico uses for final assembly took place in the United States in 1995, but was outsourced to, for instance, China until 2011. Canada, the third NAFTA member is the second most important trading partner with a share of only about 6% in 2011. Mexico and India (and to some extent Brazil) are the only NICs for which the consumption share of the major trading partner (the United States in both cases) remained fairly stable over the time of observation - or, in the case of India, even slightly increased.

Figure 3.5 takes a closer look at the degree of concentration of foreign consumption of NICs' domestic value added. For all six NICs the Lorenz Curve and the Gini co-

Figure 3.4: Foreign Consumption of Domestic Value Added for China and Mexico by Partner Country - 1995 and 2011

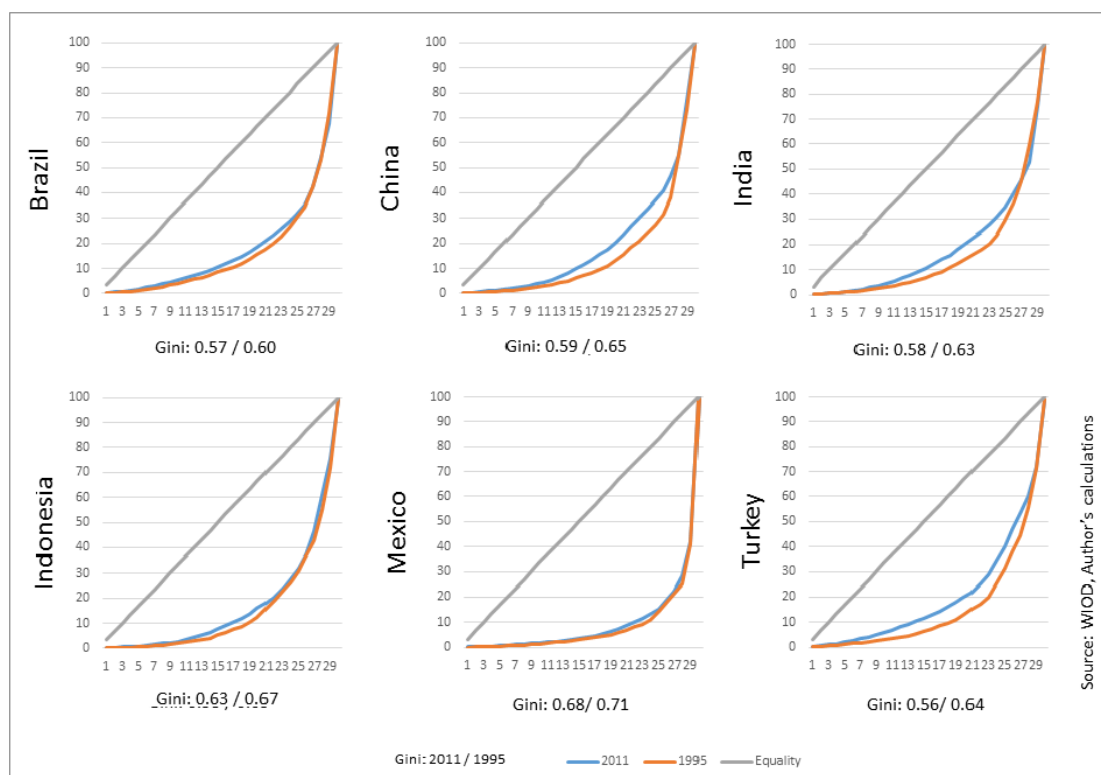


Notes: Source: WIOD, author's calculations.

efficient indicate the concentration of the thirty largest destination countries of value added consumption. The thirty largest consumers cover more than 99% of total foreign consumption for all NICs.

Again, the blue line (and the first Gini value) shows the concentration for 2011, whereas the orange line (and second Gini value) captures the year 1995. The equality line indicates a scenario in which all foreign countries consume an equal share of domestic value added. This would be equivalent to a Gini value of zero. An increase in the concentration of the consumption destination shifts the Lorenz Curve further away from the equality line and leads to a higher Gini value (one in case of maximal inequal-

Figure 3.5: Concentration and Gini of Foreign Consumption of Domestic Value Added - 1995 and 2011



Notes: Source: WIOD, author's calculations.

ity).²⁶ From all six NICs the foreign consumption of Mexico's value added is the most concentrated (both in 1995 and 2011). As shown, the United States are the dominating consumer of Mexico's foreign value added. In 2011, Turkey shows the highest dispersion followed closely by Brazil, India and China. The reason for Turkey's lead position is the proximity to the EU and thus a variety of highly industrialized trading partners that demand Turkish value added in the closer proximity. For all countries the foreign consumption of domestic value added became more dispersed from 1995 to 2011.

This shows that a growing number of countries participate in international trade. Emerging markets (including the NICs) take over trading shares from industrialized economies. A good example for this development is Turkey (see also Figure 3.12 in

²⁶Note: As discussed previously, countries that are not covered by the data are modeled as the "Rest of the World". This includes many Asian, Latin American and Middle Eastern countries that are in close proximity to the NICs. For that reason, the "Rest of the World" is one of the major destinations of foreign consumption of NICs' domestic value added. Since the "Rest of the World" includes many countries, the Lorenz Curve and the Gini coefficient shown here overestimate the concentration. Slicing up the "Rest of the World" in different countries would yield lower Gini values and a Lorenz Curve closer to the equality line.

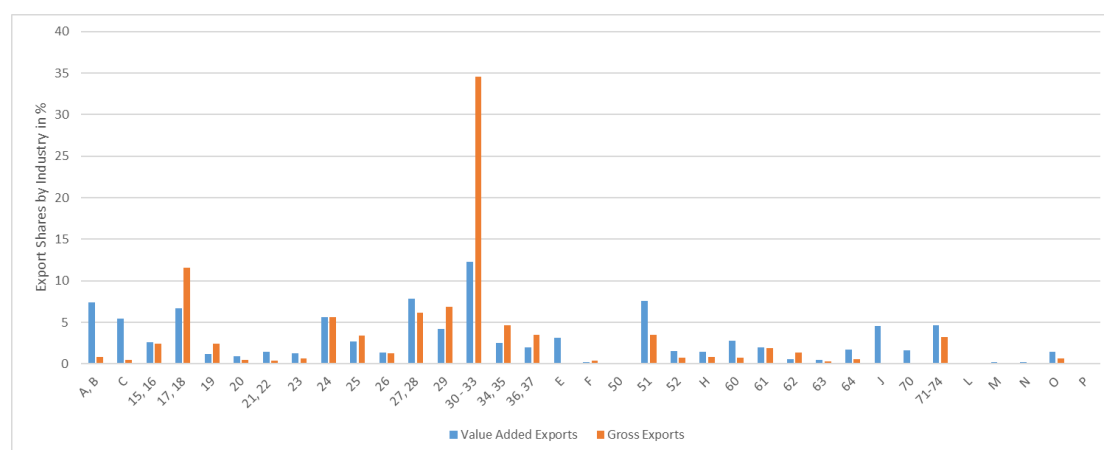
the Appendix): In 1995, Germany was the dominant foreign consumer of value added generated in Turkey (ignoring RoW). Around 27.5% of the foreign consumption of Turkish value added took place in Germany, followed by the United States with a share of 11.2%. From 1995 to 2011, the share for both countries more than halved. In 2011, Germany's share of foreign consumption of Turkey's value added accounted for 11.6%, the US' share for 6.3%. Instead, Poland, China, Brazil, Bulgaria, India and Mexico (in descending order) showed the highest relative increase in consumption shares. As a result, foreign consumption of Turkey's value added became more dispersed; the Gini coefficient decreased from 0.64 to 0.56. This finding has important implications for the risk of spillovers after a foreign shock. On the one hand, trade connection with a growing number of countries raises the probability that the domestic economy is exposed to foreign shocks. On the other hand, having trade connections and serving demand in a larger number of countries spreads the risks, and most likely mitigates the consequences compared to a scenario, in which only a few large markets are served. An example is the aftermath of the financial crisis of 2008, where demand from NICs and other emerging market economies was one of the main drivers for recovery.

I now analyze how much industries in NICs contribute to trade in value added ("the foreign consumption of domestic value added") and compare the results with their trade contribution measured on a gross basis. The differences between measurements in value added and on a gross basis are striking. Figure 3.6 shows the industry specific export shares, on the one hand measured in value added (blue) and on the other hand on a gross basis (orange) for China in 2011. The gross measure shows a much higher relative importance of sector 30-33 ("Electrical and Optical Equipment") and indicates that this sector accounts for 35% of China's total export value. On a value added basis, however, this sector is only responsible for around 12% of foreign consumption of Chinese value added. The skill intensive electrical and optical equipment products show high shares of foreign value added. It is this industry, in particular, where oftentimes China does the final assembly but does not produce the components (see for instance the iPod; Dedrick et al., 2010). For other sectors, the relative importance in trade is underestimated on a gross output basis. Similar results are obtained for the other five NICs (see Figure 3.13 in the Appendix).

Primary and service industries show a higher relative importance when trade is measured in value added rather than on a gross basis. Primary goods are often embodied in the products of manufacturing industries. Services often take a supporting role in exporting and are indirectly exported by manufacturers. These findings have important policy implication and should raise the awareness that (trade) policies focusing only on sectors with a high relative gross share may lead to distorting outcomes. Evaluating the export industry structure purely on gross output information overestimates the relative

importance of manufacturing industries for international trade, particularly for those with a high proportion of (foreign) intermediate inputs. The relative importance for service and primary sectors would be underestimated.

Figure 3.6: Industry Contribution for Foreign Consumption of China's Domestic Value and for China's Gross Exports in 2011



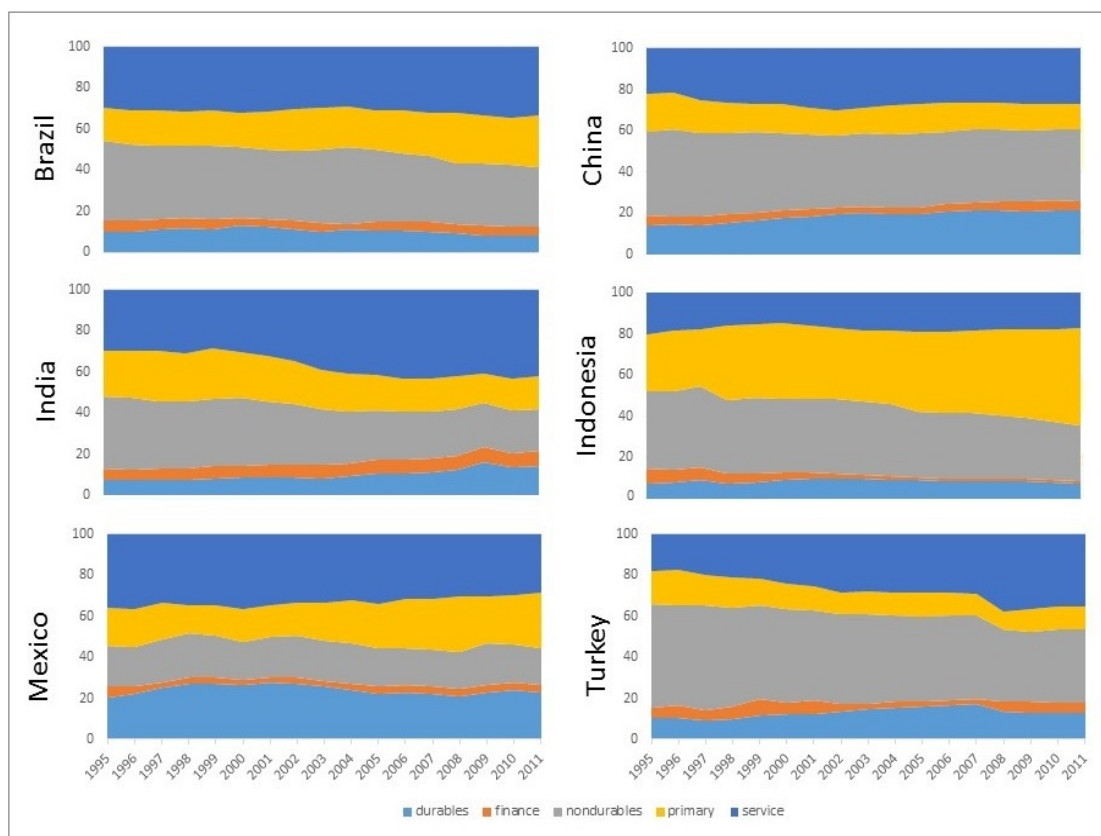
Notes: Source: WIOD, author's calculations. Industry classification: NACE Rev. 1, see Table 3.5 in the Appendix for a description.

Figure 3.7 shows value added export shares by industry category for all six NICs from 1995 to 2011. The 35 industries are aggregated to primary (in yellow), durable (in light blue, at the bottom of the figure), nondurable (in grey), finance (in orange), and service (in dark blue, at the top of the figure) categories. The figure shows that the industry structure of value added exports differs across the NICs. For instance, a huge share of Indian value added exports is generated by service and financial industries. From 1995 to 2011 both categories continuously saw their share increase. Together they account for almost 50% of India's value added exports in 2011 (see Table 3.4 in the Appendix for the exact industry category shares in 1995 and 2011 and Figure 3.14 in the Appendix for the disaggregated value added export shares of all 35 industries in 2011). For comparison, both categories only generate around 30% of total value added exports in China and Mexico in 2011. The dominating role of services in value added exports is in line with India's role as a major service outsourcing destination (Liu and Trefler, 2008).

China, on the other hand, is primarily an outsourcing destination for manufacturing. This is also reflected by the dominance of manufacturing industries in China's value added export shares. In 2011, durables and nondurables add up to a share of over 55%, more than for any other NIC.

Turkey shows relatively high shares in services (35%) and nondurables (36%), but

Figure 3.7: Six NICs: Foreign Consumption of Domestic Value Added Shares by Industry Category - 1995 to 2011



Notes: Source: WIOD, author's calculations.

has the lowest share in primary products (11%). A high share in primary products could be an indicator that either countries are rather upstream in the value chain or are not integrated well in global value chains.

Brazil, Mexico, and Indonesia show the highest value added share in primary products. Especially the figure for Indonesia is striking. Around 47% of total value added exports originate from primary products, out of which mining accounts for 37%. This is in line with previous observations that both Brazil and Indonesia are not as well integrated in global production as the other NICs. Even though mining also plays a crucial role for Mexico (close to 25%), Mexico also shows the highest share for durables (close to 23%). Despite the fact that the industry structure is rather diverse across the NICs, they also show some similarities: For all NICs, (except for Mexico) nondurables accounted for the biggest share of value added exports in 1995. This share decreased for all NICs, on average by about 25%, during the 1995 to 2011 period. Instead the share of services (except for Mexico) and durables increased.

3.4 Summary and Conclusion

One goal of this paper is to raise awareness of the limitations of traditional trade measures on a gross output basis in the light of increased vertical specialization and the dominance of trade in intermediates rather than final goods during the last two to three decades. For this purpose, this paper uses the WIOD to analyze the role of NICs in global value chains. The differences between measures on a gross output basis and value added basis are striking. The paper exemplarily shows this by measuring the relative importance of industries in exporting. Industry specific export shares measured using value added exports differed by up to around 23% for some industries compared to the shares measured using gross exports. These findings highlight the needs for more sophisticated world input output data to form a better understanding of how global production is organized.

Additionally, the paper provides insight into the role of NICs in global value chains. All NICs showed a huge increase in output, exports, imports and value added over the years of observation, underlining the increasing importance of NICs in global production. The origin of foreign value added embodied in exports became more diverse, and the same holds true for the destinations of value added exports. Generally, NICs' share of foreign value added in gross exports of other NICs increased, whereas the share of industrialized countries decreased. Despite these similarities, the role of NICs in global production is fundamentally different in many respects. The findings of this paper support the idea that the phenomenon of "global" production sharing is limited to China, Europe, and North America. Brazil shows much lower shares of foreign value added in gross exports than the other NICs. The same holds true for Indonesia which can be explained by its concentration on primary products. For China, India, Mexico, and Turkey, increasing foreign value added shares in gross exports are an indicator for increased participation in global production sharing. The reasons for this observation differ across the NICs. India is a main destination for service offshoring; almost 50% of India's value added exports originate in this sector. China concentrates on manufacturing products. The data give evidence for China's role as a final assembly destination, but also show that China's production of intermediates strongly increased over the period of observation. Mexico's production is very much focused on the United States, whereas Turkey concentrates on the European market.

The findings imply that public policy should not attempt to conduct the same "one size fits all" policies across all NICs. Instead the role and position in global value chains should be carefully analyzed to give individual policy advice. For instance, policies for countries that are not well integrated in global production such as Brazil might focus on attracting foreign capital to increase global value chain participation, whereas policies

for well integrated countries such as India or China might focus on sustainable growth and learning from global value chains.

3.5 Bibliography

- (1) Anderson, James E. and Eric Van Wincoop (2003), “Gravity with gravitas: a solution to the border puzzle”, *American Economic Review* 93(1), 170-192.
- (2) Andersen, Simon S., Peter B. Nellesmann and Casper R. Thomsen (2015), “Global Value Chains”, Working Paper Danmark Nationalbank.
- (3) Antras, Pol and Davin Chor (2013), “Organizing the global value chain”, *Econometrica* 81(6), 2127-2204.
- (4) Antras, Pol (2015), “Global Production: Firms, Contracts, and Trade Structure”, Princeton University Press.
- (5) Antras, Pol and Alonso de Gortari (2016), “On the Geography of Global Value Chains”, NBER Working Paper 23456.
- (6) Autor, David H., David Dorn and Gordon H. Hanson (2013), “The China syndrome: Local labor market effects of import competition in the United States”, *American Economic Review* 103(6), 2121-2168.
- (7) Baldwin, Richard and Frederic Robert-Nicoud (2014), “Trade-in-goods and trade-in-tasks: An integrating framework”, *Journal of International Economics* 92(1), 51-62.
- (8) Baldwin, Richard and Javier Lopez-Gonzalez (2015), “Supply-chain Trade: A Portrait of Global Patterns and Several Testable Hypotheses”, *The World Economy* 38(11), 1682-1721.
- (9) Bergin, Paul R., Robert C. Feenstra and Gordon H. Hanson (2009), “Offshoring and volatility: evidence from Mexico’s maquiladora industry”, *American Economic Review* 99(4), 1664-1671.
- (10) Boehm, Christoph E., Aaron Flaaen and Nitya Pandalai-Nayar (2018), “Input Linkages and the Transmission of Shocks: Firm-Level Evidence from the 2011 Tohoku Earthquake”, *The Review of Economics and Statistics*.
- (11) Cardoso, Eliana (2009), “A brief history of trade policies in Brazil: From ISI, export promotion and import liberalization to multilateral and regional agreements”, In conference on “The Political Economy and Trade Policy in the BRICS”, 27-28.
- (12) Cattaneo, Olivier, Gary Gereffi, Sebastien Miroudot and Daria Taglioni (2013), “Joining, upgrading and being competitive in global value chains: a strategic framework”, World Bank Policy Research Working Paper 6406.

- (13) Daudin, Guillaume, Christine Riffart and Danielle Schweisguth (2011), “Who produces for whom in the world economy?”, *Canadian Journal of Economics/Revue canadienne d’économie* 44(4), 1403-1437.
- (14) Dauth, Wolfgang, Sebastian Findeisen and Jens Südekum (2014), “The Rise Of The East And The Far East: German Labor Markets And Trade Integration”, *Journal of the European Economic Association* 12(6), 1643-1675.
- (15) Dedrick, Jason, Kenneth L. Kraemer and Greg Linden (2010), “Who profits from innovation in global value chains? a study of the iPod and notebook PCs”, *Industrial and Corporate Change* 19(1), 81-116.
- (16) Dietzenbacher, Erik, Bart Los, Robert Stehrer, Marcel Timmer and Gaaitzen De Vries (2013), “The construction of world input-output tables in the WIOD project”, *Economic Systems Research* 25(1), 71-98.
- (17) Feenstra, Robert C. and Gordon H. Hanson (1996), “Globalization, Outsourcing, and Wage Inequality”, *American Economic Review* 86, 240-245.
- (18) Feenstra, Robert C. (2010), “Offshoring in the global economy: microeconomic structure and macroeconomic implications”, Cambridge, MA: MIT Press.
- (19) Foster-McGregor, Neil and Robert Stehrer (2013), “Value added content of trade: A comprehensive approach”, *Economics Letters* 120(2), 354-357.
- (20) Grossman, Gene M. and Esteban Rossi-Hansberg (2006), “The rise of offshoring: it’s not wine for cloth anymore”, *The new economic geography: effects and policy implications*, 59-102.
- (21) Head, Keith and Thierry Mayer (2000), “Non-Europe: the magnitude and causes of market fragmentation in the EU”, *Weltwirtschaftliches Archiv* 136(2), 284-314.
- (22) Head, Keith and Thierry Mayer (2013), “What separates us? Sources of resistance to globalization”, *Canadian Journal of Economics/Revue canadienne d’économie* 46(4), 1196-1231.
- (23) Helliwell, John F. (2000), “How much do national borders matter?”, Washington, DC: Brookings Institution Press.
- (24) Hummels, David, Jun Ishii and Kei-Mu Yi (2001), “The nature and growth of vertical specialization in world trade”, *Journal of International Economics* 54(1), 75-96.

- (25) Humphrey, John and Hubert Schmitz (2002), “How does insertion in global value chains affect upgrading in industrial clusters?”, *Regional Studies* 36(9), 1017-1027.
- (26) Johnson, Robert C. and Guillermo Noguera (2012a), “Accounting for intermediates: Production sharing and trade in value added”, *Journal of International Economics* 86(2), 224-236.
- (27) Johnson, Robert C. and Guillermo Noguera (2012b), “Fragmentation and trade in value added over four decades”, NBER Working Paper 18186.
- (28) Koopman, Robert, Zhi Wang and Shang-Jin Wei (2014), “Tracing Value-Added and Double Counting in Gross Exports”, *American Economic Review* 104(2), 459-494.
- (29) Liu, Runjuan and Daniel Treffer (2008), “Much ado about nothing: American jobs and the rise of service outsourcing to China and India”, NBER Working Paper 14061.
- (30) McCallum, John (1995), “National borders matter: Canada-US regional trade patterns”, *American Economic Review* 85(3), 615-623.
- (31) Miller, Ronald E. and Peter D. Blair (2009), “Input-output analysis: foundations and extensions”, Cambridge: Cambridge University Press.
- (32) OECD (2015), “OECD Export Group on Extended Supply-Use Tables - Terms of Reference”, https://www.oecd.org/sti/ind/tiva/eSUTs_TOR.pdf
- (33) Poncet, Sandra (2003), “Measuring Chinese domestic and international integration”, *China Economic Review* 14(1), 1-21.
- (34) Saito, Mika, Michele Ruta and Jarkko Turunen (2013), “Trade Interconnectedness: The World with Global Value Chains”, IMF Policy Paper.
- (35) Srinivasan, T.N. (2006), “China, India and the world economy”, *Economic and Political Weekly* 41(34), 3716-3727.
- (36) Stehrer, Robert and Roman Stöllinger (2013), “Positioning Austria in the global economy: Value added trade, international production sharing and global linkages”, FIW Research Reports Series V-002, FIW.
- (37) Taglioni, Daria and Deborah Winkler (2016), “Making Global Value Chains Work for Development”, *Economic Premise* 143. World Bank, Washington, DC. <https://openknowledge.worldbank.org/handle/10986/18421>. License: CC BY 3.0 IGO.

- (38) Tang, Christopher S., Joshua D. Zimmerman and James Nelson (2009), “Managing new product development and supply chain risks: The Boeing 787 case”, *Supply Chain Forum: An International Journal* 10(2), 74-86.
- (39) UNECE (2015), “Draft Guide to Measuring Global Production”, https://www.unece.org/fileadmin/DAM/stats/documents/ece/ces/bur/2015/February/16Add.1-Guide_to_Measuring_Global_Production.pdf
- (40) WTO (2001), “Doha Ministerial Declaration. Ministerial Conference, Fourth Session”, Washington DC: World Trade Organization, www.wto.org/english/thewto_e/minist_e/min01_e/mindecl_e.pdf.

