Common Language and International Trade

Dissertation zur Erlangung des Grades eines
Doktors der Wirtschaftswissenschaft
eingereicht bei der Fakultät für Wirtschaftswissenschaften
der Universität Regensburg

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Tag der Disputation: 17. Mai 2021

Acknowledgements

This dissertation would not have been possible without the help of many people to whom I owe my deepest gratitude.

First of all, I want to thank my supervisor Professor Dr. Jürgen Jerger for great guidance and immense support during the past years. As a masters student, your lecture and seminar assured me to set my focus on international economics. As a supervisor, you gave the freedom to follow my own research ideas, but also gave helpful advice whenever needed.

I wish to thank my second supervisor Professor Dr. Richard Frensch. I'm grateful for many inspiring and insightful conversations and useful comments that decisively contributed to the successful completion of this dissertation.

I'm also thankful for the support and advice of my colleagues at the University of Regensburg and the Leibniz Institute for East and Southeast European Studies. Although I moved to Ingolstadt during my PhD, thanks to them, Regensburg was not only my place of employment, but still has been a center of my life. Special thanks to my colleagues at the chair of international and monetary economics. It was always a pleasure to work with you.

I want to express my deepest gratitude to my wife for always encouraging and supporting me during my studies. I thank my family, especially my parents, for their support that enabled me to study the fields of economics in my hometown Graz and in Regensburg. I also want to thank my friends that directly and indirectly helped me to accomplish my goals.

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Chapter 1

Introduction

A major problem in the gravity literature on trade is the measurement of international trade barriers. Hence, trade costs are to a large part still a mystery (Anderson and Van Wincoop, 2004). Apart from transport costs, trade is also affected by communication ability, information availability, and mutual trust. In the gravity equation of trade, these factors are usually controlled for by variables that account for other similarities of countries apart from geographical proximity or trade policy, such as colonial past, common religion, ethnicity, or language. Variables that measure common language and linguistic proximity are also suitable proxies for cultural and ethnic boundaries. This resulted in a vast literature on language and trade (Ginsburgh and Weber, 2020).

Despite this extensive research, there are still many open questions regarding the role of language and culture for trade. First, a measurement of common language is not straightforward. Commonly, a dummy is used to account for countries that share the same official (and sometimes native) language. Melitz and Toubal (2014) construct more sophisticated measures by building a worldwide data set on native and spoken languages and considering linguistic proximity between languages and countries. However, until today, these measures could not supersede the official language dummy.

Second, the impact of language on trade seems to depend crucially on the estimation method. Within the last twenty years, there has been a tremendous progress in empirical methodology in the gravity literature. While all language variables perform extremely well in an OLS regression, Melitz and Toubal (2014) show that they are insignificant in Pseudo-Poisson Maximum Likelihood (PPML) and Gamma PML regressions, which had been proposed by Santos Silva and Tenreyro (2006). For a theory-consistent estimation, Egger and Nigai (2015) proposed a two-step CANOVA PPML approach using internal trade. Anderson and Yotov (2016), using this approach, find that the official language dummy is insignificant for most manufacturing sectors.

Hence, the magnitude and relevance of language for trade is still disputable. In the first part of my dissertation, I compare the impact of common language among different measures and estimation methods to explain the varying results in the literature.

Ultimately, I estimate an effect of language consistent with the theory of structural gravity by Anderson and Van Wincoop (2003) with a two-step CANOVA approach and using domestic trade data. To do so, I construct an updated version of Melitz and Toubal's language data set, using both newly available and more detailed data.

The structure of my dissertation is as follows. In chapter 2, I give an overview of the literature on language and trade and a theoretical, yet only verbal, interpretation of the role of communication and informal trust for trade. I further present the developments in the gravity literature, resulting in the Structural Gravity Equation of Trade by Anderson and Van Wincoop (2003). Afterwards, I present my data, collected from various sources, and the language variable construction for the empirical sections in chapter 3.

In chapter 4, I proceed with the econometric analysis. I present the different econometric methods and investigate how the estimation results for language variables are affected by the choice of method in section 4.2. In sections 4.3 and 4.4, I estimate the impact of different language variables in a gravity estimation with international trade in goods as well as in services in a sample covering almost all countries of the world between 1996 and 2016.

In section 4.3.3, I study the impact of language on the extensive and intensive product margins of trade in goods to determine if language impacts trade via the fixed or the variable costs of trade, as suggested by Rubinstein et al. (2008), following the method of Chaney (2008) and Dutt et al. (2013). Finally, I use both intra- and international trade for a theory-consistent estimation of the effect of language on international trade costs in section 4.5.