B Appendix

Figure 3.8: 787 Dreamliner Suppliers; Source: Boeing, Reuters

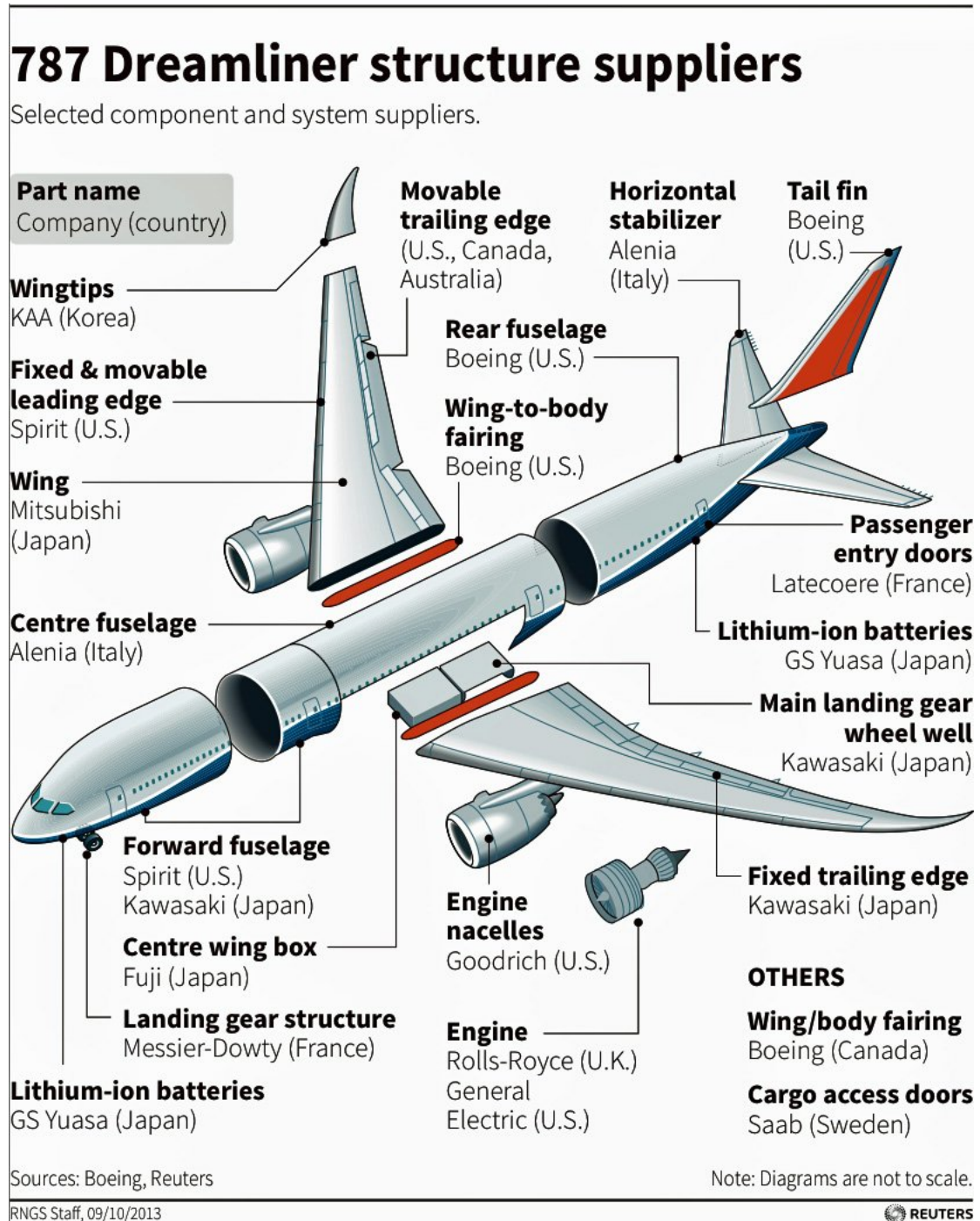


Table 3.3: Six NICs Final and Intermediate Imports and Exports in 2011 (1995=1), Base Value 1995 in Brackets (in Million USD)

	Brazil	China	India	Indonesia	Mexico	Turkey
Final Exports	3.21 (13,453)	10.33 (91,728)	9.19 (17,445)	2.75 (15,862)	6.79 (31,769)	3.98 (16,452)
Intermediate Exports	2.05 (42,466)	14.84 (78,078)	7.18 (24,745)	4.58 (38,276)	4.35 (48,989)	7.67 (11,921)
Final Imports	4.05 (24,864)	7.32 (43,027)	9.05 (11,826)	3.31 (14,602)	6 (19,207)	9.43 (12,738)
Intermediate Imports	5.13 (38,761)	14.9 (99,119)	8.45 (31,916)	3.86 (38,246)	4.32 (52,507)	4.8 (23,570)

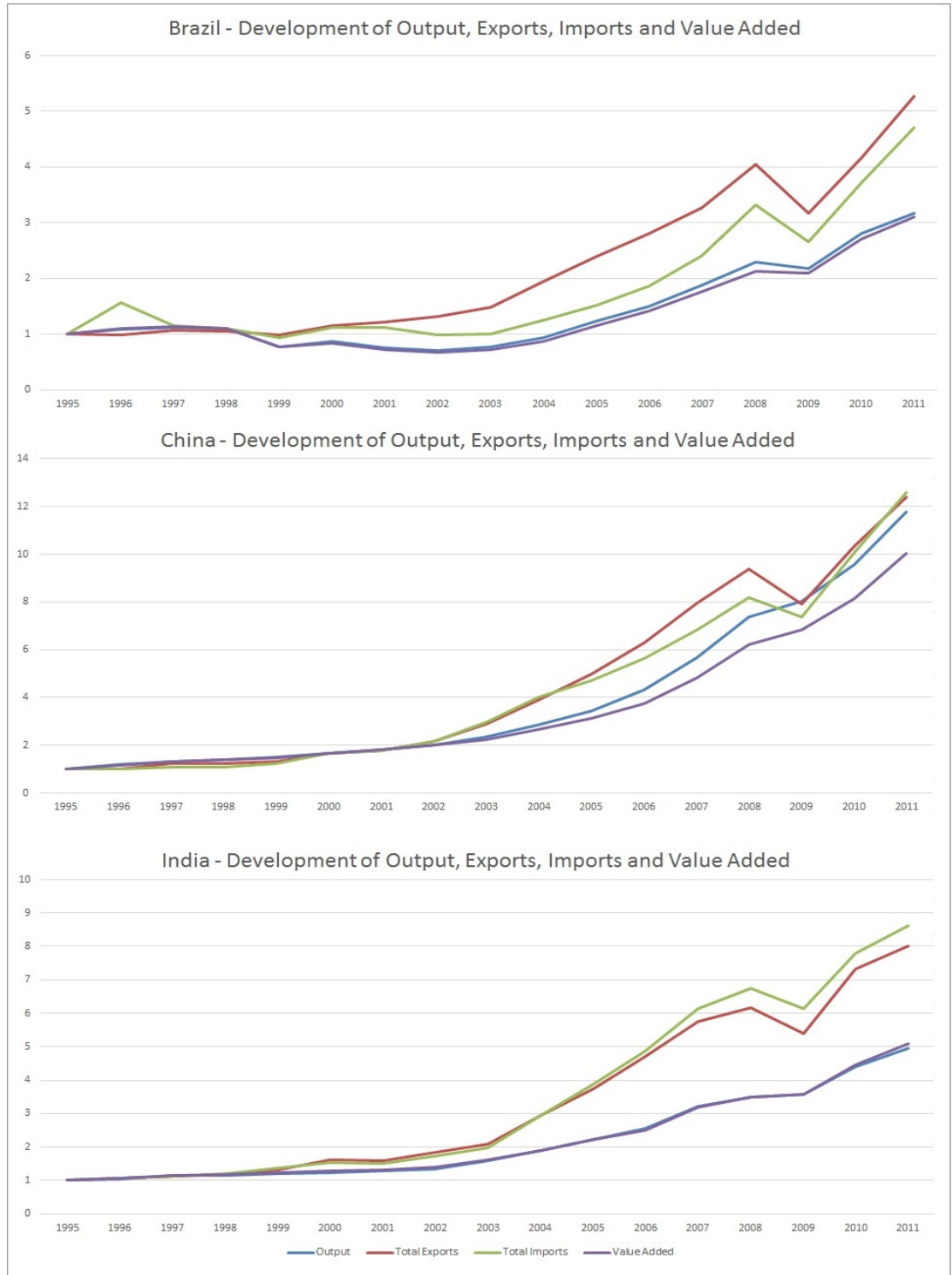
Notes: Source: WIOD, author's calculations.

Table 3.4: Six NICs: Foreign Consumption of Domestic Value Added Shares by Industry Category - 2011 and 1995 in Brackets

	Brazil	China	India	Indonesia	Mexico	Turkey
Primary	25.23 (15.93)	12.79 (19)	16.11 (22.51)	46.85 (27.41)	27.23 (18.73)	10.94 (16.37)
Durables	7.94 (10.09)	21 (14.16)	14.11 (7.81)	7.31 (7.19)	22.79 (20.26)	13.19 (10.42)
Nondurables	28.68 (38.68)	34.88 (40.47)	20.62 (34.77)	27.34 (38.08)	17.84 (19.67)	35.98 (50.3)
Finance	4.62 (5.32)	4.53 (4.5)	7.36 (5.46)	1.19 (7.24)	3.56 (5.57)	4.49 (4.94)
Service	33.52 (29.98)	26.79 (21.87)	41.8 (29.44)	17.32 (20.08)	28.58 (35.77)	35.4 (17.97)

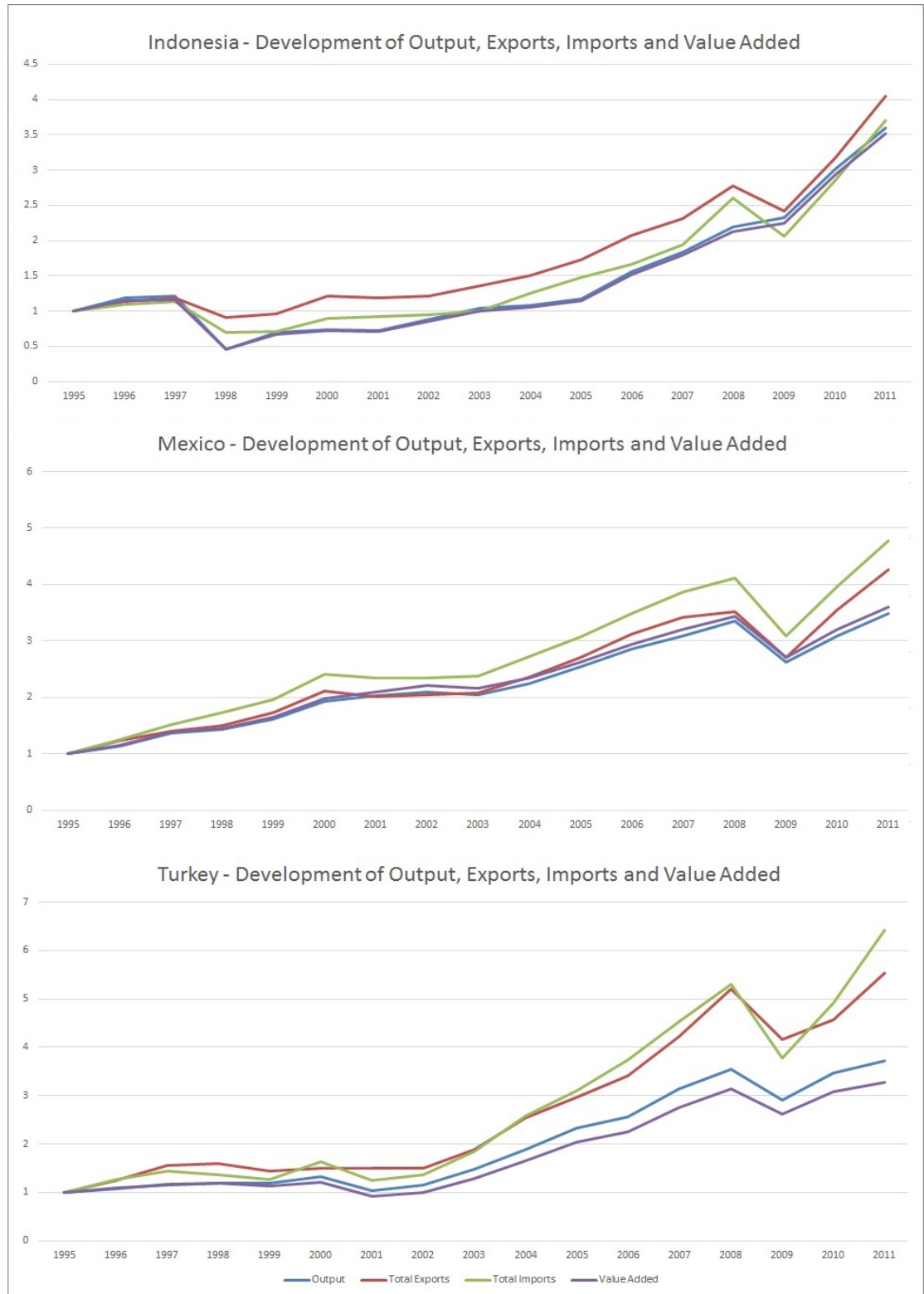
Notes: Source: WIOD, author's calculations.

Figure 3.9: Output, Exports, Imports, and Value Added for China, India, and Indonesia from 1995 to 2011



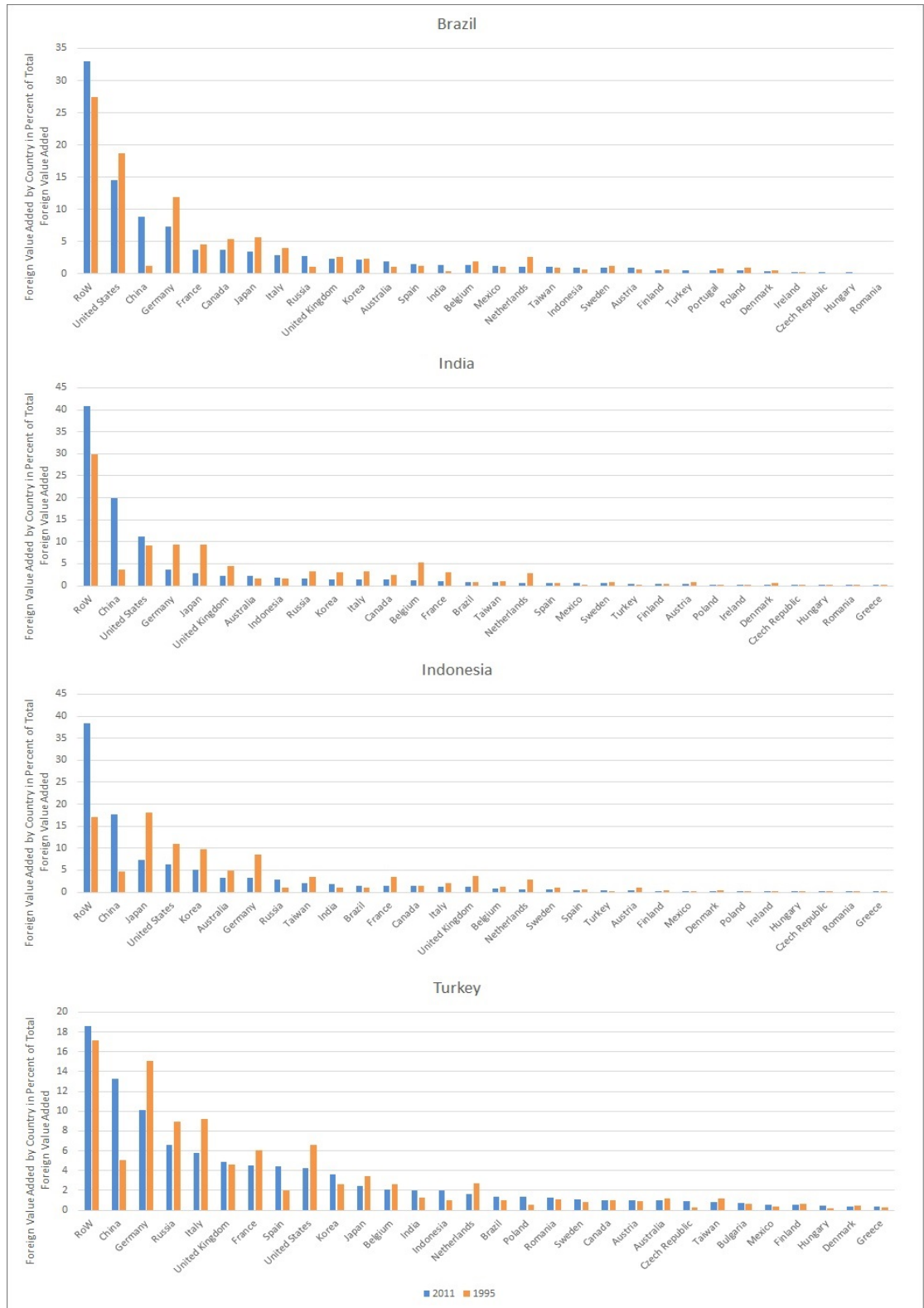
Notes: Source: WIOD, author's calculations.

Figure 3.10: Output, Exports, Imports, and Value Added for Mexico, Brazil, and Turkey from 1995 to 2011



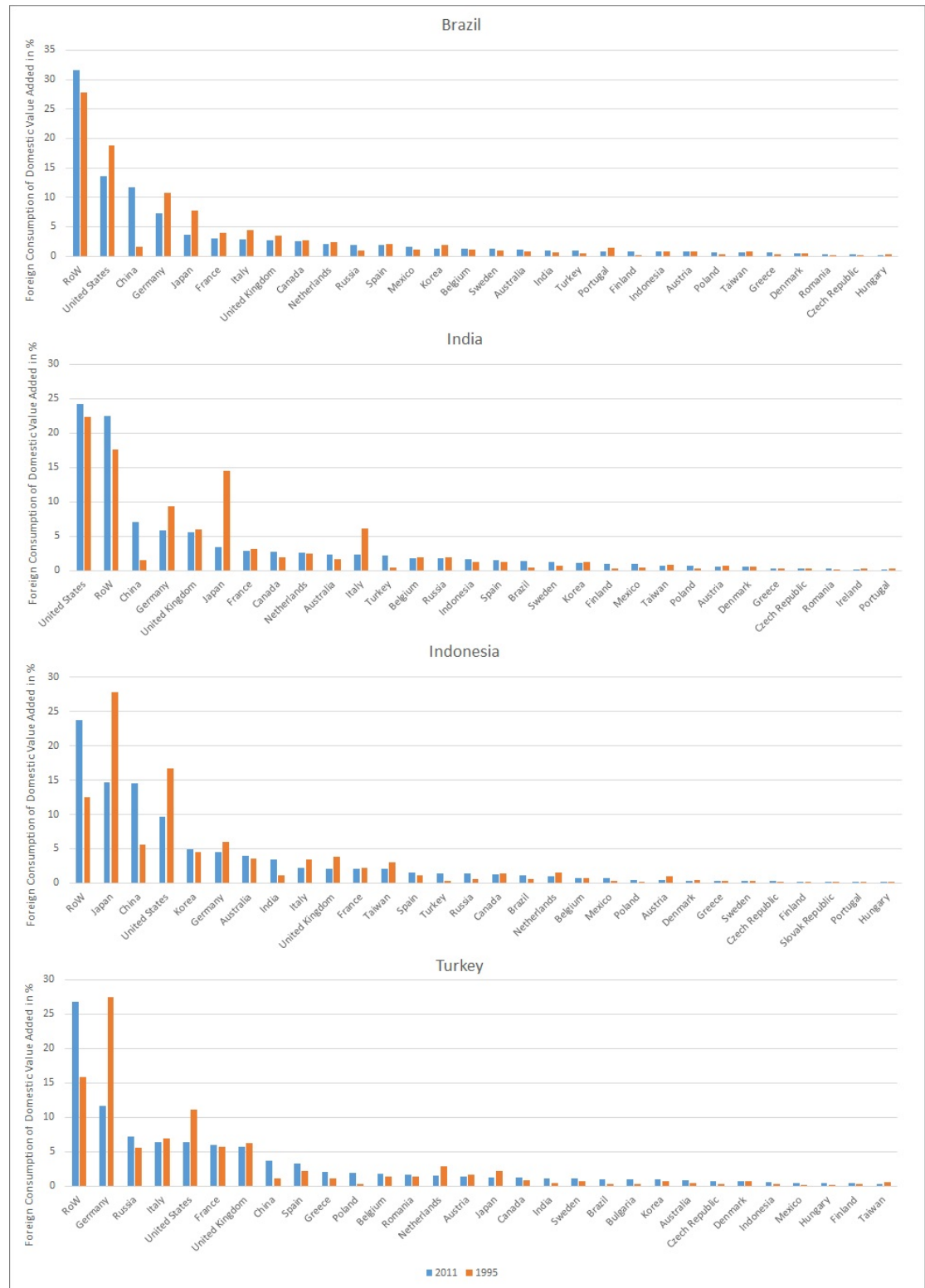
Notes: Source: WIOD, author's calculations.

Figure 3.11: Foreign Value Added by Country in Percent of Total Foreign Value Added for Brazil, Indonesia, India, and Turkey - 1995 and 2011



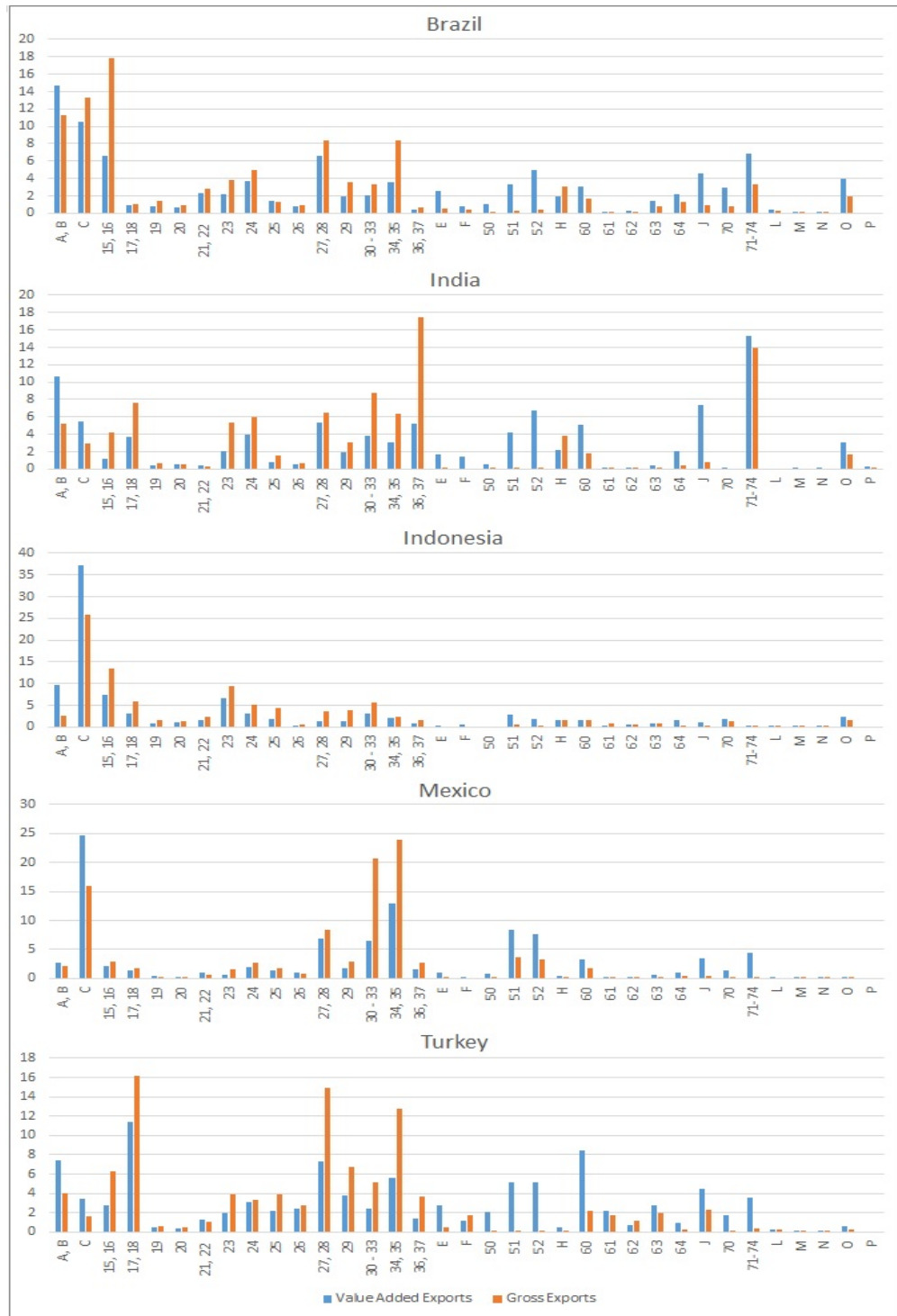
Notes: Source: WIOD, author's calculations.

Figure 3.12: Foreign Consumption of Domestic Value Added for Brazil, Indonesia, India, and Turkey by Partner Country - 1995 and 2011



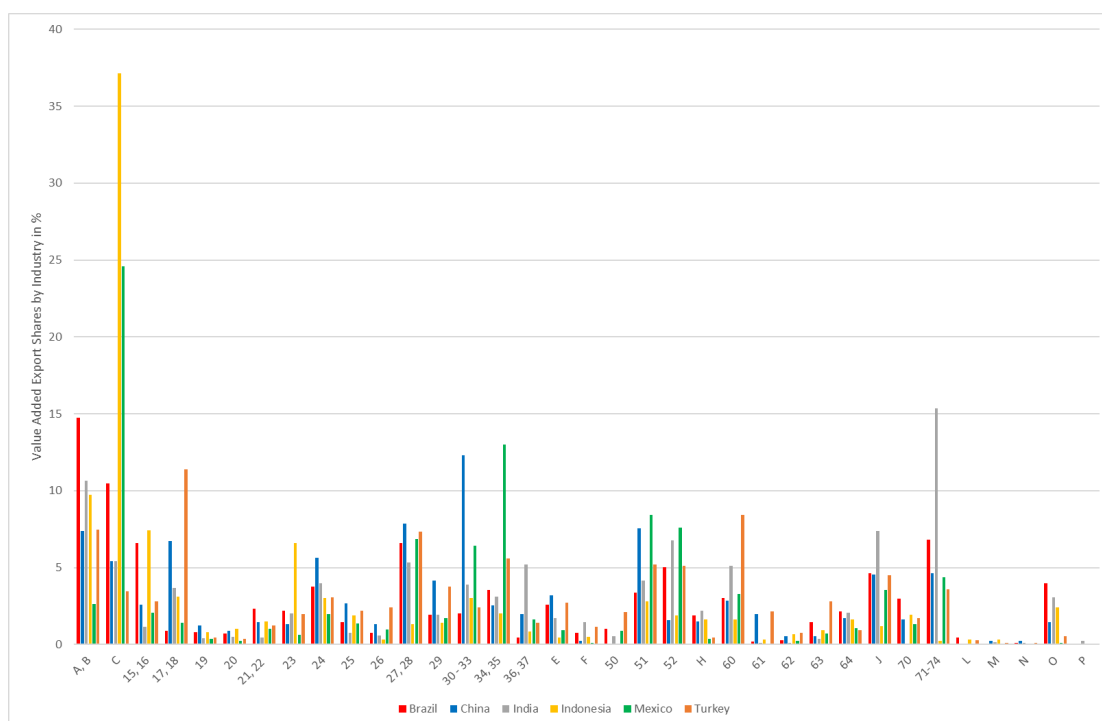
Notes: Source: WIOD, author's calculations.

Figure 3.13: Five NICs: Industry Contribution for Foreign Consumption of Domestic Value and for Gross Exports in 2011



Notes: Source: WIOD, author's calculations.

Figure 3.14: Six NICs: Foreign Consumption of Domestic Value Added Shares by Industry - 1995 to 2011



Notes: Source: WIOD, author's calculations.

Table 3.5: Industries and Industry Categories

WIOD Number	Industry Code	Description	Category
1	A, B	Agriculture, Hunting, Forestry and Fishing	primary
2	C	Mining and Quarrying	primary
3	15, 16	Food, Beverages and Tobacco	nondurables
4	17, 18	Textiles and Textile Products	nondurables
5	19	Leather, Leather and Footwear	nondurables
6	20	Wood and Products of Wood and Cork	nondurables
7	21, 22	Pulp, Paper, Paper , Printing and Publishing	nondurables
8	23	Coke, Refined Petroleum and Nuclear Fuel	nondurables
9	24	Chemicals and Chemical Products	nondurables
10	25	Rubber and Plastics	nondurables
11	26	Other Non-Metallic Mineral	nondurables
12	27, 28	Basic Metals and Fabricated Metal	nondurables
13	29	Machinery, Nec	durables
14	30 - 33	Electrical and Optical Equipment	durables
15	34, 35	Transport Equipment	durables
16	36, 37	Manufacturing, Nec; Recycling	durables
17	E	Electricity, Gas and Water Supply	nondurables
18	F	Construction	service
19	50	Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel	service
20	51	Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles	service
21	52	Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods	service
22	H	Hotels and Restaurants	service
23	60	Inland Transport	service
24	61	Water Transport	service
25	62	Air Transport	service
26	63	Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies	service
27	64	Post and Telecommunications	service
28	J	Financial Intermediation	finance
29	70	Real Estate Activities	service
30	71-74	Renting of M&Eq and Other Business Activities	service
31	L	Public Admin and Defence; Compulsory Social Security	service
32	M	Education	service
33	N	Health and Social Work	service
34	O	Other Community, Social and Personal Services	service
35	P	Private Households with Employed Persons	service

Notes: Source: Industry classification: NACE Rev. 1.

Chapter 4

Foreign Ownership and the Export and Import Propensities of Developing-Country Firms

Summary: This paper uses micro data from the World Bank Enterprise Surveys 2002-2006 to investigate how foreign ownership affects the likelihood of manufacturers in developing countries to export and/or import either directly or indirectly. Applying propensity score matching to control for differences across firms in terms of labor productivity and other characteristics, we find that foreign ownership raises the propensity of a firm to export by over 17 and the propensity to import by more than 13 percentage points. The effects are even bigger for countries with the lowest per-capita income and institutional quality.¹

¹We would like to thank an anonymous referee for very helpful comments and suggestions.

4.1 Introduction

Access to world markets is generally considered to be one of the necessary conditions for sustained economic growth and poverty reduction in developing countries (see WTO, 2001). But while much has been written on the nexus between international market access and growth at the aggregate level,² we still have little systematic evidence at the micro-level on how firms in developing countries actually connect with foreign customers and suppliers, and on the factors that may help them do so. The current paper focuses on one such factor, namely foreign ownership, and uses micro data from the World Bank Enterprise Surveys to determine how foreign ownership affects the propensity of manufacturing firms to engage in exporting and/or importing.

It is a well established stylized fact that firms generally face substantial barriers, or “fixed costs”, when accessing foreign markets (Roberts and Tybout, 1997). In the case of developing countries there is reason to believe that these barriers are especially large relative to firms’ own capacity to overcome them, and that firms therefore depend on external support. First, firms in less developed countries are less likely to have the technological and organizational know-how and the foreign contacts to identify potential customers, negotiate contracts, and meet to these customers’ needs. Moreover, given a lack of contacts and know-how, they are less likely to be able to identify and negotiate contracts with overseas suppliers of intermediate goods.³ Second, developing countries tend to have poorly developed financial markets, which tends to limit financing of the fixed costs of exporting and importing (see, for instance, Beck, 2002). Foreign owners may help on both fronts, providing know-how and contacts as well as better access to external finance, thus allowing firms to more easily jump the barriers to exporting or importing. While foreign ownership is only one way to organize this outside support, it is likely to be an important one (see also Markusen and Trefler, 2009).

Foreign ownership may thus be viewed as helping firms with the intermediation of international trade. That is, in foreign-owned firms the activities associated with exporting and importing, including finding buyers or sellers, negotiating contracts, providing financing and insurance, etc., are likely to be internalized, i.e., carried out within the firm and therefore not directly observable. We would hence expect foreign-owned firms not only to have a higher overall export or import propensity, but also to rely more on direct and less on indirect trade through independent intermediaries than local firms.

Our analysis proceeds in two steps, namely by building a simple theoretical model

²See, for instance, Frankel and Romer (1999). The large literature on the role of trade in alleviating poverty in developing countries is surveyed by Winters et al. (2004).

³Keasing (1983) explains how developing country firms have been able to export consumer goods with the help of overseas buyers that provided contacts and, more precisely, technical, logistical and management capabilities. See also Feenstra and Hamilton (2006) for a detailed discussion of the trade strategies of firms in South Korea and Taiwan.

to guide our empirical analysis, and then using propensity score matching to determine the effect of foreign ownership. In the theoretical model, accessing a foreign market involves a fixed cost, and firms are heterogeneous in terms of their productivity (or own capacity to pay for this fixed cost). Firms that are not productive enough to pay for it on their own may get help from foreign ownership, or reduce the fixed cost by using an independent intermediary. The model predicts that foreign ownership unambiguously raises the propensity of a firm to trade directly, but may raise or lower the propensity to trade indirectly depending on the firm's productivity.

We use the well suited World Bank Enterprise Survey data 2002-2006 for our empirical analysis. While they are only available in a cross section, the data contain a good deal of information on the export and import activities of firms across a wide range of countries and industries, as well as detailed information on the individual firms that we can use as controls. Importantly, the dataset also contains information on whether firms export or import directly or indirectly through independent intermediaries. We can match each firm with at least 10% foreign ownership with a control group of firms from the same industry and country that, in terms of their labor productivity, employment, and other characteristics, are equally likely to exhibit foreign ownership. By matching firms within an industry and country we control for the foreign ownership determinants suggested by the traditional theories of foreign direct investment (FDI), including the knowledge capital model (see, for instance, Markusen, 2002). Firm-level controls, such as productivity, are suggested by the more recent heterogeneous firm models of FDI (Helpman et al., 2004).

By comparing the average export and import propensities of “treated” firms with those of firms in the control group, we are able to isolate the effect of foreign ownership over and beyond the effect stemming from firm productivity and other characteristics that are already well known to be highly correlated with export and import activities of firms.⁴ Our matching procedure helps us to alleviate two concerns that arise when comparing the trade performance of foreign-owned and domestically owned firms: First, in theories of vertical FDI foreign affiliates are set up for the purpose of supplying intermediate goods to the parent company (Markusen, 2002). Finding (in an unmatched sample) that foreign-owned firms are more likely to trade would then be a trivial result and not tell us much about the barriers to trade faced by developing country firms. Second, the foreign ownership of firms is not random. There is considerable evidence that foreign investors tend to acquire the more productive local firms (Blonigen et al., 2014). Finding that foreign-owned firms have a greater likelihood to engage in trade

⁴See, for instance, Bernard and Jensen (2004) on the firm-specific determinants of trade. The large literature on firm heterogeneity and selection into exporting and importing is surveyed by Greenaway and Kneller (2007) and Wagner (2012).

would then be confounded with the effect that more productive firms tend to trade more.⁵

The matching procedure significantly reduces the effects of foreign ownership in our sample. Still we find a statistically significant and economically large effect of foreign ownership on the propensity of firms to engage in international trade. In our baseline model, foreign ownership increases the propensity to export by 17.6 percentage points and the propensity to import by 13.4 percentage points. Consistent with our theoretical model, we find significant differences between the effects of foreign ownership on direct versus indirect trade. While foreign ownership is associated with considerably higher export and import propensities, the effect on the propensity to export or import indirectly is zero, respectively negative. This supports our interpretation of foreign ownership as helping with the intermediation of foreign trade. The effects of foreign ownership turn out to be especially big for firms in countries with low per-capita incomes and low institutional development, suggesting that weak institutions are big obstacles to trade.

The effect of foreign ownership on firm performance has received considerable attention in the literature. But most studies have been concerned with direct effects on firm productivity or indirect effects, i.e., spillovers, on locally owned firms (see Görg and Greenaway (2004) for a survey, and especially Girma et al. (2015) for a recent, state-of-the-art contribution and a discussion of this strand of the literature). Only few papers have looked at the effect of foreign ownership on the trade performance of firms and these have tended to focus on developed countries (see, for instance, Raff and Wagner (2014) on the effect of foreign ownership on the extensive margins of exports of German manufacturing firms). An important exception is Wang and Wang (2015) who study the effect of foreign ownership on the export share and other performance measures of Chinese firms. We can provide insights along dimensions that are complementary to Wang and Wang (2015). In particular, we are able to examine not just exporting but also importing as well as the mode of trade (direct versus indirect trade). Moreover, given that our dataset covers a wide range of countries, we can compare the trade performance of firms across countries with different levels of per-capita income or institutional development. Another interesting exception is a paper by Manova and Zhang (2009) on exports and imports by Chinese firms. That paper shows that foreign-owned firms trade more on average than local privately owned firms and that their trading relationships tend to be more stable. However, like Wang and Wang (2015), it focuses on firms in only one country and does not attempt to measure the effect of foreign ownership on

⁵Using French micro data, Blonigen et al. (2014) find that foreign investors also tend to target firms with a large existing export network. This is obviously something that we cannot control for in our sample. However, we would expect this to be less of a concern in our sample, since firms in developing countries are less likely to have such networks.

the propensity to engage in trade.

The Wang and Wang paper is also noteworthy for the way it identifies causal effects of foreign ownership, namely by comparing changes in the pre- and post-acquisition performance of foreign-acquired firms using domestically acquired firms as the control group. Since we have only cross-section data, we are not able to use this identification strategy. However, since our empirical results are largely consistent with our theoretical predictions, it seems reasonable to interpret the conditional correlations we find as representing causal relationships.

The rest of the paper is organized as follows. The next Section 4.2 contains the theoretical framework. In Section 4.3, we describe the data and present summary statistics. In Section 4.4, we discuss the empirical methodology, present results for our baseline model, and explore several alternative empirical specifications to check the robustness of our results. In Section 4.5, we compare the effects of foreign ownership across countries exhibiting different levels of income or institutional development, and across industries. Conclusions follow in Section 4.6.

4.2 Theoretical Framework

To set the stage for our empirical analysis consider a simple theoretical framework with heterogeneous firms, based on Chaney (2016) and Raff and Wagner (2014). The model allows us to identify how foreign ownership interacts with the more standard firm-level determinants of foreign-market participation, in this case the firm's productivity. We focus on foreign market access for exports, noting that models of firm heterogeneity can be easily adapted to study firms that import intermediates or engage in both exporting and importing (as in Kasahara and Lapham, 2013).

Consider two symmetric countries, home and foreign. Each country has two industries that use labor as the only input. One industry produces a homogeneous, freely tradable good with a constant unit labor requirement of 1. This is the numeraire good and, since its price is set to 1, we also obtain a wage rate of 1. The other industry produces a continuum of differentiated goods under increasing returns to scale and monopolistic competition.

4.2.1 Households

Home and foreign each have L consumers/workers, each endowed with one unit of labor. Individual preferences are given by the utility function

$$U = q_0 + \rho \ln Q_c, \quad \rho < 1, \tag{4.1}$$

where q_0 denotes the consumption of the numeraire, and Q_c is the aggregate individual consumption of differentiated goods. Letting $q_c(i)$ denote the quantity consumed of variety i , we assume that Q_c takes the following CES form:

$$Q_c = \left(\int_{i \in \Delta} q_c(i)^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}}, \quad (4.2)$$

where $\sigma > 1$ is the constant elasticity of substitution between varieties and Δ is the set of varieties.

Maximizing utility subject to the consumer's budget constraint and aggregating individual demands over the L consumers yields the following total demand for variety i :

$$q(i) = \frac{\rho L}{P^{1-\sigma}} p(i)^{-\sigma}, \quad (4.3)$$

where $p(i)$ is the consumer price of variety i , and

$$P = \left(\int_{i \in \Delta} p(i)^{1-\sigma} di \right)^{\frac{1}{1-\sigma}} \quad (4.4)$$

is the CES price index.

4.2.2 Firms

Firms in each country have access to the same technology. In the differentiated good industry each firm draws a random unit labor productivity $z \geq 0$. When entering the domestic market a firm incurs a fixed cost F_d . To enter the export market a firm has to choose between two strategies: Strategy x is to export directly, strategy w is to export indirectly with the help of an intermediary, e.g., a wholesaler. Strategy x involves a fixed cost of exporting F_x . Going through an intermediary requires a smaller fixed cost, $F_w < F_x$, because the intermediary is able to spread market access costs across a number of exporters whose goods it distributes. The trade-off is that the intermediary has to be paid in kind for each unit that it ships abroad. This cost of intermediation is denoted by $\omega > 1$. Both exporting strategies also involve an iceberg transport cost $\tau \geq 1$. We may hence summarize the cost of producing quantities q_d for the domestic market and q_w or q_x for sale in the foreign market via indirect, respectively direct trade as follows:

$$C_d(q_d) = \frac{q_d}{z} + F_d, \quad (4.5)$$

$$C_w(q_w) = \frac{\omega\tau q_w}{z} + F_w, \quad (4.6)$$

$$C_x(q_x) = \frac{\tau q_x}{z} + F_x. \quad (4.7)$$

Profit maximization in the case of CES demand functions requires a firm with labor productivity z to set a price at a constant mark-up over its marginal cost, c , so that $p(c) = \sigma c / (\sigma - 1)$. The marginal cost c of supplying output is equal to $1/z$ in the domestic market, $\omega\tau/z$ and τ/z , respectively, in the foreign market. The corresponding profits that such a firm can earn in the domestic market and in the export market using indirect, respectively direct exports are then given by:

$$\pi_d(z) = \frac{\rho L}{\sigma} \left(\frac{\sigma}{(\sigma - 1)zP} \right)^{1-\sigma} - F_d, \quad (4.8)$$

$$\pi_w(z) = \frac{\rho L}{\sigma} \left(\frac{\sigma\omega\tau}{(\sigma - 1)zP} \right)^{1-\sigma} - F_w, \quad (4.9)$$

$$\pi_x(z) = \frac{\rho L}{\sigma} \left(\frac{\sigma\tau}{(\sigma - 1)zP} \right)^{1-\sigma} - F_x. \quad (4.10)$$

4.2.3 Foreign Ownership

A role for foreign ownership arises when a firm cannot leverage potential export proceeds to finance the fixed cost of direct or indirect exporting. In other words, we assume that a firm has to finance the fixed cost of direct or indirect exports from the profit it earns in the domestic market. Less productive firms with small domestic profits may thus not be able to afford the fixed cost of exporting, even if, ex post, export operating profits were greater than the fixed cost. Foreign ownership may help such firms to afford the fixed exporting costs.

A simple and very useful way to formally model the effect of foreign ownership is to assume that it allows a firm to draw a random endowment of an ability, A , that it can combine with the profit it earns in the domestic market to bear the fixed cost of direct or indirect exporting. We may think of A as a financial capacity, or as contacts and know-how provided by foreign owners that reduce the required investment in export market entry. We let A and z be drawn from the joint cumulative distribution $G(A, z)$, and let the marginal distribution of z be given by $G_z(z) \equiv \lim_{A \rightarrow \infty} G(A, z)$.⁶

⁶In his model, Chaney (2016) interprets A as a liquidity shock and examines how draws of z and A affect the propensity of a firm to export. Our model extends Chaney's by allowing firms to choose between direct and indirect trade.

Thus a firm can only export directly, respectively indirectly, if

$$\pi_d(z) + A \geq F_i \quad \text{for } i = w, x. \quad (4.11)$$

Since $\pi_d(z)$ is strictly increasing in z , only a very productive firm may be able to pay F_i without a large endowment of A , whereas a firm with a very low labor productivity may not be able to export indirectly even if A is big.

4.2.4 Equilibrium

To simplify the characterization of equilibrium we assume that import prices have a negligible effect on the domestic price index. That is, we approximate the price index in (4.4) by:

$$P \approx \left(\int_{z \in \Delta} p_d(z)^{1-\sigma} dG_z(z) \right)^{\frac{1}{1-\sigma}}. \quad (4.12)$$

We can now derive the equilibrium in three steps.

The first step is to use Equations (4.8) - (4.10) to examine the potential profits a firm with productivity draw z may earn domestically and from direct or indirect exporting, ignoring for the moment the financing constraint (4.11). For such a firm we can use Equations (4.8) and (4.9) to implicitly define two cut-off levels of labor productivity, \bar{z}_d and \bar{z}_w , at which it would earn exactly zero profit in the domestic market and from indirect exporting, respectively:

$$\pi_i(\bar{z}_i) = 0 \quad \text{for } i = d, w. \quad (4.13)$$

Next, we can compare (4.9) and (4.10) to derive the level of labor productivity, \bar{z}_x , at which the firm would be indifferent between exporting indirectly and directly:

$$\pi_w(\bar{z}_x) = \pi_x(\bar{z}_x). \quad (4.14)$$

Assuming, reasonably, that the trade and intermediation costs are such that $\bar{z}_d < \bar{z}_w < \bar{z}_x$, the firm may fall into one of four categories.⁷ If it is very efficient, i.e., $z > \bar{z}_x$, then the firm can earn a positive profit both on the domestic market and on the foreign market; its profit from direct exporting exceeds the profit from indirect exporting. If z is in the range $\bar{z}_w < z \leq \bar{z}_x$, then the firm can earn a positive profit at home and abroad, but in the latter case only by exporting indirectly. If $\bar{z}_d < z \leq \bar{z}_w$, then it can only

⁷Note that a sufficient condition for $\bar{z}_d < \bar{z}_w$ is simply $F_d \leq F_w$. For $\bar{z}_w < \bar{z}_x$ we require F_x to be sufficiently greater than F_w , specifically $F_x > F_w(1 + w^{\sigma-1}(1 - w^{1-\sigma}))$.

earn a positive profit on the domestic market; it is not productive enough to generate positive export profits. Finally, if $z < \bar{z}_d$, then the firm cannot even make a positive profit on the domestic market.