Until this point, I only considered aggregate trade data. However, Anderson and Yotov (2016) show that the impact of language varies by manufacturing sector, and Nordås (2018) demonstrate the same for service sectors. Therefore, I further investigate the impact of language separately by sector. I further investigate the impact by sector to re-evaluate the mostly insignificant estimates of Anderson and Yotov (2016) in section 4.5.2.

There are further open questions about language and trade I address in my dissertation. First, it might be that the impact of common language variables are only driven by English and other world languages or that these languages are more effective than others. Second, I investigate the impact of world languages in section 4.5.3. Since common language and culture both affect trade and migration, it could be that a language variable to a large part reflects the impact of migration on trade (Melitz and Toubal, 2014). Therefore, I consider the role of migration for the language-trade-relation in section 4.5.4. Translation poses the possibility to overcome language barriers and it is hence sufficient that only a small fraction of the population speaks a foreign language Melitz (2008). I hypothesize that this leads to a decreasing marginal effect of language on trade, which I try to detect in section 4.5.5.

Technological progress led to declining transportation costs in the last decades (Hummels, 2007), but did it also affect other barriers to trade? Observing declining communication costs and more exchange between countries, both regarding goods and people, might lead to the assumption that cultural and ethno-linguistic differences are less important for trade nowadays (Anderson and Yotov, 2016). On the other hand, emerging regionalism and growing trade disputes between countries suggest otherwise. In chapter 5, I therefore take on a historical perspective on the relation between language, culture and trade. In section 5.2, I try to clarify the changing role of language and culture for trade by investigating its effect from the early 1980s until the 2010s.

The estimated effects of common language are implausibly high, "compared to any reasonable accounting of the costs" (Head and Mayer, 2014, p. 189). Controlling for historical trade costs might solve this issue. If trade is determined by the past, as Campbell (2010) has shown, historical relations between linguistically similar countries might prevail. Then, the measured effect of language and other variables is nothing but a relic of past trade relations. Hence, in chapter 5.3, I estimate the effect of language on contemporaneous trade costs by controlling for past trade with a new method by Frensch and Fidrmuc (2020).

Melitz (2008) points out that moving beyond the idea that language is constant would be interesting. One should expect changing trade patterns in a country if foreign language skills change. Until now, the literature has treated language and culture as constant or slow-moving, often because of a lack of time-varying data. However, an individual is able to learn a language in two or three years. The rise of English as a *lingua franca* in the last decades is only one example of relatively rapid changing language skills (Melitz, 2018).

In chapter 6, I thus construct a panel on language data and investigate the effect of changing language skills on trade in over thirty, mostly European, countries from the mid-90s to the beginning of the 2010s. In this period, European countries have witnessed an advancing trade integration and large changes in foreign language skills. An increasing number of people learned to communicate in English. At the same time, Russian knowledge declined in many countries of the former Eastern Bloc. To my knowledge, I am the first who uses time-varying data on language in a gravity framework. By this, I come closer to estimating a causal effect, using country-pair fixed effects to control for historical trade relations that could have caused language skills to increase and time-trends to control for trade integration and general globalization. I also test for strict exogeneity of my language variable with a 'feedback test', proposed by Wooldridge (2002) and already used in the gravity literature by Baier and Bergstrand (2007).

Fidrmuc and Fidrmuc (2016) investigate trade between Eastern and Western European countries, where the Iron Curtain led to an exogenous divergence in language skills. This 'natural experiment' enabled them to estimate a potentially exogenous effect of language on trade. In section 6.5, I revise their empirical findings, using language data from the mid-90s and making use of the most recent methodological developments in gravity literature, following Egger and Nigai (2015).

Chapter 7 summarizes the findings of my dissertation.

Chapter 2

Language in the Gravity Model of Trade

2.1 Literature Review

Controlling for a common language is well established in the empirical trade literature. Usually, the standard gravity equation is extended by a dummy variable that equals one if two countries share a common official or native language. In a meta-analysis, Egger and Lassmann (2012) investigate the estimated effects of a common language dummy in gravity equations from 81 articles. They conclude that a common official or native language increases trade by 44 percent on average.

Starting in the late 1990s, several authors explicitly studied the role of language for international trade to explain the so-called 'mystery of the missing trade' (Trefler, 1995). Boisso and Ferrantino (1997) are the first who use fractional variables that measure the likelihood that two randomly assigned individuals from two country speak the same (native) language. Hutchinson (2002) finds a significant effect of English proficiency for U.S. trade partners. Rauch and Trindade (2002) focus on the effect of ethnic Chinese networks on trade and control for the effect of a common birth language. Wagner et al. (2002) estimate the effect of migration on trade between Canadian provinces and their trading partners but find no additional effect of common language.

Melitz (2008) was the first who described in detail the channels through which language might influences trade. He constructed a worldwide data set on native language and 'open-circuit languages', i.e. official and widely spoken (foreign) languages. His results suggested that both variables have a significant impact on trade volumes, but that the effect of common native language (measured as a fractional variable) is three times larger than the 'open-circuit' dummy variable.

Melitz and Toubal (2014) refine this work and distinguish between official, native and spoken language and linguistic distance. Spoken language includes native and foreign languages, while linguistic distance is a measure of the distance between two languages. Hutchinson (2005) was the first who used a measure of linguistic distance in a gravity equation of trade. This index was based on language test scores by non-native speakers of English from Chiswick and Miller (1998). Melitz and Toubal, however, measure linguistic distance in two distinctive ways: the distance between languages on a language tree and the *Levenshtein distance* between languages. They test their variables in a worldwide sample on international trade in the 2000s. Their language variables have a significant impact on trade in OLS regressions, while the coefficients are insignificant for PPML and Gamma PML. The impact of common native language though disappears once they control for migration. They also find that language plays a larger role for heterogeneous goods, as suggested by Rauch (1999). Melitz and Toubal and Melitz (2008) also test for a particular role of English in foreign trade, but find no evidence. Melitz (2018) summarizes the importance of English as a world language, also apart from trade in goods.

Melitz and Toubal also mention the problem of endogeneity, especially for foreign language skills: Increased trade between countries with different languages might also increase the attractiveness to learn the other's language. In this case, a common spoken language could simply reflect long-lasting trade relations. The following studies address this problem.

Fidrmuc and Fidrmuc (2016) try to estimate the causal effect of spoken language on trade by focusing on a '(quasi-)natural experiment', i.e. a situation in which reverse causality can be ruled out. They find a suitable environment in the trade between Western and Eastern Europe after the Fall of the Iron Curtain. Before 1991, Russian was the prevailing foreign language in the Eastern Bloc due to the predominance of the Soviet Union. In Western Europe, English was the most important foreign language. Fidrmuc and Fidrmuc estimate a relatively high impact of English and German on East-West-trade. French and Russian do not show any significant impact, which is not surprising, given that only few people learned Russian in the West or French in the East.

Egger and Lassmann (2015) study the effect of native language for the Swiss and their trading partners. Three major native languages are prevalent in different parts of the country. The fact that in the internal border regions of these parts the alternate major language is spoken as well enables them to estimate the (cultural) effect of native language on international trade. Their results show an effect on the extensive margin of trade, i.e. the selection of trading partners.

Egger and Toubal (2018) estimate the effects of native and spoken language on the extensive and intensive margins of trade on disaggregated (HS-6-digit-)level. Their findings for a worldwide sample of international trade show that language is a relevant barrier for entering a market, but less so for the volume of trade. This is in line with the results of Rubinstein et al. (2008) and Dutt et al. (2013), which suggest that language mainly impacts fixed trade costs, following the interpretation of Chaney (2008). Egger and Toubal find that spoken language has also a more significant impact on trade than native language.

The aforementioned literature focused on trade in (manufacturing) goods. A strand of the gravity literature also investigated the impact of language on trade in services. Nordås (2018), for example, finds a positive and significant impact of language for trade with the Nordic countries, both on the aggregated level and for most service sectors on the sectoral level.

The effect of language has been studied as well in the migration literature in gravity-like regressions. Belot and Ederveen (2012) find that common language has a significant effect on migration behavior within Europe. Adserà and Pytliková (2015) confirm the importance of language for international migration in a worldwide sample. The well-known migration-trade-link could therefore lead to an overestimation of the language effect on trade. Melitz and Toubal (2014) include migration stocks in one of their specifications, which enters positive and significant and reduces the estimated coefficients for language.

I contribute to this literature by (i) updating Melitz and Toubal's data on native and spoken language, as described in section 3.2. Additionally, I (ii) make use of the most recent developments in gravity estimation to estimate the impact of language on trade and demonstrate the impact of the method on the resulting effect of language. I (iii) also investigate the change in the language effect and the impact of language on contemporaneous trade costs, controlling for past trade costs. I further (iv) study the effect of time-varying language skills, which none of the aforementioned studies has done so far.