Using (4.12) in (4.13), we can derive implicit expressions for these cutoffs. From $\pi_d(\bar{z}_d) = 0$ we obtain

$$\bar{z}_d = \left(\frac{\sigma F_d}{\rho L} \int_{z \geq \bar{z}_d} z^{\sigma-1} dG_z(z) \right)^{\frac{1}{\sigma-1}}. \quad (4.15)$$

For what follows it turns out to be convenient to define a function $h(\cdot)$ with $h' > 0$ such that

$$\bar{z}_d = h(F_d). \quad (4.16)$$

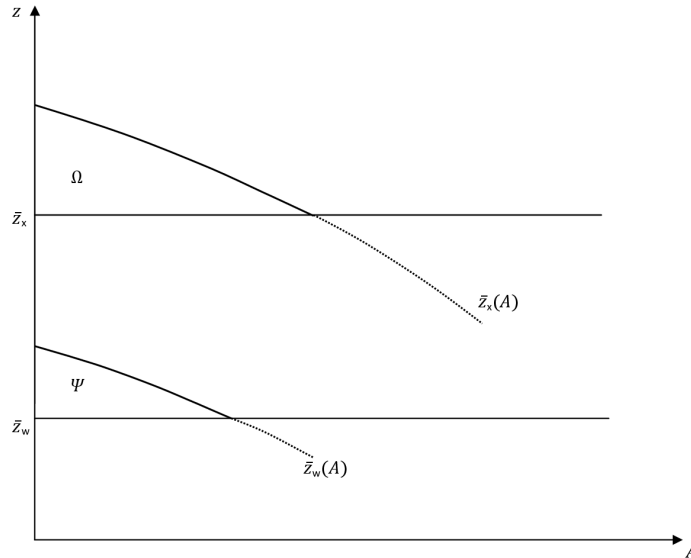
Likewise for the other two cutoffs we have

$$\bar{z}_w = \omega \tau \left(\frac{F_w}{F_d} \right)^{\frac{1}{\sigma-1}} h(F_d), \quad (4.17)$$

$$\bar{z}_x = \tau \left(\frac{F_x - F_w}{(1 - w^{1-\sigma}) F_d} \right)^{\frac{1}{\sigma-1}} h(F_d). \quad (4.18)$$

Figure 4.1 shows cutoffs \bar{z}_w and \bar{z}_x as horizontal lines, as they are independent of A .

Figure 4.1: Equilibrium Export Modes



The second step is to use Equation (4.11) to determine whether a firm with productivity z can afford the fixed costs of exporting directly or indirectly given its domestic

profit and its draw of A . Specifically, we implicitly define $\bar{z}_w(A)$ and $\bar{z}_x(A)$ such that a firm below the respective cut-off cannot afford to export indirectly, respectively directly:

$$\pi_d(\bar{z}_i(A)) + A = F_i \quad \text{for } i = w, x. \quad (4.19)$$

Using (4.19) we obtain

$$\bar{z}_w(A) = \left(\frac{F_d + F_w - A}{F_d} \right)^{\frac{1}{\sigma-1}} h(F_d), \quad (4.20)$$

$$\bar{z}_x(A) = \left(\frac{F_d + F_x - A}{F_d} \right)^{\frac{1}{\sigma-1}} h(F_d). \quad (4.21)$$

Notice that $\bar{z}_w(A)$ and $\bar{z}_x(A)$ are both decreasing in A with $\bar{z}_w(A) < \bar{z}_x(A)$. These two curves are also shown in Figure 4.1.

The third step is to combine the cut-off lines from step 1 that tell us whether a firm can potentially earn positive profits from exporting indirectly or even greater profits from exporting directly with the cut-off curves from step 2 that tell us how much A a firm with productivity z needs at a minimum in order to be able to afford the fixed cost of direct or indirect exporting. First consider the two curves $\bar{z}_x(A)$ and \bar{z}_x , where we have assumed that $(F_d + F_x) > (F_x - F_w)\tau^{\sigma-1}(1 - w^{1-\sigma})^{-1}$ so that $\bar{z}_x(0) > \bar{z}_x$ and the two curves intersect at a positive level of A . Firms with a $z \geq \bar{z}_x$ could earn positive profits from direct exporting and would prefer direct to indirect exporting. But if their A is so small that they fall into set Ω in Figure 4.1, they cannot afford to pay the fixed cost of direct exporting and thus have to resort to indirect exporting. For these firms having more A (to the right of $\bar{z}_x(A)$) would enable them to switch from indirect to direct exporting. Hence, the more A they have, the more likely they are to export directly and the less likely they are to export indirectly.

Next, consider the two curves $\bar{z}_w(A)$ and \bar{z}_w . In Figure 4.1 they are drawn assuming that $(F_d + F_w) > F_w(\omega\tau)^{\sigma-1}$ so that $\bar{z}_w(0) > \bar{z}_w$ and the intersection is again at a positive level of A . Firms with a productivity between \bar{z}_w and \bar{z}_x are productive enough to potentially earn positive profits from indirect exporting, although not from direct exporting. Those in the set Ψ have insufficient A to afford the fixed cost of indirect exporting. Hence, for firms in the productivity range $\bar{z}_w < z \leq \bar{z}_x$ having more A (to the right of $\bar{z}_w(A)$) increases the probability of exporting indirectly.

4.2.5 Implications

Finally, consider what the model's results imply about the effect of foreign ownership on the export propensity of firms drawn from a given productivity distribution. First, consider the effect on the propensity to export directly. For firms with productivities below \bar{z}_x or above $\bar{z}_x(0)$ foreign ownership does not affect the direct exporting propensity. In the former case, firms cannot earn positive profits from direct exporting, no matter what their ownership structure is; in the latter case, firms are so productive that they can afford the fixed cost of direct exporting even without foreign ownership. For firms with productivities between \bar{z}_x and $\bar{z}_x(0)$ foreign ownership raises the propensity to export directly. Hence we conclude that foreign ownership on average raises the propensity that a firm exports directly.

Second, consider the propensity to export indirectly. Here we observe that for firms with productivities in the interval \bar{z}_w to $\bar{z}_w(0)$ foreign ownership unambiguously raises their likelihood of exporting indirectly. This is because these firms could earn positive profits from indirect exports, but cannot afford the respective fixed cost without foreign ownership. For firms with productivities between \bar{z}_x and $\bar{z}_x(0)$ being foreign owned reduces the likelihood of exporting indirectly, as firms that previously exported indirectly switch to direct exporting if they draw a large enough A . Which effect dominates and hence whether the average effect of foreign ownership on the propensity to export indirectly is positive or negative depends on the distribution of productivities in the sample. If, as in our sample, the more productive (and therefore larger) firms are overrepresented, we would expect to find perhaps even a negative effect of foreign ownership on the propensity to export indirectly.

Third, regarding the overall propensity to export (either directly or indirectly) we observe that foreign ownership on average increases this propensity. This is because some firms that did not export will switch to indirect exporting when they are foreign-owned, and the firms that stop exporting indirectly when they are foreign owned do so only because they switch to direct exporting.

4.3 Data and Summary Statistics

Our empirical analysis is based on firm-level data collected by the World Bank as part of the Enterprise Surveys project (more information about the surveys is available at <http://www.enterprisesurveys.org>). The data cover the period of 2002 to 2006 and provide a representative sample of a country's private sector firms. The firms are not followed up in later years, so the data do not constitute a panel. We restrict the sample to those countries for which there are enough observations with sufficient information across all variables of interest after cleaning the data for missing values and obvious

errors. Our final sample contains 14,585 firms from 30 countries and 14 industries.⁸ Ranking the countries according to income, we distinguish between low-income countries (Bangladesh, Benin, India, Kyrgyzstan, Moldova, Uzbekistan, and Vietnam), lower-middle-income countries (Armenia, Ecuador, Egypt, El Salvador, Guatemala, Guyana, Honduras, Kazakhstan, Morocco, Nicaragua, Philippines, Romania, Serbia, Sri Lanka, and Syria) and upper-middle-income countries (Brazil, Chile, Costa Rica, Hungary, Poland, Russia, South Africa, and Turkey).⁹ The data cover light industries (beverages, food, garments, leather and textiles) and heavy industries (auto and auto components, chemicals and pharmaceuticals, electronics, metals and machinery, non-metallic and plastic materials, other manufacturing, other transport equipment, paper, wood and furniture).¹⁰

The survey records information on a number of firm characteristics, such as the firm’s location, industry, ownership structure, employment, etc. The survey also records detailed information on the distribution of sales between domestic and foreign markets, where foreign sales are broken down into direct and indirect exports (exports through a distributor), and on the domestic and foreign sourcing of intermediate goods, where foreign sourcing is divided into direct and indirect imports.

Table 4.1 shows the export structure of the data. We group the firms in each industry and country by productivity terciles (“low”, “medium”, and “high”). On average 40.6% of the firms in the sample are exporters, ranging from 48.9% among the group of high-productivity firms to 32.1% among the low-productivity firms. Of those firms that export about 73.5% only export directly, 15.5% export only indirectly, and 11% are classified as mixed exporters that export both directly and indirectly. The share of direct exporters ranges from 77.6% among the most productive firms to 67% for the least productive firms. The share of indirect exporters is highest for firms in the low-productivity range (21.2%).¹¹

We also observe variation in the selection into export modes across low-, lower-middle-, and upper-middle-income countries (not reported in the table). The share

⁸To be precise, the data are provided at the establishment (plant) level. We use “firm”, “plant” and “establishment” interchangeably.

⁹We follow the World Bank Atlas Method to determine the income group of a country. We take each country’s per capita GNI over the five-year sample period and classify the countries according to the average World Bank Atlas intervals to account for country classification changes that occur within that period.

¹⁰We set the minimum requirement for the number of firms in an industry in a country to 60 to guarantee a sufficiently large number of observations. Results are essentially unaffected if we increase the minimum amount. Applying the restriction, industries contain 182 firms on average.

¹¹The relatively high share of exporting firms in the sample is probably due to the fact that the Enterprise Surveys oversample large firms (100 and more employees). Large firms are generally more likely to trade internationally, even if they are not foreign owned. This suggests that our estimates of the effect of foreign ownership on the propensity to trade should be regarded as lower bounds of the true effect.

Table 4.1: Export Structure by Productivity Level

Productivity	#Firms	#Exporters	Share Exporters	Mode of Exp. cond. on being Exporter		
				Only Directly	Only Indirectly	Mixed
low	4,916	1,578	32.1%	67.0%	21.2%	11.8%
medium	4,814	1,968	40.9%	73.7%	14.9%	11.3%
high	4,855	2,374	48.9%	77.6%	12.1%	10.2%
Total	14,585	5,920	40.6%	73.5%	15.5%	11.0%

Table 4.2: Import Structure by Productivity Level

Productivity	#Firms	#Importers	Share Importers	Mode of Imp. cond. on being Importer		
				Only Directly	Only Indirectly	Mixed
low	4,916	1,868	38.0%	45.2%	42.6%	12.2%
medium	4,814	2,278	47.3%	54.5%	32.5%	12.9%
high	4,855	2,753	56.7%	61.8%	24.4%	13.8%
Total	14,585	6,899	47.3%	54.9%	32.0%	13.1%

of exporters is higher for upper-middle-income countries (45.9%) than for low-income countries (34.2%), with lower-middle-income countries in between (41.1%). The share of direct exporters is highest among low-income country exporters (77%). The share of indirect exporters is higher for lower-middle-income countries (20.5%) than for low-income countries (15.9%) and upper-middle-income countries (10.7%). 27.7% of the firms engage in exporting and importing simultaneously, ranging from 20% in lower-middle-income countries to 31.4% in upper-middle-income countries. On average, direct exporters export a slightly higher share of their production (56.7%) than indirect exporters (53.3%).

Table 4.2 shows the import structure by productivity tercile. More firms in the sample (47.3%) engage in importing than in exporting. The share of direct importers (54.9%) is lower than the share of direct exporters (73.5%). Instead, the use of intermediaries is of greater importance for importers than for exporters. 32% of importers import only indirectly, and 13.1% are mixed importers. The share of importers is highest among the most productive firms (56.7%) and lowest for the least productive firms (38%). Likewise the share of direct importers and mixed importers is highest among high-productivity firms, whereas the share of indirect importers is largest among low-productivity firms. Additional evidence (not reported in the table) reveals that the share of importers is lowest in the low-income countries (36.5%) and higher for lower-middle-income countries (53.2%) than for upper-middle-income countries (41.1%). The data show a much larger share of direct importers for low-income and lower-middle-income countries than for upper-middle-income countries. Direct importers on average import 17.2% and indirect importers on average import 8.3% of their intermediates.

For our study, we follow the IMF convention and define a firm as foreign owned if it reports a share of ownership by foreigners of at least 10%.¹² Based on this definition, about 9% of plants in the sample are foreign owned. The share of foreign owned firms increases with productivity. About 5.6% of the lowest productivity firms and about 13.1% of the highest productivity firms are foreign owned. The share of foreign owned firms is highest in lower-middle-income countries (12.1%) and lowest in low-income countries (5.9%).

4.4 Empirical Methodology and Results

In this section we present our empirical analysis of the role of foreign ownership. As suggested by our theoretical model, in order to isolate the effect of foreign ownership as much as possible, it is essential to control for firm characteristics that are likely to

¹²In our estimation, we also tried thresholds of 20%, 30%, 40% and 50%. Results are largely unaffected by the choice of threshold.

affect a firm’s propensity to trade whether or not it is foreign owned. To reduce the dimensionality problem when considering a large number of observable firm characteristics, these characteristics are distilled into a single scalar (propensity score) reflecting the probability of a firm to be foreign owned. In our baseline model, we apply standard nearest neighbor propensity score matching. The results of the baseline model are presented in the next subsection. We then explain in more detail why we consider this choice of matching procedure to be reasonable and report the results of alternative statistical procedures (propensity score reweighting as well as propensity score matching with kernel and caliper specifications).

4.4.1 Baseline Model

In our basic setup we pair each foreign-owned firm with three otherwise very similar domestic firms, where similarity is based on a number of background characteristics. In addition to labor productivity (sales per worker), we include as covariates the number of employees, R&D-intensity (R&D expenditure relative to sales), the employment structure (share of skilled production workers, share of professionals), whether the firm offers formal training for its employees, the manager’s education, and whether the firm has problems to access external sources of finance.¹³ Specifically, we use propensity scores to match each foreign owned firm to three domestic firms within the same industry and country that have a similar predicted probability of being foreign owned based on the covariates. We opt for this 3-to-1 matching due to this estimator’s lower variability at the cost of potentially greater bias in comparison to 1-to-1 matching, since our balancing tests (details are reported below) indicate that bias is not a concern in our sample.

As Table 4.3 indicates, foreign owned and domestic firms differ widely in their propensity to engage in international trade, especially in direct trade. The first three columns show the propensities of foreign owned firms and domestic firms to engage in various modes of trade for an unmatched sample and the difference between them. The last three columns show the same information after matching every foreign owned firm with the three most similar domestic firms. In the unmatched sample, the difference can be as large as 40.9 percentage points for firms engaging in both im- and exporting. This is because in the entire pool of domestic firms the average propensity to engage in trade is generally much lower than for foreign owned firms. It is only after we focus on the subgroup of domestically owned firms that are very similar to the foreign owned ones that we see a higher propensity to trade. As a consequence a lot of the difference in

¹³We also tried a large number of other covariates as robustness check. These included lagged firm performance (sales per worker and employment 2 and 3 years ago), productivity relative to the industry average, whether the firm received an ISO certification, introduced a new technology within the past three years, launched a new product within the last three years and uses the web and email. Results remained largely unaffected and thus proved to be robust to the choice and combination of covariates.

trade propensities disappears when we match firms. But the outcome of the matching procedure reported in the last column of the table shows that an economically sizeable and statistically significant difference in trade propensities still exists. Foreign owned firms are 17.6 percentage points more likely to export, 13.4 percentage points more likely to import, and 18.8 percentage points more likely to both import and export than their domestic counterparts.

Table 4.3: Effect of Foreign Ownership on Trade Propensities

Mode of Trade	Before Matching			After Matching		
	Foreign Owned	Domestic	Effect Size	Foreign Owned	Domestic	Effect Size
Exporting	0.7706	0.3939	0.3768*** (0.0154)	0.7706	0.5943	0.1759*** (0.0181)
Direct Exporting	0.6618	0.2831	0.3787*** (0.0145)	0.6618	0.4787	0.1826*** (0.0202)
Indirect Exporting	0.0490	0.0667	-0.0177** (0.0079)	0.0490	0.0590	-0.0100 (0.0119)
Mixed Exporting	0.0598	0.0441	0.0158** (0.0067)	0.0598	0.0566	0.0033 (0.0099)
Importing	0.8368	0.4751	0.3617*** (0.0156)	0.8368	0.7036	0.1338*** (0.0165)
Direct Importing	0.6482	0.2680	0.3802*** (0.0143)	0.6482	0.4756	0.1729*** (0.0247)
Indirect Importing	0.0734	0.1436	-0.0702*** (0.0109)	0.0734	0.1226	-0.0490*** (0.0140)
Mixed Importing	0.1151	0.0635	0.0517*** (0.0081)	0.1151	0.1054	0.0100 (0.0184)
Im- and Exporting	0.6791	0.2701	0.4090*** (0.0143)	0.6791	0.4914	0.1880*** (0.0196)

Notes:

Heteroskedasticity-consistent analytical standard errors (Abadie and Imbens, 2006) in parentheses;

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

N=9,408, Foreign Owned: 1,103

Consistent with the theoretical model, we observe different effects of foreign ownership on direct and indirect trade. The effect is especially big and positive for direct trade: Foreign owned firms are about 18.3 percentage points more likely to export directly and 17.3 percentage points more likely to import directly than domestic firms.¹⁴ Also in

¹⁴Our data do not permit us to distinguish between intra-firm and arm's-length trade. We thus do

line with the theoretical model, we find that foreign ownership leaves the propensity to export indirectly unaffected, but reduces the propensity to import indirectly. Recall that zero or negative effects were predicted by the theoretical model for samples in which, like in the current one, very productive firms are oversampled.¹⁵ We do not observe significant differences in the propensity to engage in mixed exporting or mixed importing.

Finally, we find considerable heterogeneity in treatment effects when we divide our sample of firms into productivity terciles. As reported in Table 4.4, the effects of foreign ownership differ in magnitude across the productivity terciles. The effects tend to be smaller the higher is productivity. We find the largest difference in trade propensities across productivity levels for direct importing. Foreign ownership raises the direct-importing propensity of low productivity firms by 27.2 percentage points, whereas foreign-owned high-productivity firms are only 13.7 percentage points more likely to import directly. For exporting and direct exporting as well as for importing and indirect importing the effect size differs by about 2 to 6 percentage points between low and high productivity firms.

4.4.2 Balancing Test and Alternative Specifications

The validity of our findings obviously depends on the quality of the matching. Table 4.5 summarizes the balancing test for our baseline model. The test reveals that the matching is successful and the covariates are well balanced. In particular, for all covariates the bias after matching is either below or very close to the 5% criterion. The t-tests indicate that after matching the difference between the treated and untreated groups does not differ from zero, while before matching the two groups differed significantly in all but two covariates. After matching the Pseudo- R^2 is close to zero and the LR- χ^2 -Test is insignificant indicating a high matching quality.¹⁶

not observe whether foreign ownership would also raise the propensity of firms to trade with independent parties. Our results are consistent with both the internalization of trade within foreign-owned firms, as this would correspond to the complete internalization of intermediation functions within the firm, and also a greater likelihood of arm's-length trade, for instance, due to foreign owners' better market knowledge abroad or greater financial capacity.

¹⁵Another potential explanation for smaller effects for indirect as compared to direct modes of trade could be the quality of reporting. Indirect exports and imports could be poorly reported (especially in survey data) as the firm may not be aware that some of the goods it sells domestically may end up being exported by the buyer, or may not know the primary origin of domestically purchased products.

It could also be that foreign-owned firms are better at observing and hence reporting indirect trade than locally owned firms. In this case, we might wrongly attribute indirect trade activity to foreign ownership. This potential bias, however, cannot account for either zero or negative and statistically significant effects of foreign ownership on indirect modes of trade.

¹⁶We additionally conduct a Rosenbaum sensitivity analysis. The results indicate that our estimated treatment effects are very robust with respect to a potential hidden bias. We still find significant effects (at a 10%-level) up to $\Gamma = 2.6$.

Table 4.4: Heterogeneous Treatment Effects

Mode of Trade	Low Productivity Firms	Medium Productivity Firms	High Productivity Firms
Exporting	0.1934*** (0.0420)	0.1803*** (0.0332)	0.1756*** (0.0289)
Direct Exporting	0.2284*** (0.0537)	0.1876*** (0.0460)	0.1643*** (0.0320)
Indirect Exporting	-0.0309 (0.0393)	-0.0124 (0.0219)	0.0113 (0.0107)
Mixed Exporting	-0.0041 (0.0253)	-0.0181 (0.0235)	0 (0.0165)
Importing	0.1564*** (0.0503)	0.1424*** (0.0410)	0.1065*** (0.0233)
Direct Importing	0.2716*** (0.0520)	0.2294*** (0.0455)	0.1371*** (0.0327)
Indirect Importing	-0.0823** (0.0401)	-0.0576* (0.0295)	-0.0426** (0.0200)
Mixed Importing	-0.0329 (0.0379)	-0.0294 (0.0284)	0.0120 (0.0242)
Im- and Exporting	0.1831*** (0.0496)	0.1751*** (0.0458)	0.1929*** (0.0313)
N	1,254	1,603	2,371

Notes:
Heteroskedasticity-consistent analytical standard errors (Abadie and Imbens, 2006) in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 4.5: Balancing Tests

Covariate	Unmatched Matched	Mean		%Reduct		T-Test	
		Treated	Control	%bias	bias	t	p> t
Log (Employment)	U	5.3173	4.2885	70.6		21.89	0.000
	M	5.3158	5.2307	5.8	91.7	1.36	0.174
Log (Sales per Worker)	U	6.2244	5.3423	28.4		8.94	0.000
	M	6.2255	6.2517	-0.8	97.0	-0.20	0.842
Job Training	U	0.5802	0.4008	36.5		11.41	0.000
	M	0.5795	0.6061	-5.4	85.1	-1.27	0.203
R&D	U	0.0531	0.7920	-1.9		-0.45	0.655
	M	0.0531	0.0294	0.1	96.8	1.19	0.234
Share Skilled Production	U	0.4722	0.4957	-3.0		-0.74	0.460
	M	0.4718	0.4728	-0.1	95.5	-0.07	0.948
Share Professionals	U	0.0078	0.0326	-11.9		-2.79	0.005
	M	0.0078	0.0088	-0.5	96.2	-0.64	0.520
Degree Manager	U	0.7425	0.5565	39.7		11.84	0.000
	M	0.7421	0.7520	-2.1	94.6	-0.54	0.590
Access to Capital	U	0.3681	0.5145	-29.8		-9.18	0.000
	M	0.3688	0.3875	-3.8	87.2	-0.91	0.364
Sample	Ps R2	LR chi2	p >chi2	MeanBias	MedBias	B	R
Unmatched	0.092	628.31	0.000	27.7	29.1	27.9*	0.04*
Matched	0.002	7.26	0.509	2.3	1.5	11.4	1.07

One of the disadvantages of our baseline propensity score method is the fact that it discards a lot of potentially useful information. Specifically we match 1,103 foreign owned firms with at most 3,309 ($3 * 1,103$) domestic firms, thereby ignoring at least 4,996 other domestic firms in the sample that could potentially be included in the analysis. Alternative methods, such as propensity score matching with kernel and caliper specification as well as propensity-score reweighting, make use of the full (or at least a larger proportion of the) untreated sample. Kernel matching uses weighted averages of all (or almost all) untreated observations and caliper matching uses the untreated observations that, in our specification, lie within a range of a quarter standard deviation of the propensity score. The propensity score reweighting estimator has been shown to generate an efficient estimate of the average treatment effects on the basis of reweighting by the inverse of the propensity score.¹⁷ Intuitively, this method adjusts for differences between foreign owned and domestic firms by assigning higher weights to domestic firms that are more similar to the foreign owned firms. Rather than completely dismissing domestic firms that are not very similar, this method simply assigns a lower weight to such firms.

Columns two to four of Table 4.6 contain the estimation results for caliper matching, kernel matching, and propensity score reweighting. Column one reproduces the results from the baseline nearest neighbor matching in Table 4.3 to allow for easier comparison. The main point to note about the new results is that they are remarkably similar to the effects found in our baseline nearest neighbor propensity score analysis.¹⁸ The results are thus highly robust with respect to the choice of the statistical procedure. The fact that nearest neighbor matching produces relatively conservative estimates of the effects of foreign ownership is another reason for selecting this specification as our baseline model.

4.5 Comparisons Across Country and Industry Groups

In this section, we compare the effects of foreign ownership across groups of countries and industries. In Table 4.7, we break down the analysis according to the income level of the country. Specifically, we investigate the differences between low-income, lower-middle-income, and upper-middle-income countries. Foreign owned firms are more likely to engage in international trade in all country groups, but the difference in trade propensities is biggest for low-income countries and smallest for lower-middle-income countries. This holds for exporting and importing and for direct exporting and importing, where

¹⁷See, for instance, Hirano et al. (2003) and Cerulli (2014) for further information.

¹⁸The balancing tests for the alternative specification mostly show well balanced covariates. For two covariates, however, t-tests indicate that after matching the difference between treated and untreated does still differ from zero.

Table 4.6: Alternative Statistical Procedures

Mode of Trade	Nearest Neighbor	Caliper	Kernel	PSR
Exporting	0.1759*** (0.0181)	0.1944*** (0.0281)	0.1647*** (0.0245)	0.2144*** (0.0148)
Direct Exporting	0.1826*** (0.0202)	0.1916*** (0.0287)	0.1688*** (0.0243)	0.2253*** (0.0183)
Indirect Exporting	-0.0100 (0.0119)	-0.0064 (0.0126)	-0.0063 (0.0127)	-0.0142* (0.0082)
Mixed Exporting	0.0033 (0.0099)	0.0091 (0.0139)	0.0022 (0.0114)	0.0033 (0.0075)
Importing	0.1338*** (0.0165)	0.1399*** (0.0261)	0.1309*** (0.0238)	0.1643*** (0.0143)
Direct Importing	0.1729*** (0.0247)	0.1817*** (0.0289)	0.1652*** (0.0242)	0.2113*** (0.0162)
Indirect Importing	-0.0490*** (0.0140)	-0.0544*** (0.0183)	-0.0464*** (0.0165)	-0.0562*** (0.0094)
Mixed Importing	0.0100 (0.0184)	0.0127 (0.0176)	0.0121 (0.0146)	0.0093 (0.0112)
Im- and Exporting	0.1880*** (0.0196)	0.2013*** (0.0286)	0.1806*** (0.0239)	0.2275*** (0.0188)

Notes:

Heteroskedasticity-consistent analytical standard errors (Abadie and Imbens, 2006) in parentheses; bootstrapped standard errors for PSR; *** p<0.01, ** p<0.05, * p<0.1
N=9,408, Foreign Owned: 1,103; for PSR: N=12,949

the magnitude of the effect differs by up to 14.3 percentage points between low- and lower-middle-income countries. Specifically foreign owned firms in low-income countries are 28.1 percentage points more likely to export directly and 25.5 percentage points more likely to import directly than domestic firms. For lower-middle income countries we estimate a treatment effect of only 13.8 percentage points for direct exporting and 11.9 percentage points for direct importing. In the case of indirect importing we find a highly significant negative effect of foreign ownership in low-income countries, but no or only weak evidence for an effect for lower-middle-income countries and high-middle-income countries, respectively.

Table 4.7: Effect of Foreign Ownership on Trade Propensities by Country Income

Mode of Trade	Low- Income Countries	Lower-Middle- Income Countries	Upper-Middle- Income Countries
Exporting	0.2496*** (0.0363)	0.1624*** (0.0266)	0.1791*** (0.0345)
Direct Exporting	0.2814*** (0.0389)	0.1380*** (0.0294)	0.1801*** (0.0384)
Indirect Exporting	0 (0.0181)	-0.0159 (0.0217)	-0.0083 (0.0112)
Mixed Exporting	-0.0317* (0.0173)	0.0177 (0.0134)	0.0072 (0.0219)
Importing	0.1688*** (0.0387)	0.0800*** (0.0207)	0.2008*** (0.0341)
Direct Importing	0.2554*** (0.0416)	0.1190*** (0.0406)	0.2070*** (0.0385)
Indirect Importing	-0.0808*** (0.0254)	-0.0379 (0.0222)	-0.0435* (0.0230)
Mixed Importing	-0.0058 (0.0188)	-0.0012 (0.0316)	0.0373 (0.0302)
Im- and Exporting	0.2063*** (0.0401)	0.1447*** (0.0280)	0.2453*** (0.0376)
N	3,285	3,761	2,577

Notes:
Heteroskedasticity-consistent analytical standard errors (Abadie and Imbens, 2006) in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Even though correlated with the country's income level, institutional quality may also influence how strongly foreign ownership increases the likelihood to engage in in-

ternational trade. It seems plausible that foreign ownership is particularly important in countries with poor institutional quality as it may help overcome institutional barriers to trade. To test this hypothesis, we use an institutional quality dataset compiled by Kuncic (2014), who combines more than 30 legal, political, and economic indicators to group countries in five different clusters depending on the institutional quality.¹⁹ Table 4.8 shows the effects of foreign ownership by institutional quality cluster with the lowest institutional quality countries being in cluster one (column one) and the (in our dataset) highest institutional quality countries being in cluster four (column four).²⁰ We see that effects of foreign ownership for all modes of trade except simultaneous im- and exporting are largest for the countries with the lowest institutional quality (cluster one). For these countries we observe an especially strong positive impact of foreign ownership on direct imports, and a significant negative impact on indirect imports, suggesting that foreign-owned firms tend to internalize the intermediation of imports. For countries with higher institutional quality the effect of foreign ownership is non-monotonic across different institutional quality clusters, as we obtain the second largest effects for countries with the highest institutional quality.

We also compare the effects across different industry groups. In Table 4.9, we distinguish between light industries (beverages, food, garments, leather and textiles) and heavy industries (auto and auto components, chemicals and pharmaceuticals, electronics, metals and machinery, non-metallic and plastic materials, other manufacturing, other transport equipment, paper, wood and furniture).²¹ Foreign ownership increases the likelihood to trade internationally for both groups. However, the effects are bigger for heavy than for light industries for all modes of trade. For instance, foreign owned firms in heavy industries are 20.4 (21.7) percentage points more likely to export (import) than domestic firms, whereas foreign owned firms in light industries are 15.0 (14.2) percentage points more likely to export (import) than their domestic counterparts. This may be an indication that fixed trade costs are substantially higher in heavy than in light industries.

¹⁹We additionally use a country-specific creditor rights index provided by Djankov et al. (2007); results are largely unaffected by the choice of the institutional quality index.

²⁰Our sample does not contain countries with the highest institutional quality as defined by Kuncic (2014) (cluster five).

²¹Unfortunately, we cannot break down our sample further into particular industries as the sample size would become too small for reasonable matching.

Table 4.8: Effect of Foreign Ownership by Country's Institutional Quality

Mode of Trade	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Exporting	0.1963*** (0.0383)	0.1660*** (0.0280)	0.1481** (0.0470)	0.1801*** (0.0407)
Direct Exporting	0.2420*** (0.0406)	0.1489*** (0.0314)	0.1704*** (0.0509)	0.1896*** (0.0464)
Indirect Exporting	-0.0051 (0.0198)	-0.0184 (0.0219)	0.0123 (0.0267)	-0.0095 (0.0150)
Mixed Exporting	-0.0406* (0.0195)	0.0355* (0.0147)	-0.0346 (0.0266)	0 (0.0253)
Importing	0.1760*** (0.0418)	0.1242*** (0.0231)	0.0123 (0.0390)	0.1596*** (0.0391)
Direct Importing	0.2910*** (0.0444)	0.1534*** (0.0428)	0.0593 (0.0552)	0.1580*** (0.0448)
Indirect Importing	-0.1151*** (0.0272)	-0.0545*** (0.0243)	-0.0222 (0.0299)	-0.0222 (0.0299)
Mixed Importing	0 (0.0216)	0.0253 (0.0329)	-0.0247 (0.0370)	0.0142 (0.0385)
Im- and Exporting	0.2267*** (0.0436)	0.1667*** (0.0306)	0.1235** (0.0486)	0.2541*** (0.0419)
N	2,446	4,719	746	1,409

Notes:

Heteroskedasticity-consistent analytical standard errors (Abadie and Imbens, 2006) in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 4.9: Heterogeneous Treatment Effects: Industry Groups

Mode of Trade	Light Industries	Heavy Industries
Exporting	0.1496*** (0.0244)	0.2042*** (0.0263)
Direct Exporting	0.1694*** (0.0293)	0.1978*** (0.0270)
Indirect Exporting	-0.0072 (0.0207)	-0.0153 (0.0110)
Mixed Exporting	-0.0126 (0.0128)	0.0217 (0.0148)
Importing	0.0916*** (0.0226)	0.1743*** (0.0236)
Direct Importing	0.1239*** (0.0309)	0.2165*** (0.0376)
Indirect Importing	-0.0227 (0.0202)	-0.0763*** (0.0191)
Mixed Importing	-0.0096 (0.0168)	0.0340 (0.0320)
Im- and Exporting	0.1418*** (0.0275)	0.2400*** (0.0276)
N	4,808	4,730

Notes:
Heteroskedasticity-consistent analytical standard errors (Abadie and Imbens, 2006)
in parentheses; *** p<0.01, ** p<0.05, * p<0.1

4.6 Conclusions

The paper uses micro data from the World Bank Enterprise Surveys to study to what extent foreign ownership helps manufacturing firms in developing countries to connect with overseas customers and suppliers. Defining foreign owned firms as firms with a foreign equity participation of at least 10%, we find that foreign ownership has a statistically significant and in many cases economically large effect on the export and import propensities of developing-country firms. In our baseline specification foreign owned firms are 17.6 percentage points more likely to engage in exporting and 13.4 percentage points more likely to engage in importing than domestic firms. This advantage of foreign owned firms over domestic firms in the propensity to trade is especially large when it comes to direct trade, namely 18.3 percentage points in case of direct exporting and 17.3 percentage points in case of direct importing. While foreign owned firms are significantly more likely to trade than matched domestic firms, they are around 4.9 percentage points less likely to import through intermediaries, and no more likely to export through intermediaries. This suggests that foreign owners help firms intermediate foreign trade, and, at least for firms that are not highly productive, act as a substitute for intermediation through independent distributors.

Closer inspection reveals that the impact of foreign ownership differs across country and industry groups. When we distinguish between countries in different income groups, we find that the impact tends to be highest for low-income countries, where foreign ownership boosts the propensity to export by 25 percentage points and the propensity to export directly by 28.1 percentage points. Both numbers are substantially higher than the averages across all countries reported in the previous paragraph. Similarly, foreign ownership also has a bigger effect on the propensity to import in these countries, with direct importing being 25.5 percentage points more likely for foreign owned than for domestic firms, compared with 18.3 percentage points for the sample as a whole. This indicates that foreign owners provide capabilities that are most relevant for countries with a low income level.

Two additional results suggest why this may be so. First, when we classify countries according to the quality of their institutions, a measure that is highly correlated with income level, we find that foreign ownership has the biggest effect in countries with the lowest degree of institutional quality. This suggests that foreign ownership may act as a substitute for institutional development. Second, when we look at differences in the impact of foreign ownership across industry groups, we observe a bigger impact for heavy than for light industries. If we assume that heavy industries are more capital- and technology-intensive, then this suggests that foreign owners provide relevant financial and technological capabilities. Not surprisingly, these capabilities seem especially

important for low-income countries.

Of course, our findings have to be interpreted with caution, especially when it comes to drawing conclusions for public policy. First, since we cannot distinguish between intra-firm and arm's-length trade, we do not know to what extent foreign ownership may help firms connect with customers or suppliers outside the firm. Second, we cannot make any statements about the effect on the intensive and extensive margins of trade, although we know from other research, e.g., Raff and Wagner (2014), that foreign ownership may have a significant positive impact on the extensive margin of trade. Third, we do not know to what extent our findings reflect only a change in the trade composition, i.e., a substitution of direct for indirect trade. This is especially relevant for imports, where foreign ownership leads to an increase in the propensity to import directly but a decrease in the propensity to import indirectly. However, a complete substitution in this case seems unlikely, because our results show that the magnitude of the foreign ownership effect is much bigger for the increase in the direct-import propensity than for the decrease in the indirect-import propensity. Fourth, although our matching procedure controls to some extent for potentially selective acquisition by foreign owners of productive domestic firms that are more likely to trade even pre-acquisition, we cannot directly compare the pre- and post-acquisition trade propensities of firms, because we only have cross-section data.

Finally, what do our results imply for the prospects of firms in developing country to connect with foreign markets following the recent financial crisis? According to UNCTAD (2011, Table I.3), cross-border mergers and acquisitions fell by over 75% measured in net purchases between 2007 and 2009 and have been very slow to recover. Given the potential importance of foreign ownership in facilitating trade, this drop in M&A activity does not bode well for these prospects.

4.7 Bibliography

- (1) Abadie, Alberto and Guido W. Imbens (2006), “Large Sample Properties of Matching Estimators for Average Treatment Effects”, *Econometrica* 74(1), 235-267.
- (2) Beck, Thorsten (2002), “Financial Development and International Trade. Is There a Link?”, *Journal of International Economics* 57(1), 107-31.
- (3) Bernard, Andrew B. and J. Bradford Jensen (2004), “Why Some Firms Export”, *Review of Economics and Statistics* 86(2), 561-569.
- (4) Blonigen, Bruce, Lionel Fontagné, Nicholas Sly and Farid Toubal (2014), “Cherries for Sale: The Incidence and Timing of Cross-Border M&A”, *Journal of International Economics* 94(2), 341-357.
- (5) Cerulli, Giovanni (2014), “Treatreg: A User-written Command for Estimating Average Treatment Effects by Reweighting on the Propensity Score”, *Stata Journal* 14(3), 541-561
- (6) Chaney, Thomas, (2016), “Liquidity Constrained Exporters”, *Journal of Economic Dynamics and Control* 72, 141-154.
- (7) Djankov, Simeon, Caralee McLiesh and Andrei Shleifer (2007), “Private Credit in 129 Countries”, *Journal of Financial Economics* 84(2), 299-329.
- (8) Feenstra, Robert C. and Gary G. Hamilton (2006), “Emergent Economies, Divergent Paths: Economic Organization and International Trade in South Korea and Taiwan”, Cambridge University Press, Cambridge.
- (9) Frankel, Jeffrey A. and David H. Romer (1999), “Does Trade Cause Growth?”, *American Economic Review* 89(3), 379-399.
- (10) Girma, Sourafel, Yundan Gong, Holger Görg and Sandra Lancheros (2015), “Estimating Direct and Indirect Effects of Foreign Direct Investment on Firm Productivity in the Presence of Interactions Between Firms”, *Journal of International Economics* 95(1), 157-169.
- (11) Görg, Holger and David Greenaway (2004), “Much Ado About Nothing? Do Domestic Firms Really Benefit from Foreign Direct Investment?”, *World Bank Research Observer* 19(2), 171-197.
- (12) Greenaway, David and Richard Kneller (2007), “Firm heterogeneity, exporting and foreign direct investment”, *Economic Journal* 117(51), F134-F161.

- (13) Helpman, Elhanan, Marc J. Melitz and Stephen R. Yeaple (2004), "Export versus FDI with Heterogeneous Firms," *American Economic Review* 94(1), 300-316.
- (14) Hirano, Keisuke, Guido W. Imbens and Geert Ridder (2003), "Efficient Estimation of Average Treatment Effects Using the Estimated Propensity Score", *Econometrica* 71(4), 1161-1189.
- (15) Kasahara, Hiroyuki and Beverly Lapham (2013), "Productivity and the Decision to Import and Export: Theory and Evidence", *Journal of International Economics* 89(2), 272-282.
- (16) Keesing, Donald B. (1983), "Linking Up to Distant Markets: South to North Exports of Manufactured Consumer Goods", *American Economic Review* 73(2), 338-342.
- (17) Kunic, Aljaz (2014), "Institutional Quality Dataset", *Journal of Institutional Economics* 10(1), 135-161.
- (18) Manova, Kalina and Zhiwei Zhang (2009), "China's Exporters and Importers: Firms, Products and Trade Partners", NBER Working Paper 15249.
- (19) Markusen, James R. (2002), "Multinational Firms and the Theory of International Trade", Cambridge MA: MIT Press.
- (20) Markusen, James R. and Natalia Trofimenko (2009), "Teaching Locals New Tricks: Foreign Experts as a Channel of Knowledge Transfers", *Journal of Development Economics*, 88(1), 120-131.
- (21) Raff, Horst and Joachim Wagner (2014), "Foreign Ownership and the Extensive Margins of Exports: Theory and Evidence for Manufacturing Enterprises in Germany", *The World Economy* 37(5), 579-591.
- (22) Roberts, Mark J. and James R. Tybout (1997), "The Decision to Export in Colombia: An Empirical Model of Entry with Sunk Cost", *American Economic Review* 87(4), 545-564.
- (23) United Nations Conference on Trade and Development (2011), "World Investment Report 2011", United Nations, New York.
- (24) Wagner, Joachim (2012), "International Trade and Firm Performance: A Survey of Empirical Studies since 2006", *Review of World Economics* 148(2), 235-267.
- (25) Wang, Jian and Xiao Wang (2015), "Benefits of Foreign Ownership: Evidence from Foreign Direct Investment in China", *Journal of International Economics* 97(2), 325-338.

- (26) Winters, Alan L., Neil McCulloch and Andrew McKay (2004), "Trade Liberalization and Poverty: The Evidence so far", *Journal of Economic Literature* 42(1), 72-115.
- (27) World Trade Organization (2001), "Doha Ministerial Declaration", Ministerial Conference, Fourth Session. Washington DC: World Trade Organization, www.wto.org/english/thewto_e/minist_e/min01_e/mindecl_e.pdf

Chapter 5

International Trade and the Occupational Mix in Manufacturing: Evidence from German Micro Data

Summary: We use the Establishment History Panel from 1975 to 2010 provided by the German Federal Employment Office to examine the impact of international trade on the occupational structure of the German manufacturing sector. To capture trade, we match the Establishment History Panel with UN Comtrade trade data. For this purpose, we develop a new matching approach that takes the input and output structure of the German manufacturing sector into account. We identify three different trade channels: intermediate imports, import competition, and exports. Using a fixed-effects Poisson regression model, we find diverse occupational effects from trade at the industry-level, while establishment-level estimations show only few significant effects.¹

¹We are grateful to Johannes Bröcker, Annkatrin Niebuhr and Horst Raff for their support and detailed comments.

5.1 Introduction

The impact of international trade on employment has been a widely discussed topic in the economic literature, political debates, and the popular press. Surprisingly enough, rather little empirical research has been conducted to shed light on how trade openness impacts the employment in different occupations, despite the fact that the employment structure in industrialized nations has undergone a substantial change during the past decades. In Germany, for instance, the share of employment in service occupations within manufacturing experienced a steep increase of about 29% from 1975 to 2010. During the same time period the inflation-adjusted trade volume increased approximately by factor five. While much has been written on structural change as an inter-sectoral process², we, by contrast, focus on intra-sectoral employment changes within the German manufacturing sector.

The purpose of the current paper therefore is to examine the role of international trade as one potential driving force behind the change of the occupational mix within establishments in the manufacturing sector in Germany. We identify three potential channels through which establishments are affected by trade and thus adapt their employment: first, the import of inputs and intermediate goods used in the production process (“intermediate imports”), second, the import of goods that compete with final goods of domestic establishments (“import competition”), third, the export of goods that are produced by domestic establishments (“exports”).

To our knowledge, this paper is among few papers that examine the effect of international trade on the employment of very disaggregated occupational groups and the only one that simultaneously considers three trade channels. In contrast to other studies that only distinguish between highly aggregated employment groups, e.g., high-skilled and low-skilled employees or production and non-production workers, we are able to investigate much more precisely which employees benefit or suffer from the increasing exposure to international trade. This is of great relevance for policy implications, e.g., in the field of labor market policies or educational policies, because our results allow for more targeted actions compared to studies that analyze more aggregated employment groups. In our empirical analysis, we use the Establishment History Panel (in German: “Betriebs-Historik-Panel” (BHP)), a very detailed micro dataset provided by the German Federal Employment Office covering the years from 1975 to 2010, a time span that exceeds that of all other studies in the field. The dataset allows us to have unique insight into the occupational mix of all German establishments in the manufacturing sector over a 36-year period and to observe changes in the employment composition in

²See for example Kuznets (1966), Jorgenson and Timmer (2011) and Alvares-Cuadrado and Long (2017).

detail. Beyond the estimation at the industry-level, we are able to estimate the impact of international trade at the establishment-level and control for establishment fixed-effects, which improves the estimation quality in comparison to various other studies that only use industry-level data.³

We match the BHP at the industry-level with trade data provided by the UN Comtrade database at the commodity-level, as the core dataset does not contain information on activities in international trade. We then apply a fixed-effects Poisson model for the estimations at both the industry- and the establishment-level. The former level of aggregation allows us to estimate our empirical model with data that are all on the same level of aggregation, whereas the latter specification is able to control for the substantial establishment heterogeneity.

The results at the industry-level indicate that intermediate imports and import competition decrease employment and exports increases employment. It is the employment in unskilled service occupations that mainly face job losses from an increase in imports of intermediates. Employees in lower skilled occupations, especially in services and administration, suffer most from an increase in competition with foreign firms, whereas the employment of these occupations rises the most from an increase in exports. Among the production occupations, the employment of technicians reacts the most to changes in trade. Our results at the establishment-level only show few significant trade effects on the occupational mix.

This paper is related to four strands of literature. First, there is a large body of literature that explores employment effects of changes in intermediate imports. This channel is commonly named “offshoring” or “trade in tasks”. According to Grossman and Rossi-Hansberg (2008), firms are able to unbundle the production process into a continuum of tasks. Decreasing costs of offshoring are associated with an increasing number of tasks that can be outsourced to low-wage countries. Offshorable tasks are generally considered to be routine tasks, whereas non-routine tasks remain in the domestic firm (Baldwin and Robert-Nicoud, 2007). As production tasks are more likely to be the ones that are of a routine nature and do not require physical proximity, outsourcing is supposed to decrease the employment of (low-skilled) production occupations. While these papers can give theoretical explanations for changes in the occupational mix, few empirical studies distinguish between different occupational groups (e.g., Hogrefe, 2013). Most papers only distinguish between aggregated employment groups, for example between routine and non-routine tasks (e.g., Becker et al., 2013) or between different skill-levels (e.g. Hijzen et al., 2005). Using disaggregated plant data for Germany, Becker et al. (2013) estimate that offshoring leads to a significant shift towards non-routine tasks and high-skilled workers, in particular, if offshoring to low-income countries is considered.

³See for example Feenstra and Hanson (1996).

Hijzen et al. (2005) and Hogrefe (2013) confirm these findings. However, these studies focus exclusively on employment effects of offshoring. In contrast, we analyze the employment effects of three trade channels on very disaggregated occupational groups.

Second, there is a growing literature on employment effects of import competition. Increasing import competition is supposed to reduce employment, especially in production occupations, since imported final goods substitute the goods of domestic suppliers. In contrast to most papers in the field⁴, we analyze the employment effects of rising import competition on a much more disaggregated level. An exception is the paper by Biscourp and Kramarz (2007), who regard the effect of all three trade channels on employment at the firm-level. Their focus, however, is the skill structure rather than the occupational mix of firms. The authors confirm job losses due to increasing imports of final goods. Furthermore, they observe that especially large firms mostly reduce the employment in (low-skilled) production occupations.

Third, there is a comparatively small literature on the role of exporting as a determinant of the occupational mix. Preexisting literature in this field⁵, however, mainly focuses on total employment effects or, at most, distinguishes between a limited number of groups of employees such as production and non-production or high-skilled and low-skilled.

Fourth, this paper contributes to the growing literature that discusses the link between international trade and firm organization. However, the emphasis of this literature is mainly on firm organization from a management perspective rather than on the organization formed by different occupational groups.⁶

To match the commodity classification of trade data and the industry classification of the BHP, we use the “Statistic concerning Materials and Commodities received by the Industries” (in German: Material- und Wareneingangserhebung im Verarbeitenden Gewerbe, hereafter called “Input Statistic”) and the “Survey of Production” (in German: Produktionserhebung im Bereich Verarbeitendes Gewerbe), both provided by the German Federal Statistical Office. The first allows us to allocate the imported inter-

⁴Among the papers are Autor et al. (2013), who analyze the regional employment effects of import competition from China in the United States. They conclude that regions competing with Chinese imports to a high degree have suffered from rising unemployment. This result is confirmed by Tomiura (2003) for Japan.

⁵Among the papers are Bernard and Jensen (1997), Maurin et al. (2002), and Biscourp and Kramarz (2007). Biscourp and Kramarz (2007) find that for French firms exports have a negative impact on the unskilled share in manufacturing employment, but a positive impact on the share of production jobs, because increasing exports require a rise in the production of domestic firms. Davidson et al. (2013) distinguish between different occupational groups. They find that exporters, especially multinational exporters, have an occupational distribution toward the more skilled.

⁶For instance, Caliendo and Rossi-Hansberg (2012) develop a model that shows an increase in management layers as a result of exporting. Marin et al. (2014) implement trade in tasks into a theory of the firm organization à la Marin and Verdier (2012). They show both theoretically and empirically that offshoring leads to a more decentralized management.

mediate goods according to the input structure of the German manufacturing sector to obtain a measure of “intermediate imports”. The latter allows us, on the one hand, to construct a measure of “import competition” by allocating imports according to the output structure of the German manufacturing sector. On the other hand, we construct a measure for “exports” by allocating export flows according to the output structure.

The rest of the paper is organized as follows. In the next two sections, we present the data (Section 5.2) and some stylized facts (Section 5.3) about changes in the employment in Germany. Section 5.4 discusses the matching approach, the estimation strategy, and the empirical results. The final Section 5.5 concludes and summarizes.

5.2 Data

We base our calculations on the Establishment History Panel provided by the Research Data Centre of the German Federal Employment Office.⁷ The Establishment History Panel is a detailed micro-level dataset that covers all establishments in Germany from 1975 to 2010 (for the 1975-1990 period, it includes only establishments in West Germany) with at least one employee subject to social insurance contributions before June 30th of the respective year.⁸ For our calculations, we are able to use a 50% random sample of the entire dataset. The BHP builds on the “Employee History” (in German: Beschäftigten-Historik (BeH)) of the IAB. It cumulates the individual data of the BeH to the establishment-level and assigns individual establishment numbers (“artificial establishment numbers”). Thus, it is possible to identify the establishments in subsequent years and create a panel dataset for the entire 1975-2010 period. Because the Establishment History Panel is based on the “Employee History”, it provides very detailed information on the general employment structure of each establishment, e.g., the total number of full-time employees, the composition of employment regarding employees’ educational and vocational qualifications and the occupational status according to the Blossfeld occupational groups (see Blossfeld (1987) and Section C.1 in the Appendix for more details). In addition, the dataset also contains information on general establishment characteristics, such as the three-digit classification of economic activities and a proxy for activities in R&D.⁹ For our analysis, we concentrate on the manufacturing sector. Since the BHP only provides information on establishments rather than

⁷This study uses the weakly anonymous Establishment History Panel (Years 1975 - 2010). Data access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and via remote data access (Project Number: fdz469).

⁸Since 1999, there are also all establishments with at least one part-time employee included in the panel.

⁹For further information concerning the BHP, see Gruhl et al. (2012) (German version) or Hethey-Maier and Seth (2010) (English version).

on firms, changes in the occupational mix of firms are not observable because we do not know if single establishments are part of a parent firm or not.

We match the BHP with a dataset that contains constructed time-consistent industry codes, because the classification of economic activities changes several times within the 1975-2010 period.¹⁰ Hence, we are able to consistently control for industry-specific effects at the three-digit level (according to the Industrial Classification of Economic Activities, 1993 Edition) in our regressions.

We additionally match the BHP with trade data, which we obtain from the UN Comtrade database. For the matching process, we use the Input Statistic and the Survey of Production provided by the German Federal Statistical office that gives us detailed information on the input and output structure of the German manufacturing sector. A more detailed description of the matching process used will be provided in Section 5.4.1. We only consider establishments with at least 20 employees.¹¹ Overall, our sample consists of 379,805 observations, which includes 69,069 different establishments. For every establishment, the dataset contains information on the number of employees in each Blossfeld occupational group (Blossfeld, 1987). The classification includes three main categories: production, service, and administration - each of which contains three to four sub-categories ordered by their skill-level.

5.3 Stylized Facts

Using the occupational information of the BHP, we can show that the increasing share of service employment, measured at the establishment-level, is much higher than indicated by standard measurements at the industry-level (Henze, 2014).

Figure 5.1 shows the change in the occupational mix in the German manufacturing sector between 1975 and 2010. The dashed line shows the increase in employment of full-time employees in service occupations in manufacturing establishments.¹² In the 36-year period, the employment in service occupations increased by 29%. For the German economy as a whole, it increased by 34% during the same period (solid line). In contrast, the employment in production occupations in the manufacturing sector decreased by 12%. These findings highlight the substantial change of the occupational mix in manufacturing, but give little evidence of the occupational changes behind the transition.

To shed light on this issue, Table 5.1 depicts the employment growth of each occupa-

¹⁰For a more detailed description concerning the construction of the dataset, see Eberle et al. (2011).

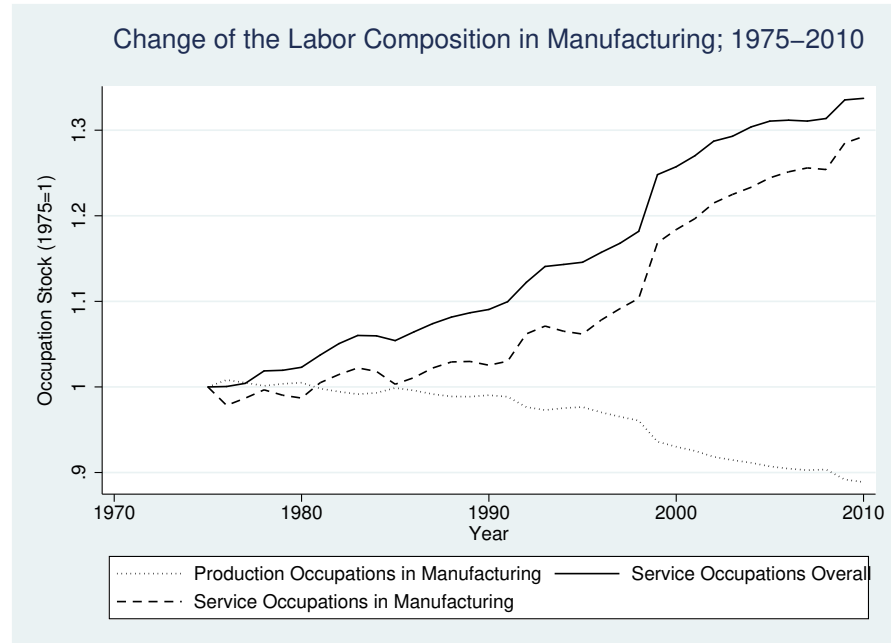
¹¹We restrict the establishment size as the Survey of Production, our basis for the derivation of German export flows, only captures establishments with at least 20 employees.

¹²Here, administrative occupations are considered to be related to services, too. Therefore, service occupations also include administrative occupations.

Table 5.1: Employment Growth of Occupational Groups in the Manufacturing Sector, 1975-2010

Occupational Group	Abs. Employment (1975)	Growth overall
Production		
Unskilled manual occupations	1,506,494	-33.66%
Skilled manual occupations	934,780	-14.60%
Technicians	269,634	+4.74%
Engineers	82,243	+105.81%
Services		
Unskilled services	306,833	-18.91%
Skilled services	22,146	-19.32%
Semiprofessions	10,684	+66.26%
Professions	7,765	+51.33%
Administration		
Unskilled commercial and administrative occupations	196,622	+6.31%
Skilled commercial and administrative occupations	412,995	+20.01%
Managers	70,592	+17.05%
Source: Establishment History Panel, authors' computation.		

Figure 5.1: Change in the Occupational Mix in Manufacturing



Notes: Source: Establishment History Panel, authors' computation.

tional group. Column two shows the absolute employment in 1975 and column three the overall change until 2010. It becomes obvious that the increase in the employment share of service occupations was largely driven by a decrease in the employment in production occupations. Within the 36 years of observation, more than half a million production jobs (about 20%) were lost - the biggest part can be attributed to a decrease in the employment in unskilled manual occupations. Overall, the number of non-production workers in manufacturing slightly increased. This was mostly driven by an increase in the employment in administrative occupations, whereas employment in service occupations overall showed a slight decrease. Since the employment in production occupations decreased to such a large extent, the share of employment in service and administrative occupations increased. Moreover, it is the employment in the most skilled occupations that grew, whereas employment in unskilled occupations declined. This observation holds for both production and service occupations. While the employment in the two least skilled production and service occupations decreased by about 34% and 19%, respectively, the two most skilled occupational groups experienced employment increases of about 106% and 51%, respectively. In administration, the employment in all categories showed an increase, while the employment in less skilled occupations experienced the lowest employment growth. Thus, the occupational structure in manufacturing also changed towards the more skilled.

5.4 Empirical Evidence

5.4.1 Matching of Commodity Trade Data

As there is no long-term micro dataset for Germany available that includes information on both employment structure and trade flows, we create our dataset by merging trade data from the UN Comtrade database with the BHP. This requires converting commodity trade data into industry trade data. However, instead of using correspondence tables to assign each trade commodity to the most similar industries, we allocate the trade flows according to the actual input and output structure of the German manufacturing sector. For that, we use two datasets provided by the German Federal Statistical Office: the Input Statistic (in German: Material- und Wareneingangserhebung im Verarbeitenden Gewerbe) to allocate the imports and generate intermediate imports, and the Survey of Production (in German: Produktionserhebung im Bereich Verarbeitendes Gewerbe) to allocate German exports and imports to generate data for exports and for import competition. See Section C.2 in the Appendix for a more detailed description of the data, the matching process of the commodity trade data, and all classifications.

The Input Statistic is published every four years starting in 1978. It provides information on all incoming materials and commodities in Germany at the two-digit or three-digit level for all three-digit manufacturing industries. With this information at hand, we derive the intermediate imports for the German manufacturing sector in the following way:

$$ImpInt_{it} = \sum_{c=1}^N \frac{x_{cit}}{x_{ct}} * \gamma_{ct} * Import_{ct}, \quad (5.1)$$

where intermediate imports $ImpInt_{it}$ is the calculated import flow into a specific industry i in year t . x_{cit} stand for the input of commodity c in this industry i in year t , x_{ct} is the total input of commodity c in year t over all industries, and $Import_{ct}$ is the import flow¹³ for each commodity in a given year. As the trade data do not distinguish between the usage of imports, e.g., manufacturing inputs or private and government consumption, we weigh the commodity-specific import with its share of manufacturing input, γ_{ct} , before we allocate the commodity imports to the industries.¹⁴ Accordingly, we avoid overestimating the importance of commodities mostly used by recipients other

¹³All trade flows obtained from the UN Comtrade database are inflation-adjusted.

¹⁴The commodity-specific import shares of manufacturing are obtained from the input-output tables provided by the German Federal Statistical Office. Since the input-output tables for Germany are only available for the 1995-2010 period, we have to assume that the industry-specific input shares from 1975-1995 are constant. A comparison of later years shows that the input shares are rather stable. Therefore, our assumption seems to be appropriate.

than manufacturing (e.g., consumer intensive goods such as textiles).¹⁵ By weighing the imports, we additionally make sure that to a great extent only intermediates rather than final goods are accounted for. We expect import penetration to increase on the input side, as, over time, better but above all cheaper inputs become available on the global market.

A comparison between the “traditional” allocation process with standard correspondence tables and our approach reveals that our approach shows a much more detailed import structure. For example, the Input Statistic in 2000 shows that goods of “Leather and Leather Manufactures” are used in 17 industries as an input factor. Using a single correspondence table instead, we would allocate leather imports to only four industries. (see Appendix Section C.3 for a complete comparison).

To obtain the “export” values, we allocate the commodity exports using the Survey of Production. The Survey of Production reports all commodities at the eight-digit level that are produced in each four-digit industry for the 1995-2010 period.¹⁶ Analogously to our approach for intermediate imports, we derive exports by:

$$Exp_{it} = \sum_{c=1}^N \frac{z_{cit}}{z_{ct}} * Export_{ct}, \quad (5.2)$$

where exports Exp_{it} is the calculated export of industry i in year t , z_{cit} is the output of commodity c in this industry i and year t , and z_{ct} stands for the total output of commodity c in year t . $Export_{ct}$ is the export flow for each commodity in a given year. Similar to the import flows, we are able to allocate the export commodities to industries on the basis of the actual production structure that the Survey of Production provides.¹⁷

To generate import competition, we again use the Survey of Production. This time, however, we allocate the imports according to the output structure such that the import competition is derived by:

$$ImpComp_{it} = \sum_{c=1}^N \frac{z_{cit}}{z_{ct}} * Import_{ct}. \quad (5.3)$$

¹⁵We believe that mostly recipients other than manufacturing use final good imports, whereas imports flowing into the manufacturing sector will mostly be intermediate goods. Accordingly, final goods are filtered out if we only use the share of imports flowing into the manufacturing sector. The only cases in which final goods are allocated to the manufacturing sector are if either the product is used as capital input (e.g., machinery) or if the establishment is partly reselling final products. Establishments that mostly or purely resell are part of the service sector.

¹⁶We have to assume a constant output structure from 1975 to 1994 that is equal to the structure of 1995, because the Survey of Production only starts in 1995.

¹⁷As before, the example of the “Leather and Leather Manufactures” shows that we allocate exports to 24 industries, compared to only four industries in case of a single correspondence table.

Here, we assume that establishments face import competition when products are being imported that match the domestic establishments' production at the nine-digit commodity-level.

In the following section, we introduce these measures of trade exposure to estimate the effects of an increasing openness to trade on the occupational mix of German manufacturing establishments.

5.4.2 Empirical Strategy

In order to explain the effects of international trade on the occupational mix, we use a fixed-effects Poisson model. We investigate how international trade affects the absolute number of employees of different occupational groups, such that our dependent variable only consists of integer values (count data) that follow a Poisson distribution. We estimate the employment effects of international trade both at the establishment-level and at the industry-level. To apply the fixed-effects Poisson model, we use the Generalized Method of Moments (GMM). One concern of our empirical analysis is to control for the substantial individual heterogeneity by including fixed-effects for establishments or industries (depending on the specification) in our estimations, i.e., introduce a dummy variable for each establishment or industry. We thus follow Blundell et al. (2002) to apply a GMM estimation approach of the Poisson model in a panel data context that uses a moment condition. Thus, we are able to account for the substantial individual heterogeneity without using dummy variables for each establishment or industry.

A "standard Poisson regression model" that is commonly used for count data can be written as:

$$E(y_{jt}|x_{jt}) = \exp(x'_{jt}\beta), \quad (5.4)$$

where y_{jt} is the dependent discrete count variable for establishment j at time t , x_{jt} the vector of explanatory variables and β the vector of estimated coefficients.¹⁸ This Poisson regression model can be rewritten as the following moment condition (under the assumption that all independent variables are strictly exogenous):

$$E\left[x_{jt} \left\{ y_{jt} - \exp(x'_{jt}\beta) \right\}\right] = 0. \quad (5.5)$$

An important issue in our estimations is the unobserved heterogeneity of industries and establishments. We use the moment condition according to Equation (5.5) for panel

¹⁸For regressions at the industry-level, the derivation of the moment condition is very similar to the one at the establishment-level. In case of industry-level estimations, we only substitute the index j for each establishment by the index i for each industry. Hence, we are able to account for the individual heterogeneity of each industry.

data and additionally include a term for individual heterogeneity (a fixed-effect), η_j . For count data models, this term is generally added multiplicatively. Then, we obtain

$$\mathbb{E}(y_{jt}|x_{jt}, \eta_j) = \exp(x'_{jt}\beta + \eta_j) = \mu_{jt}\nu_j, \quad (5.6)$$

where $\mu_{jt} = \exp(x'_{jt}\beta)$ and $\nu_j = \exp(\eta_j)$ is the permanent scaling factor for the individual mean. Hence, our regression model looks as follows:

$$y_{jt} = \mu_{jt}\nu_j + \epsilon_{jt}, \quad (5.7)$$

where ϵ_{jt} is the error term. If all x_{jt} are strictly exogenous¹⁹, we can finally rewrite our sample moment condition as:

$$\sum_{j=1}^N \sum_{t=1}^T x_{jt} \left(y_{jt} - \mu_{jt} \frac{\bar{y}_j}{\bar{\mu}_j} \right) = 0. \quad (5.8)$$

Here, \bar{y}_j and $\bar{\mu}_j$ are the means of y_j and μ_j for panel j , i.e., the respective establishment. This moment condition, where the fixed-effects are substituted by the ratio of within group means is now equivalent to a “standard Poisson regression model” with establishment fixed-effects. The “mean scaling” model can now be written as:

$$y_{jt} = \mu_{jt} \frac{\bar{y}_j}{\bar{\mu}_j} + \epsilon_{jt}^*. \quad (5.9)$$

Blundell et al. (2002) describe this estimator as the “within group mean scaling estimator”.

Finally, we are able to estimate our extensive micro dataset by using a GMM Poisson model with the moment condition according to Equation (5.8), which yields the same results as the “standard Poisson regression model” with dummy variables for each establishment or each industry, respectively. In addition, the GMM estimator has very strong robustness properties concerning the possible presence of overdispersion and serial correlation (Wooldridge, 2002).²¹

To estimate the effects of international trade on the occupational mix, we develop two specifications of our empirical model. As mentioned above, the BHP provides detailed

¹⁹If the explanatory variables are strictly exogenous, the conditional mean of y_{jt} satisfies $\mathbb{E}(y_{jt}|\nu_j, x_{jt}) = \mathbb{E}(y_{jt}|\nu_j, x_{j1}, \dots, x_{jT})$.

²⁰ $\epsilon_{jt}^* = \epsilon_{jt} - (\epsilon_{jt}/\bar{\epsilon}_j) \bar{\epsilon}_j$.

²¹One of the crucial assumptions of the Poisson distribution is that the variance of the dependent variable Y equals its mean: $\text{Var}(Y) = \mathbb{E}(Y)$. In our approach, we allow for overdispersion and allow $\text{Var}(Y)$ to be proportional to $\mathbb{E}(Y)$. Accordingly, the standard errors are also calculated under the overdispersion assumption.

information at the establishment-level, but our trade data are only available at the three-digit industry-level. Hence, we first estimate our empirical model at the industry-level. For this purpose, we aggregate the information of the BHP to the three-digit industry-level. This specification has the advantage that all variables are measured at the same level of aggregation. Moreover, it allows us to compare our results with the related literature that mainly focuses on industry-level data. However, this specification does not allow us to control for a wide range of establishment characteristics as well as for establishment fixed-effects. Therefore, we apply a second specification that estimates our empirical model as disaggregated as possible. Here, we estimate all variables except the trade flows and some control variables at the establishment-level, which allows us to account for the unobserved establishment heterogeneity, i.e., establishment fixed-effects. However, we now measure the variables for employment and international trade at different levels of aggregation. Thus, it might be difficult to determine employment effects within establishments due to changing trade flows of the corresponding industry. In addition, there is the chance that decisions about occupational structures are made at the firm-level rather than at the establishment-level. Accordingly, changes in the occupational mix of firms due to international trade might not be observable, since we only see single establishments without knowing whether they are part of a parent firm or not.

First, we estimate the employment effects of international trade at the industry-level. We set the respective industry identifier (three-digit industry classification) as the panel variable in our moment condition and thus control for all industry-specific characteristics that may also have an effect on the occupational mix of employment. Our estimated Poisson model looks as follows:

$$Y_{it} = \exp(\beta_1 \ln(ImpInt_{it}) + \beta_2 \ln(ImpComp_{it}) + \beta_3 \ln(Exp_{it})) * \exp(\delta' (V_{it}) + \nu' (Z_t) + \eta_i) + \epsilon_{it}. \quad (5.10)$$

The dependent variable, Y_{it} , measures the number of employees in industry i at time t attributed to a Blossfeld occupational group. We estimate Equation (5.10) for each occupation (except agricultural occupations) included in the BHP.

The first independent variable $ImpInt_{it}$ measures the intermediate imports of industry i at time t , i.e., the (real) value of imported inputs. The second independent variable, $ImpComp_{it}$, includes import competition that is defined as the (real) value of imports of final goods. Exp_{it} stands for the (real) value of exports. The estimated coefficients β_1 , β_2 and β_3 show the effects on the employment of each occupational group if the exposure to international trade of the respective industry changes. V_{it} is a vector of (logarithmized) control variables at the industry-level accounting for further

determinants that may affect the employment, such as the establishment size, activities in R&D, and the average share of high-skilled workers. Z_t is another vector of (logarithmized) control variables at the macro-level. We include macro variables to control for year-specific effects.²² We use German GDP and the annual “ifo Business Climate Index”²³ to account for any business cycle effects. Additionally, we include the overall education level of the German population and the size of the labor force to control for any systematic changes of the working population.²⁴ As the respective industry is the panel variable, the moment condition accounts for industry fixed-effects η_i . ϵ_{it} represents the error term.

To simplify the interpretation, we convert all right-hand side variables of Equation (5.10) into the logarithmic form before we include them into the estimation. Therefore, the estimated coefficients can be interpreted as elasticities. Since we control for the industry size in terms of total employment, we are able to interpret the estimated employment effects in relative terms, i.e., the coefficients indicate whether the occupational mix of an industry shifts toward a certain occupational group or not.

Second, we calculate our empirical model at the establishment-level:

$$Y_{jit} = \exp(\beta_1 \ln(\text{ImpInt}_{it}) + \beta_2 \ln(\text{ImpComp}_{it}) + \beta_3 \ln(\text{Exp}_{it})) * \exp(\delta' (V_{jit}) + \nu' (Z_t) + \eta_j) + \epsilon_{jit}. \quad (5.11)$$

Here, we set the establishment identifier j as the panel variable and thus control for all unobserved establishment-specific characteristics. The empirical model represented by Equation (5.11) is constructed in the same way as Equation (5.10), but exploits the information of the BHP at the establishment-level. Hence the dependent variable Y_{jit} measures the number of employees in each occupation in establishment j in industry i at time t , and V_{jit} and Z_t are vectors of (logarithmized) control variables at the establishment-level and the macro-level, respectively. Furthermore, we do not need to include industry fixed-effects, as the number of establishments changing their respective industry classification is negligible. Thus, the establishment fixed-effects η_j also control for any industry-specific fixed-effects. The remaining variables of Equation (5.11) equal those of Equation (5.10).²⁵

²²Due to software limitations that limit the number of fixed effects used, we are not able to implement year fixed-effects, i.e., a dummy variable for each of the 36 years.

²³In order to use the annual “Business Climate Index”, we aggregate the monthly “Business Climate Index” that is published by the “ifo Center for Business Cycle Analysis and Surveys”.

²⁴The data for German GDP, the education level, i.e., the percentage share of German citizens with post secondary education, and the overall labor force are obtained from the German Federal Statistical Office.

²⁵We are aware about the limitations of our approach in terms of endogeneity. If background variables such as structural change, skill change etc. simultaneously influence the foreign trade relationship and the development of the occupational structure, concerns that we do estimate causal effects but correlations

5.4.3 Results

Table 5.2 presents the results from our estimations at the three-digit industry-level represented by Equation (5.10). The estimations include all control variables as well as industry fixed-effects. We estimate Equation (5.10) for each Blossfeld occupational group except agricultural occupations. Hence, columns one to eleven of Table 5.2 show the effects of a change in intermediate imports, import competition, and exports on the employment in each occupation. The reported coefficients are elasticities. Hence, the coefficient of 0.0384 for the effect of an increase in exports on the number of technicians in a given industry reports that an increase in exports by 1% leads to an increase in the employment of technicians by approximately 0.04%.

The estimations show various employment effects from the different trade channels. Intermediate imports, i.e., the import of inputs and intermediate products, have negative employment effects on all occupations except skilled administrative occupations and managers. The coefficients are significant for all service occupations except professions and all administrative occupations except skilled administration, indicating that especially the employees in lower-skilled service and administrative occupations suffer most from an increase in intermediate imports. These results support the literature on offshoring that finds negative employment effects from outsourcing, especially for employees with less complex tasks (e.g., Hogrefe, 2013). However, we cannot identify a negative employment effect from offshoring on (low-skilled) production occupations.

In case of import competition, i.e., the import of goods that compete with final goods of domestic suppliers, the results provide evidence that the employees in most occupations suffer from a more competitive environment. The employment effects are negative for all occupations except unskilled manual, service professions, and managers. Significance is displayed for technicians, unskilled services, and all administrative occupations except managers. Moreover, the negative effects of import competition on the employment in unskilled service occupations and in unskilled administrative occupations are substantially larger than the effects of intermediate imports. Findings are also in line with the literature that finds job losses due to increased competition with imported goods (e.g., Biscourp and Kramarz (2007) and Autor et al. 2013).

might arise.

Table 5.2: Employment Effects of International Trade (Three-Digit Level), 1975-2010

Dependent Variable:	Fixed-Effects Poisson Model (GMM)										
	Production Occupations			Service Occupations			Administration Occupations				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Intermediate Imports	-0.0086 (0.0109)	-0.0166 (0.0186)	-0.0024 (0.0093)	-0.0109 (0.0101)	-0.0417** (0.0171)	-0.0505* (0.0263)	-0.0703** (0.0339)	-0.0162 (0.0270)	-0.0811*** (0.0147)	0.0020 (0.0051)	0.0494** (0.0196)
Import Competition	0.0019 (0.0197)	-0.0111 (0.0177)	-0.0457*** (0.0124)	-0.0073 (0.0085)	-0.1223*** (0.0323)	-0.0614 (0.0470)	-0.0717 (0.0637)	0.0087 (0.0247)	-0.2480*** (0.0578)	-0.0362*** (0.0113)	0.0347 (0.0226)
Exports	0.0069 (0.0202)	-0.0123 (0.0209)	0.0384*** (0.0129)	0.0210 (0.149)	0.0931*** (0.0291)	0.0749* (0.0441)	0.0987 (0.0627)	-0.0135 (0.0342)	0.2332*** (0.0582)	0.0346*** (0.0127)	-0.0480** (0.0242)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	3,094	3,094	3,094	3,094	3,094	3,094	3,094	3,094	3,094	3,094	3,094

Notes: Clustered standard errors (by industry) in parentheses, *** p<0.01, ** p<0.05, * p<0.1

For exports, i.e., the export of goods by domestic establishments, we find positive signs for the employment effects for all but three occupations. The coefficients for technicians, unskilled services, skilled services, as well as unskilled and skilled administrative occupations are positive and significant; only for managers, the impact is negative and significant. Thus, it seems that employees in lower skilled occupations gain from an increase in exports. The employment effect of exports on the employment in unskilled administrative occupations is considerably larger than the effect of import competition.

Table 5.3 presents the results from the regression model estimated at the establishment-level according to Equation (5.11). The estimation strategy and column interpretation is identical to Table 5.2 with the difference that the employment of each occupational group is now observed at the establishment-level. Hence, the coefficient of 0.0448 for the export effect on the number of technicians, for example, reports that an establishment will increase the number of technicians by approximately 0.04% if the industry it belongs to experiences an export growth of 1%.

Compared to the industry-level estimation, the establishment-level estimations only show few significant employment effects from the different channels of international trade. To a great extent, the signs of the coefficients are unchanged, implying an employment change in the same direction as before. The estimated coefficients, however, lose significance. This most likely has to do with the fact that trade information is measured at the industry-level, whereas the employment is measured at the establishment-level. Additionally, we now control for the substantial unobserved establishment heterogeneity.

Intermediate imports now show a negative and significant impact on the employment of technicians and unskilled administrative occupations. Although the former group represents a high-skilled occupation, this result is in line with the literature that shows an increasing offshorability of high-skilled jobs (Baldwin and Robert-Nicoud, 2007). In contrast, the employment effect on managers is positive and significant.

In case of the import competition, the results now show negative and significant employment effects on technicians and skilled administrative occupations. The coefficients on all other occupations are insignificant. The estimation for exports at the establishment-level shows that technicians benefit from increasing exports, whereas the employment of managers decreases, which is in line with Maurin et al. (2002), but contradicts Caliendo and Rossi-Hansberg (2012).

Table 5.3: Employment Effects of International Trade (Establishment-Level), 1975-2010

Dependent Variable:	Fixed-Effects Poisson Model (GMM)										
	Production Occupations			Service Occupations			Administration Occupations				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Intermediate Imports	-0.0031 (0.0064)	-0.0055 (0.0170)	-0.0140** (0.0067)	-0.0130 (0.0126)	-0.0065 (0.0112)	0.0121 (0.0179)	0.0097 (0.0207)	0.0230 (0.0278)	-0.0280** (0.0115)	-0.0023 (0.0038)	0.0522** (0.0215)
Import Competition	-0.0126 (0.0201)	-0.0176 (0.0231)	-0.0398* (0.0208)	-0.0050 (0.0113)	0.0028 (0.0222)	0.0050 (0.0833)	-0.0140 (0.0770)	0.0101 (0.0287)	-0.0150 (0.0257)	-0.0314** (0.0140)	0.0382 (0.0279)
Exports	0.0207 (0.0254)	0.0013 (0.0305)	0.0448* (0.0269)	0.0256 (0.0214)	-0.0244 (0.0248)	-0.0177 (0.1022)	0.0344 (0.0862)	-0.0444 (0.0422)	0.0291 (0.0303)	0.0300* (0.0179)	-0.0820* (0.0488)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Establishment Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	379,805	379,805	379,805	379,805	379,805	379,805	379,805	379,805	379,805	379,805	379,805

Notes: Clustered standard errors (by industry) in parentheses, *** p<0.01, ** p<0.05, * p<0.1

In summary, we find evidence at the industry-level that an increase in intermediate imports and in import competition decreases the employment in almost all occupations, whereas the employment increases in almost all occupations if exports increase. However, the estimations provide no evidence that international trade is a driving force behind the substantial employment decline in unskilled and skilled production occupations that is depicted in Table 5.1.²⁶ At the establishment-level, we find that the three channels of international trade only affect the employment of a few occupations although the signs of the coefficients are in line with the estimations at the industry-level. Mostly administrative occupations and technicians show significant employment effects. These results may have four causes: First, employment effects might become insignificant if we account for establishment heterogeneity by using establishment-fixed effects as well as control variables at the establishment-level. Second, our estimated coefficients may be mostly insignificant because of level differences. While the employment of the respective occupation and most of the control variables are reported at the establishment-level, the trade variables are measured at the three-digit industry-level. Third, there might be changes in the occupational structure of firms due to international trade we cannot identify, since we only observe single establishments, not firms, which may have more than one establishment. Fourth, applying to both the estimation at the establishment-level and at the industry-level, the panel regression assumes a contemporary response of professional groups to changes in the foreign trade structure. However, it is likely that foreign trade is much more volatile than occupational adjustments. A change in the occupational structure is associated with high adjustment costs and is thus probably subject to a high degree of sluggishness.

5.5 Conclusion

In this paper, we build on the fact that rather little empirical research has been conducted to investigate how trade openness impacts the occupational mix of manufacturing firms.

We identify three different trade channels: intermediate imports, import competition, and exports. To investigate the employment effects of these three channels, we match the BHP with UN Comtrade data by using a new matching approach. We take the input and output structure of the German manufacturing sector into account and allocate the trade flows accordingly.

Our stylized facts highlight the change of the employment structure of manufacturing establishments. To identify the relationship between the three channels of international

²⁶Thus, it might mostly be skilled-biased technological change and not international trade that explains job losses in low-skilled occupations. See for instance Acemoglu and Autor (2011) for an overview.

trade and the employment in different occupations, we apply a fixed-effects Poisson model that especially accounts for the substantial individual heterogeneity of industries and establishments. We estimate our empirical model both at the industry-level and at the establishment-level using industry fixed-effects or establishment fixed-effects, respectively.

Our results at the industry-level indicate that increasing intermediate imports and import competition lead to decreasing employment, whereas rising export activities increase employment. The employees in unskilled and skilled service occupations suffer from an increase in imports of intermediate products. Hence, increasing imports contribute to the decline in employment of these two occupations displayed in Table 5.1. In contrast, employees of the same occupational groups benefit most from an increase in exports. However, our estimations cannot determine international trade as a driving force behind the substantial employment decline in unskilled and skilled production occupations described in Table 5.1. If we estimate our empirical model at the establishment-level, our results suggest that only the employment of few occupations is affected by changes in international trade. The estimated coefficients lose significance, which is most likely due to level differences between the dependent variable and the independent variables and the inclusion of establishment fixed-effects. Furthermore, we are not able to identify changes in the occupational structure of firms, since we only observe single establishments.

Thus, a natural step for future research would be to check to what extent our results can be confirmed with a dataset at the firm-level, which additionally includes information on activities in international trade.

5.6 Bibliography

- (1) Acemoglu, Daron and David Autor (2011), “Skills, tasks and technologies: Implications for employment and earnings”, *Handbook of labor economics* 4, 1043-1171.
- (2) Altomonte, Carlo, Filippo Di Mauro, Gianmarco Ottaviano, Armando Rungi and Vincent Vicard (2013), “Global Value Chains during the Great Trade Collapse: A Bullwhip Effect?”, *Firms in the International Economy: Firm Heterogeneity meets International Business*, 277-308, MIT Press.
- (3) Alvares-Cuadrado, Francisco and Ngo Van Long (2017), “Capital-Labor Substitution, Structural Change and Growth”, *Theoretical Economics* 12(3), 1229-1266.
- (4) Autor, David H., David Dorn and Gordon H. Hanson (2013), “The China syndrome: Local labor market effects of import competition in the United States”, *American Economic Review* 103(6), 2121-2168.
- (5) Baldwin, Richard and Frederic Robert-Nicoud (2007), “Offshoring: General Equilibrium Effects on Wages, Production and Trade”, CEPR Discussion Paper 6218, London.
- (6) Becker, Sascha O., Karolina Ekholm and Marc-Andreas Muendler (2013), “Offshoring and the Onshore Composition of Tasks and Skills”, *Journal of International Economics* 90(1), 91-106.
- (7) Bernard, Andrew B. and J. Bradford Jensen (1997), “Exporters, Skill Upgrading, and the Wage Gap”, *Journal of International Economics* 42(1/2), 3-31.
- (8) Biscourp, Pierre and Francis Kramarz (2007), “Employment, Skill Structure and International Trade: Firm-level Evidence for France”, *Journal of International Economics* 72(1), 22-51.
- (9) Blossfeld, Hans-Peter (1987), “Labor Market Entry and the Sexual Segregation of Careers in the Federal Republic of Germany”, *American Journal of Sociology* 93(1), 89-118.
- (10) Blundell, Richard, Rachel Griffith and Frank Windmeijer (2002), “Individual Effects and Dynamics in Count Data Models”, *Journal of Econometrics* 108(1), 113-131.
- (11) Caliendo, Lorenzo and Esteban Rossi-Hansberg (2012), “The Impact of Trade on Organization and Productivity”, *The Quarterly Journal of Economics* 127(3), 1393-1467.

- (12) Davidson, Carl, Fredrik Heyman, Steven Matusz, Fredrik Sjöholm and Susan Chun Zhu (2013), “Globalization and the Organization of the Firm”, IFN Working Paper 1026, Stockholm.
- (13) Eberle, Johanna, Peter Jacobebbinghaus, Johannes Ludsteck and Julia Witter (2011), “Generation of Time-Consistent Industry Codes in the Face of Classification Changes - Simple Heuristic Based on the Establishment History Panel (BHP)”, FDZ Methodenreport 05/2011, Methodological Aspects of Labour Market Data, Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB).
- (14) Feenstra, Robert C. and Gordon H. Hanson (1996), “Globalization, Outsourcing and Wage Inequality”, *American Economic Review* 86(2), 240-245.
- (15) Grossman, Gene M. and Esteban Rossi-Hansberg (2008), “Trading tasks: A simple theory of offshoring”, *American Economic Review* 98(5), 1978-1997.
- (16) Gruhl, Anja, Alexandra Schmucker and Stefan Seth (2012), “Das Betriebs-Historik-Panel 1975-2010, Handbuch Version 2.1.1, FDZ Datenreport 04/2012, Dokumentation zu Arbeitsmarktdaten”, Forschungsdatenzentrum (FDZ) der Bundesagentur für Arbeit (BA) im Institut für Arbeitsmarkt- und Berufsforschung (IAB).
- (17) Henze, Philipp (2014), “Structural Change and Wage Inequality: Evidence from German Micro Data”, CEGE Discussion Paper 204, Göttingen.
- (18) Hethey-Maier, Tanja and Stefan Seth (2010), “The Establishment History Panel (BHP), Handbook Version 1.0.2, FDZ Methodenreport 04/2010, Documentation of Labour Market Data”, Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB).
- (19) Hijzen, Alexander, Holger Görg and Robert C. Hine (2005), “International Outsourcing and the Skill Structure of Labour Demand in the United Kingdom”, *Economic Journal* 115, 860-978.
- (20) Hogrefe, Jan (2013), “Offshoring and Relative Labor Demand from a Task Perspective”, ZEW Discussion Paper 13-067, Mannheim.
- (21) Jorgenson, Dale W. and Marcel P. Timmer (2011), “Structural change in advanced nations: a new set of stylised facts”, *Scandinavian Journal of Economics* 113(1), 1-29.
- (22) Kuznets, Simon (1966), “Modern Economic Growth”, New Haven, Conn., Yale University Press.

- (23) Marin, Dalia, Jan Schymik and Alexander Tarasov (2014), “Trade in Tasks and the Organization of Firms”, *European Economic Review* 107, 99-132.
- (24) Marin, Dalia and Thierry Verdier (2012), “Globalization and the Empowerment of Talent”, *Journal of International Economics* 86(2), 209-223.
- (25) Maurin, Eric, David Thesmar and Mathias Thoenig (2002), “Globalization and the Demand for Skill: An Export Based Channel”, CEPR Discussion Paper Series 3406, London.
- (26) Tomiura, Eiichi (2003), “The Impact of Import Competition on Japanese Manufacturing Employment”, *Journal of the Japanese and International Economies* 17(2), 118-133.
- (27) Wooldridge, Jeffrey M. (2002), “Econometric Analysis of Cross Section and Panel Data”, Cambridge, Mass., MIT Press.

Data Sources:

- (28) Establishment History Panel (in German: Betriebs-Historik-Panel (BHP)), Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB).
Annual Mirco Data Set from 1975 to 2010.
http://fdz.iab.de/en/FDZ_Establishment_Data.aspx
- (29) Statistisches Bundesamt (Editor): Volkswirtschaftliche Gesamtrechnung, Input-Output-Rechnung in: Fachserie 18 / 2, Wiesbaden. Annual statistics from 1995 to 2010.
- (30) Statistisches Bundesamt (Editor): Kostenstruktur der Unternehmen im Bergbau, Grundstoff- und Produktionsgütergewerbe, in: Fachserie / 4 / 4 / 1, Wiesbaden. Annual Statistics from 1975 to 2010.
- (31) Statistisches Bundesamt (Editor): Kostenstruktur der Unternehmen im Investitionsgüter produzierenden Gewerbe, in: Fachserie / 4 / 4 / 2, Wiesbaden. Annual Statistics from 1975 to 2010.
- (32) Statistisches Bundesamt (Editor): Kostenstruktur der Unternehmen im Verbrauchsgüter produzierenden Gewerbe und im Nahrungs- und Genussmittelgewerbe, in: Fachserie / 4 / 4 / 3, Wiesbaden. Annual Statistics from 1975 to 2010.

- (33) Statistisches Bundesamt (Editor): Material- und Wareneingangserhebung im Verarbeitenden Gewerbe sowie im Bergbau und in der Gewinnung von Steinen und Erden (“Input Statistic”), in: Wirtschaft und Statistik, Wiesbaden. Quadrennial Statistics: 1978, 1982, 1986, 1990, 1994, 1998, 2002, 2006 and 2010.
- (34) Statistisches Bundesamt (Editor): Produktionserhebung im Bereich Verarbeitendes Gewerbe, Bergbau und Gewinnung von Steinen und Erden (“Survey of Production”), in: Wirtschaft und Statistik, Wiesbaden. Quarterly Statistics from 1995 to 2010.
- (35) United Nations Commodity Trade Statistics Data Base. Annual Trade Data Statistics from 1975 to 2010. <http://comtrade.un.org/>

C Appendices

C.1 Structure of Employees by Blossfeld Occupational Groups

Name of Occupational Group	Description of Occupational Group	Examples
Production		
Unskilled manual occupations (EMB)	All manual occupations that showed at least 60 percent unskilled workers in 1970	Miners, rock breakers, paper makers, wood industry occupations, printing industry occupations, welders, unskilled workers, road and railroad construction workers
Skilled manual occupations (QMB)	All manual occupations that showed at most 40 percent unskilled workers in 1970	Glassblowers, bookbinders, typesetters, locksmiths, precision instrument makers, electrical mechanics, coopers, brewers
Technicians (TEC)	All technically trained specialists	Machinery technicians, electrical technicians, construction technicians, mining technicians
Engineers (ING)	Highly trained specialists who solve technical and natural science problems	Construction engineering, electrical engineers, production designers, chemical engineers, physicists, mathematicians

Name of Occupational Group	Description of Occupational Group	Examples
Service		
Unskilled services (EDB)	All unskilled personal services	Cleaners, security guards
Skilled services (QDB)	Essentially order and security occupations as well as skilled service occupations	Locomotive engineers, registrars
Semiprofessions (SEMI)	Service positions which are characterized by professional specialization	Interpreters, educators
Professions (PROF)	All liberal professions and service positions which require a university degree	Statisticians, economists, social scientist
Administration		
Unskilled commercial and administrative occupations (EVB)	Relatively unskilled office and commerce occupations	Postal occupations, office hands, typists
Skilled commercial and administrative occupations (QVB)	Occupations with medium and higher administrative and distributive functions	Credit and financial assistants, foreign trade assistants, data processing operators, book-keepers, goods traffic assistants
Managers (MAN)	Occupations which control factors of production as well as functionaries of organizations	Managers, business administrators, deputies, CEOs

C.2 Description of Matching Process of Commodity Trade Data

As the BHP does not include establishment-level information on trade activities, we merge the BHP with trade data obtained from the UN Comtrade database. To do so, we use the industry classification of the respective establishment in the BHP as identifier. Thus, we have to convert commodity imports and exports into industry imports and exports.

Index for Intermediate Imports

To generate intermediate imports at the industry-level, we use the Input Statistic to allocate the import value by commodity (from the UN Comtrade database) according to the input shares of this particular good in the industry production. The Input Statistic shows the use of commodity inputs at the three-digit and four-digit industry-level²⁷ and is published every four years from 1978 onwards. The BHP covers the years 1975-2010 such that we have to assume constant input structures for four years.

As the product classifications of both the import data and the Input Statistic vary over the years, we use correspondence tables to reclassify the classification of the commodity trade into the classification of the commodity input. Table 5.4 shows the process. Column two and column seven show the product classification of the UN Comtrade import data²⁸ and the Input Statistic, respectively. Columns three to six depict the correspondence tables we use to reclassify the data. The correspondence tables are partly incomplete. In these cases, we directly allocate the import values to the correct Input Statistic classification “by hand” using the “Product Classifications for Production Statistics” (in German: “Güterverzeichnis für Produktionsstatistiken”) provided by the German Federal Statistical Office. Table 5.9 gives an overview of the matching success before and after hand allocation. On average, we can match 99.18% of the imports.²⁹ As the analysis is restricted to the manufacturing sector, we additionally weigh the commodity import data with input shares in manufacturing. Input-output tables³⁰ provided by the German Federal Statistical Office show the share of imports used in manufacturing by commodity. Hence, we eliminate imports used for other purposes such as private, government or service consumption. After distributing the import values ac-

²⁷The level of commodity aggregation varies by industry. Hence, we need to aggregate commodities to the two-digit level before allocating the import values to the various industries.

²⁸Import commodities are classified at the five-digit level for both SITC classifications and at the six-digit level for HS classifications. In case of the SITC classification, import values are partly incomplete at the five-digit level. Hence, we use four-digit level import data (and three-digit level import data for SITC1) for the remainder that is not included in the five-digit data.

²⁹Before hand allocation we can successfully match 64.35% of the import values.

³⁰The Input-Output Statistic is only available from 1995 onwards. For earlier years we also use the Input-Output table of 1995 and thus assume a constant composition of import use for the years 1975-1995. A comparison of later years shows that import shares in manufacturing by commodity are rather stable. Thus it seems that our assumption is valid.

ording to the input shares, we aggregate the import values by industry to obtain an index of intermediate imports for every industry. Finally, we convert the intermediate imports from the industry classification of the Input Statistic (Table 5.4, column eight) into the industry classification of the BHP (Table 5.4, column nine). Appendix Section C.3 contains an example of the commodities “Leather and Leather Manufactures” to illustrate the allocation process in 2000.

Index for Exports

To generate our export data, we follow a strategy that is very similar to the process described above. We use the Survey of Production to convert commodity exports into industry exports. The Survey of Production shows the output of industries at the nine-digit commodity-level. We allocate the export values by commodity according to the output shares of that particular good in the industry production. The matching process follows the method described above and is depicted in Table 5.5. Column interpretation is identical except that columns six and seven now show the Survey of Production rather than the Input Statistic. As the Survey of Production is only available from 1995 onwards, we also use the 1995 survey data to allocate exports for previous years. Thus we assume a constant output structure until 1995. On average, we can match 99.55% of the exports (see Table 5.9).³¹

Index for Import Competition

To obtain coefficients for import competition, we again use the Survey of Production with the only difference that we allocate import values by commodity according to the output structure. Thus, again Table 5.5 shows the reclassification of import classifications into output classification. On average, we can match 99.87% of all imports.

³¹Before hand allocation we can successfully match 63.14% of the export values.

Table 5.4: Matching Process for Intermediate Imports Data

Import Data		Correspondence Tables				Input Statistic			BHP	
(1) Year	(2) Product Classification	(3) Correspondence 1	(4) Correspondence 2	(5) Correspondence 3	(6) Correspondence 4	(7) Product Classification	Year	(8) Industry Classification	(9) Industry Classification	Year
1975	SITC1	to	Prodcom95	to	GP95	WI75	1978	Sypro	WZ93	1975
1976	SITC1	to	Prodcom95	to	GP95	WI75	1978	Sypro	WZ93	1976
1977	SITC1	to	Prodcom95	to	GP95	WI75	1978	Sypro	WZ93	1977
1978	SITC2	to	Prodcom95	to	GP95	WI75	1978	Sypro	WZ93	1978
1979	SITC2	to	Prodcom95	to	GP95	WI75	1978	Sypro	WZ93	1979
1980	SITC2	to	Prodcom95	to	GP95	GP82	1982	Sypro	WZ93	1980
1981	SITC2	to	Prodcom95	to	GP95	GP82	1982	Sypro	WZ93	1981
1982	SITC2	to	Prodcom95	to	GP95	GP82	1982	Sypro	WZ93	1982
1983	SITC2	to	Prodcom95	to	GP95	GP82	1982	Sypro	WZ93	1983
1984	SITC2	to	Prodcom95	to	GP95	GP82	1986	Sypro	WZ93	1984
1985	SITC2	to	Prodcom95	to	GP95	GP82	1986	Sypro	WZ93	1985
1986	SITC2	to	Prodcom95	to	GP95	GP82	1986	Sypro	WZ93	1986
1987	SITC2	to	Prodcom95	to	GP95	GP82	1986	Sypro	WZ93	1987
1988	SITC2	to	Prodcom95	to	GP95	GP89	1990	Sypro	WZ93	1988
1989	SITC2	to	Prodcom95	to	GP95	GP89	1990	Sypro	WZ93	1989
1990	SITC2	to	Prodcom95	to	GP95	GP89	1990	Sypro	WZ93	1990
1991	HS 1992	to	Prodcom95	to	GP95	GP89	1990	Sypro	WZ93	1991
1992	HS 1992	to	Prodcom95	to	GP95	GP89	1994	Sypro	WZ93	1992
1993	HS 1992	to	Prodcom95	to	GP95	GP89	1994	Sypro	WZ93	1993
1994	HS 1992	to	Prodcom95	to	GP95	GP89	1994	Sypro	WZ93	1994
1995	HS 1992	to	Prodcom95	to	GP95	GP89	1994	Sypro	WZ93	1995
1996	HS 1992	to	Prodcom95	to	GP95	GP95	1998	WZ93	WZ93	1996
1997	HS 1992	to	Prodcom95	to	GP95	GP95	1998	WZ93	WZ93	1997
1998	HS 1992	to	Prodcom95	to	GP95	GP95	1998	WZ93	WZ93	1998
1999	HS 1992	to	Prodcom95	to	GP95	GP95	1998	WZ93	WZ93	1999
2000	HS 1992	to	Prodcom95	to	GP95	GP02	2002	WZ93	WZ93	2000
2001	HS 1992	to	Prodcom95	to	GP95	GP02	2002	WZ93	WZ93	2001
2002	HS 2002	to	Prodcom2002	to	GP95	GP02	2002	WZ93	WZ93	2002
2003	HS 2002	to	Prodcom2002	to	GP95	GP02	2002	WZ93	WZ93	2003
2004	HS 2002	to	Prodcom2002	to	GP95	GP02	2006	WZ93	WZ93	2004
2005	HS 2002	to	Prodcom2002	to	GP95	GP02	2006	WZ93	WZ93	2005
2006	HS 2002	to	Prodcom2002	to	GP95	GP02	2006	WZ93	WZ93	2006
2007	HS 2002	to	Prodcom2002	to	GP95	GP02	2006	WZ93	WZ93	2007
2008	HS 2007	to	Prodcom2008	to	GP95	GP09	2010	WZ08	WZ08	2008
2009	HS 2007	to	Prodcom2008	to	GP95	GP09	2010	WZ08	WZ08	2009
2010	HS 2007	to	Prodcom2008	to	GP95	GP09	2010	WZ08	WZ08	2010

Notes:

For 1975-1977: 3-level Matching: SITC 1 trade data at five-digit level; remainder at four-digit and three-digit level.

For 1978-1990: 2-level Matching: SITC 1 trade data at five-digit level; remainder at four-digit level.

Table 5.5: Matching Process for Import Competition and Export Data

Export Data			Correspondence Tables			Survey of Production			BHP	
(1) Year	(2) Product Classification	(3) Correspondence 1	(4) Correspondence 2	(5) Correspondence 3	(6) Product Classification	(7) Industry Classification	(8) Industry Classification	Year	Year	
1975	SITC1	to	Prodcom95	to	GP95	WZ93	to	1995	1975	
1976	SITC1	to	Prodcom95	to	GP95	WZ93	to	1995	1976	
1977	SITC1	to	Prodcom95	to	GP95	WZ93	to	1995	1977	
1978	SITC2	to	Prodcom95	to	GP95	WZ93	to	1995	1978	
1979	SITC2	to	Prodcom95	to	GP95	WZ93	to	1995	1979	
1980	SITC2	to	Prodcom95	to	GP95	WZ93	to	1995	1980	
1981	SITC2	to	Prodcom95	to	GP95	WZ93	to	1995	1981	
1982	SITC2	to	Prodcom95	to	GP95	WZ93	to	1995	1982	
1983	SITC2	to	Prodcom95	to	GP95	WZ93	to	1995	1983	
1984	SITC2	to	Prodcom95	to	GP95	WZ93	to	1995	1984	
1985	SITC2	to	Prodcom95	to	GP95	WZ93	to	1995	1985	
1986	SITC2	to	Prodcom95	to	GP95	WZ93	to	1995	1986	
1987	SITC2	to	Prodcom95	to	GP95	WZ93	to	1995	1987	
1988	SITC2	to	Prodcom95	to	GP95	WZ93	to	1995	1988	
1989	SITC2	to	Prodcom95	to	GP95	WZ93	to	1995	1989	
1990	SITC2	to	Prodcom95	to	GP95	WZ93	to	1995	1990	
1991	HS 1992	to	Prodcom94	to	GP95	WZ93	to	1999	1991	
1992	HS 1992	to	Prodcom94	to	GP95	WZ93	to	1995	1992	
1993	HS 1992	to	Prodcom94	to	GP95	WZ93	to	1995	1993	
1994	HS 1992	to	Prodcom94	to	GP95	WZ93	to	1995	1994	
1995	HS 1992	to	Prodcom94	to	GP95	WZ93	to	1995	1995	
1996	HS 1992	to	Prodcom94	to	GP95	WZ93	to	1996	1996	
1997	HS 1992	to	Prodcom94	to	GP95	WZ93	to	1997	1997	
1998	HS 1992	to	Prodcom94	to	GP95	WZ93	to	1998	1998	
1999	HS 1992	to	Prodcom94	to	GP95	WZ93	to	1999	1999	
2000	HS 1992	to	Prodcom94	to	GP95	WZ93	to	2000	2000	
2001	HS 1992	to	Prodcom94	to	GP95	WZ93	to	2001	2001	
2002	HS 2002	to	Prodcom2002	to	GP02	WZ93	to	2002	2002	
2003	HS 2002	to	Prodcom2002	to	GP02	WZ03	to	2003	2003	
2004	HS 2002	to	Prodcom2002	to	GP02	WZ03	to	2004	2004	
2005	HS 2002	to	Prodcom2002	to	GP02	WZ03	to	2005	2005	
2006	HS 2002	to	Prodcom2002	to	GP02	WZ03	to	2006	2006	
2007	HS 2002	to	Prodcom2002	to	GP02	WZ03	to	2007	2007	
2008	HS 2002	to	Prodcom2002	to	GP02	WZ03	to	2008	2008	
2009	HS 2007	to	Prodcom2008	to	GP09	WZ08	to	2009	2009	
2010	HS 2007	to	Prodcom2008	to	GP09	WZ08	to	2010	2010	

Notes:

For 1975-1977: 3-level Matching; SITC 1 trade data at five-digit level; remainder at four-digit and three-digit level.

For 1978-1990: 2-level Matching; SITC 1 trade data at five-digit level; remainder at four-digit level.

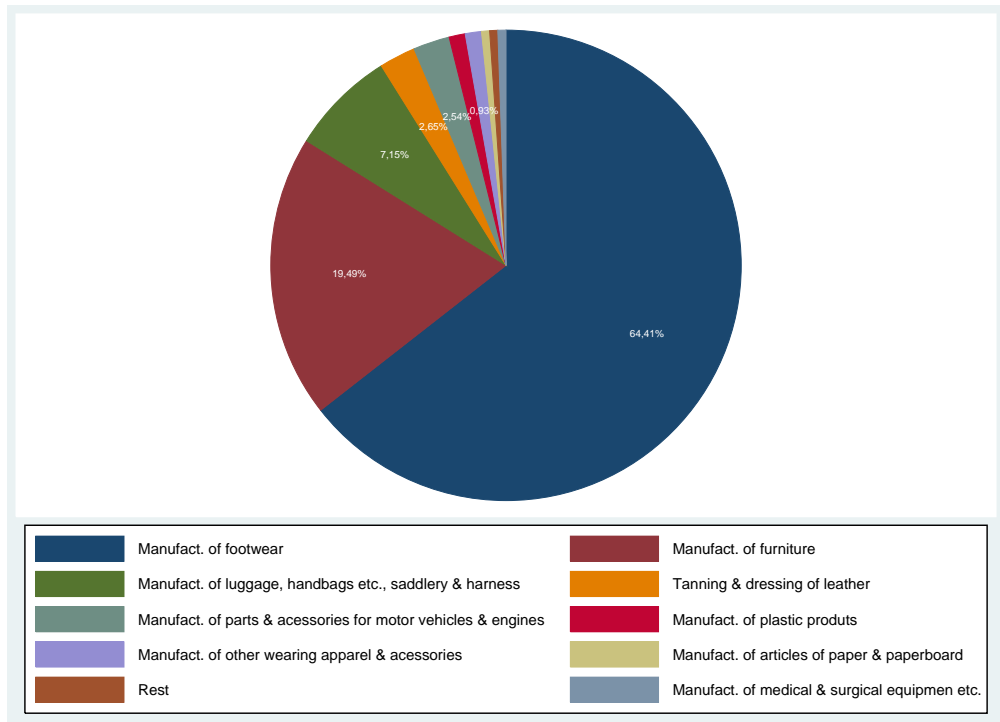
C.3 Example: Allocation of Imports of “Leather and Leather Manufactures” to the Industries of the BHP

This section provides a comparison between the standard way to use correspondence tables in order to create trade data at the industry-level and our approach to use input-output information instead. Here, we present the example of “Leather and Leather Manufactures” imports (in German: “Leder und Lederwaren”, “leather” in the following) including footwear.

“Our Approach”

Figure 5.2 shows a pie chart that depicts how we allocate imported leather commodities to various industries. Using the Input Statistic, we allocate leather imports to 17 industries in which leather products are used as inputs. All industries that receive less than 0.5% of the import values are summarized as “Rest”. Table 5.6 shows the allocation structure in detail. The column “Share” shows the share of leather imports that is allocated to each industry given in the column “Industry”. This share is identical to the share of leather inputs that is used in these industries.

Figure 5.2: Allocation of Leather Imports to the Industries of the BHP (in 2000)



Notes: Source: UN Comtrade database and Input Statistic, authors’ computation.

Table 5.6: Allocation of Leather Imports to the Industries of the BHP (in 2000)

GP 95	WZ 1993	Share	Industry
19	102	0.00026313	Mining and agglomeration of lignite
19	174	0.00136164	Manufacture of made-up textile articles, except apparel
19	175	0.00033050	Manufacture of other textiles
19	182	0.00927598	Manufacture of other wearing apparel and accessories
19	191	0.02651121	Tanning and dressing of leather
19	192	0.07146845	Manufacture of luggage, handbags and the like, saddlery and harness
19	193	0.64408863	Manufacture of footwear
19	212	0.00616514	Manufacture of articles of paper and paperboard
19	221	0.00040870	Publishing
19	222	0.00072203	Printing and service activities related to printing
19	252	0.01072427	Manufacture of plastic products
19	286	0.00135952	Manufacture of cutlery, tools and general hardware
19	331	0.00556807	Manufacture of medical and surgical equipment and orthopaedic appliances
19	343	0.02539422	Manufacture of parts and accessories for motor vehicles and their engines
19	361	0.19478314	Manufacture of furniture
19	365	0.00027423	Manufacture of games and toys
19	366	0.00130114	Miscellaneous manufacturing n.e.c.

Notes:

This example presents how we allocate leather imports (product classification “GP 95” = 19) to all industries that use leather as inputs according to the Input Statistic.

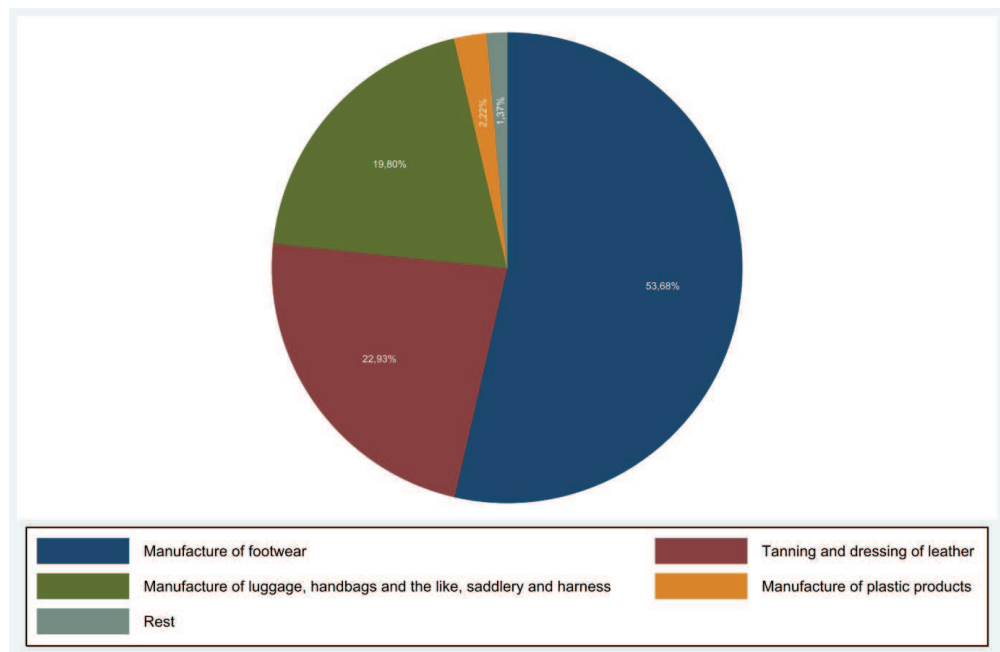
Source: UN Comtrade database and Input Statistic, authors’ computation.

Allocation of Exports of “Leather and Leather Manufactures” to the Industries of the BHP

“Our Approach”

Figure 5.3 depicts how we allocate leather exports to industries and Table 5.7 shows the allocation structure in detail. The interpretation is identical to that of Figure 5.2 and Table 5.6 for the imports. Using the Survey of Production, we identify 24 industries that produce leather goods and thus receive a share of the allocated leather exports.

Figure 5.3: Allocation of Leather Exports to the Industries of the BHP (in 2000)



Notes: Source: UN Comtrade database and Survey of Production, authors' computation.

Table 5.7: Allocation of Leather Exports to the Industries of the BHP (in 2000)

GP 95	WZ 1993	Share	Industry
19	174	.0024244	Manufacture of made-up textile articles, except apparel
19	175	*	Manufacture of other textiles
19	177	*	Manufacture of knitted and crocheted articles
19	182	.0003852	Manufacture of other wearing apparel and accessories
19	191	.2293406	Tanning and dressing of leather
19	192	.1979861	Manufacture of luggage, handbags and the like, saddlery and harness
19	193	.5367885	Manufacture of footwear
19	212	.000902	Manufacture of articles of paper and paperboard
19	221	*	Publishing
19	222	*	Printing and service activities related to printing
19	246	*	Manufacture of other chemical products
19	247	*	Manufacture of man-made fibers
19	251	.0003326	Manufacture of rubber products
19	252	.0222259	Manufacture of plastic products
19	261	*	Manufacture of glass and glass products
19	291	*	Manufacture of machinery for the production and use of mechanical power
19	292	*	Manufacture of other general purpose machinery
19	295	*	Manufacture of other special purpose machinery
19	331	.0006351	Manufacture of medical and surgical equipment and orthopaedic appliances
19	332	*	Manufacture of instruments and appliances for measuring, navigating and other purposes
19	343	*	Manufacture of parts and accessories for motor vehicles and their engines
19	354	*	Manufacture of motorcycles and bicycles
19	361	*	Manufacture of furniture
19	366	*	Miscellaneous manufacturing n.e.c.

Notes:

This example presents how we allocate leather exports (product classification “GP 95” = 19) to all industries that produce leather goods according to the Survey of Production.

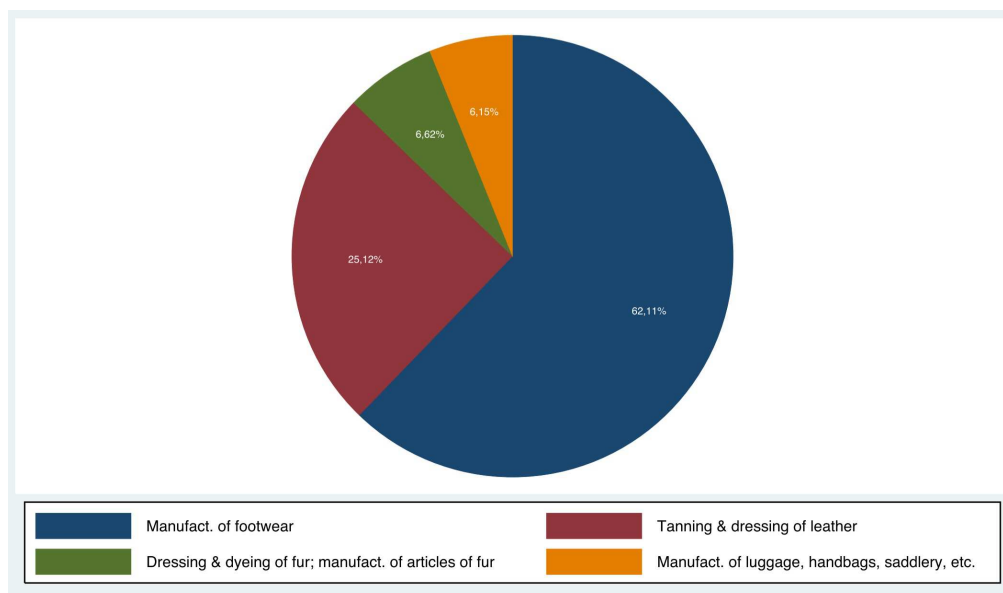
* 15 missing industries due to confidentiality (insufficient number of firms that produce leather goods within these industries).

Source: UN Comtrade database and Survey of Production, authors’ computation.

“Traditional Approach”

Figure 5.4 and the corresponding Table 5.8 show the allocation of leather imports or leather exports following the standard way to use correspondence tables (here taken from the UN Statistics Division, as e.g., by Altomonte et al. (2013) and Dauth, Findeisen and Südekum (2014) among many). The results differ a lot compared to our approach. Not only is commodity trade merely allocated to four industries, but also - except the industry of “Manufacturing of Footwear” - these industries do not seem to be the most relevant ones judging by the input and output structure. Accordingly, we argue that using input and output tables rather than correspondence tables, we are able to allocate imports much more accurately.

Figure 5.4: Allocation of Leather Imports and Exports to the Industries of the BHP (in 2000) - “Traditional Approach”



Notes: Source: UN Comtrade database and UN Statistics Division, authors' computation.

Table 5.8: Allocation of Leather Imports to the Industries of the BHP (in 2000) - “Traditional Approach”

SITC, Rev. 3	WZ 1993	Share	Industry
61 & 85	191	0.25124481	Tanning and dressing of leather
61 & 85	192	0.06148816	Manufacture of luggage, handbags and the like, saddlery and harness
61 & 85	183	0.06618976	Dressing and dyeing of fur; manufacture of articles of fur
61 & 85	193	0.62107728	Manufacture of footwear

Notes:

This example presents the “traditional” matching procedure of leather imports. Here, we combine the SITC, Rev. 3 commodity groups 61 (“Leather, Leather Manufactures, n.e.s., and dressed Furskins”) and 85 (“Footwear”). Thus, this commodity group contains the same goods as the “GP 95” group above.

Source: UN Comtrade database and UN Statistics Division, authors' computation.

Table 5.9: Comparison of Matched Commodity Trade Flows Before and After Hand Allocation

Year	Imports				Exports	
	Intensity		Competition		After Hand Allocation	Before Hand Allocation
	After Hand Allocation	Before Hand Allocation	After Hand Allocation	Before Hand Allocation	After Hand Allocation	Before Hand Allocation
1975	98.54%	43.05%	98.59%	43.24%	97.88%	68.64%
1976	98.44%	42.75%	98.55%	43.00%	98.24%	68.75%
1977	98.21%	48.09%	98.46%	48.48%	98.42%	69.70%
1978	99.30%	45.67%	99.96%	46.37%	99.95%	54.81%
1979	99.38%	44.88%	99.96%	45.50%	99.95%	54.83%
1980	99.73%	43.97%	99.97%	44.24%	99.95%	54.39%
1981	99.76%	42.41%	99.97%	42.65%	99.92%	53.21%
1982	99.76%	42.34%	99.97%	42.57%	99.93%	52.33%
1983	99.75%	43.56%	99.97%	43.81%	99.94%	52.45%
1984	99.76%	44.35%	99.97%	44.59%	99.96%	52.36%
1985	99.74%	44.35%	99.97%	44.61%	99.95%	52.58%
1986	99.72%	48.79%	99.97%	49.07%	99.96%	53.17%
1987	99.73%	49.64%	99.97%	49.91%	99.96%	52.61%
1988	95.15%	48.44%	99.97%	51.46%	99.97%	53.48%
1989	95.45%	48.51%	99.98%	51.41%	99.97%	52.85%
1990	95.13%	47.48%	99.97%	50.60%	99.97%	52.98%
1991	99.89%	60.25%	100.00%	60.45%	100.00%	61.35%
1992	99.87%	61.08%	100.00%	61.22%	100.00%	60.92%
1993	99.89%	61.52%	100.00%	61.47%	100.00%	60.10%
1994	99.86%	62.31%	100.00%	62.26%	100.00%	61.16%
1995	99.88%	63.50%	100.00%	63.43%	100.00%	61.31%
1996	100.00%	78.86%	100.00%	61.51%	100.00%	60.85%
1997	100.00%	78.45%	100.00%	60.91%	100.00%	61.19%
1998	98.63%	80.69%	100.00%	62.05%	100.00%	61.50%
1999	100.00%	80.83%	100.00%	62.43%	100.00%	60.68%
2000	99.52%	78.28%	100.00%	60.63%	100.00%	58.88%
2001	99.49%	77.78%	100.00%	61.00%	100.00%	60.91%
2002	99.46%	93.36%	100.00%	78.98%	100.00%	76.70%
2003	99.48%	93.51%	100.00%	79.18%	100.00%	73.61%
2004	99.50%	93.78%	100.00%	79.40%	100.00%	73.32%
2005	99.54%	93.72%	100.00%	78.57%	100.00%	75.52%
2006	99.59%	93.67%	100.00%	78.40%	100.00%	74.75%
2007	99.56%	93.20%	100.00%	76.32%	100.00%	71.87%
2008	99.60%	79.86%	100.00%	76.11%	100.00%	71.67%
2009	99.56%	82.19%	100.00%	80.70%	94.99%	93.87%
2010	99.65%	81.38%	100.00%	79.90%	94.96%	93.84%
Average	99.18%	64.35%	99.87%	59.07%	99.55%	63.14%

Notes:

In the years from 2002 to 2010 we eliminate imports classified as HSCode 999999 “Commodities not specified according to kind” since we are not able to match these imports with commodities in the Input Statistic at all.

Chapter 6

Eidesstattliche Versicherung

Ich erkläre hiermit, dass ich meine Doktorarbeit “Essays in International Trade” selbständig und ohne fremde Hilfe angefertigt habe und dass ich alle von anderen Autoren wörtlich übernommenen Stellen, wie auch die sich an die Gedanken anderer Autoren eng anlehrenden Ausführungen meiner Arbeit, besonders gekennzeichnet und die Quellen nach den mir angegebenen Richtlinien zitiert habe.

Kiel, March 7, 2019

Dominik M. Boddin

Chapter 7

Hilfsmittel

Die Aufbereitung der Daten, die Erstellung der deskriptiven Statistiken sowie die statistischen und ökonomischen Berechnungen erfolgten vor allem mit der Statistik-Software “STATA 14” und “STATA 15”. In einigen Fällen erfolgte die Datenverarbeitung zudem mit der Statistik-Software “R” und die Erstellung von deskriptiven Statistiken mit “Microsoft Excel”. Das Crawlen der Daten erfolgte mit “Python”. Das vorliegende Dokument wurde mit “TeXShop” erstellt.

Kiel, March 7, 2019

Dominik M. Boddin