2.2 Communication, Trust and Transaction Costs

A common language can influence trade costs via ease of communication, but it also reflects aspects of common culture (Melitz, 2008). Therefore, language can decrease trade costs via higher informal trust between speakers as well. In the following, I give a short intuition why common language, via communication ability and informal trust, should affect international trade.

With informal trust, I refer to intrinsic trust that is established within a certain group and based on common norms and values. Informal trust can be distinguished from formal trust, i.e. the rule of law (den Butter and Mosch, 2003). Importantly, I don't refer to the Whorfian thesis that language has a direct causal effect on cultural norms (Chen, 2013), which theoretical and psycho-linguists are skeptical about (Fabb, 2016). I rather think about common language increasing trust as Melitz (2008) describes it, in the same way as sharing the same religious affiliation, nationality or even having a similar appearance, i.e. via the belief that the other person shares some of my norms and values and is therefore more trustworthy. This belief does not have to rational, of course, but can be based on misinformation or prejudice. Furthermore, easier communication decreases the possibility of misunderstandings and therefore increases trust.

I relate to transaction cost economics (Williamson, 2000) to explain the two channels of communication and trust on trade. In a trade transaction, three stages can be distinguished: (i) contact, (ii) contract and (iii) control. den Butter and Mosch (2003) describe those phases in the following way:

In the contact phase, traders invest in information search on products and possible partner. This information must neither be for free, nor complete or easily accessible. Differences in language, information distribution or business norms increase the search costs. The easier the communication between potential trading partners, the lower the transaction costs in this phase. Additionally, higher trust in the received information decreases the transaction costs.

Rauch (1999), in his network/search view on international trade, describes this contact phase thoroughly: He distinguishes between goods traded on organized exchanges, those that poses 'reference prices' and other goods, such as shoes or cars. Rauch claims that the prices of these 'other goods', also named 'differentiated goods', must be adjusted for various differences in characteristics that also depend on the location. If setting up organized international markets is too costly, especially for differentiated goods, traders engage in a search for buyers and sellers in foreign markets. The search comes to a halt once search costs exceed the expected revenues. Because geographical proximity and a common language facilitates the search process, a trader's network is strongly influenced by these factors, as well as by pre-existing ties. Melitz and Toubal (2014) empirically confirms that common language has a larger impact on differentiated goods. Chaney (2014) develops a network theory of international trade, but only focuses on geographic proximity. Importance of common language in the contact phase would result in a strong impact on the extensive (product) margin of trade, as suggested by Rubinstein et al. (2008). I investigate this hypothesis in section 4.3.3.

After establishing contact, partners must sign a contract. Negotiations about details in the contract impose transaction costs. Due to differences in legal systems and business norms, contracting can be rather complicated in an international context. There can be a trade-off between formal and informal trust as well: writing down every detail creates legal security on one hand, but on the other hand it can give a signal of distrust.

In the control phase, monitoring and enforcing the contract involves transaction costs. The control transaction costs are lower if the partners comply with the terms of the agreement. Trust, both formal and informal, decreases these costs (den Butter and Mosch, 2003).

The idea behind the effect of language on transaction costs via communication is straightforward. To enable contact, to set up a contract and to enforce this contract, the partners must communicate. A common spoken language eases communication and the higher the proficiency level, the easier is communication. Hence, it should be easiest for two native speakers. The more individuals within two groups, e.g. a country's population), speak a common language, the more likely it is that two trading partners drawn from these groups can communicate with each other in one language.

As Melitz (2008) points out, a translation is needed if partners don't speak the same language. Translation complicates the meaning of a common spoken language for two trading partners. A small number of bilinguals could be sufficient to distribute information to both countries. According to Melitz, the absence of a common language can reduce trade insofar as translation is costly and that direct communication is superior to indirect translation. I complement this analysis with the argument that the costs of a translator or an interpreter decrease with the percentage of speakers in a population, assuming a classical market structure on the translation market. Moreover, countries with only few people speaking the same language are still in the contact phase of trade, where common language and culture are larger restrictions according to Rauch (1999).

In general, transaction costs due to communication barriers and informal trust should decrease with the possibility that two individuals randomly drawn from two populations speak the same language. Since a common mother tongue is more related to common cultural and ethnic background than a common foreign language, the informal trust channel might be stronger for common native languages. However, the reasons for learning a foreign language are certainly related to cultural and historical aspects and hence informal trust. Therefore, measuring the effect of common spoken language, which includes foreign languages, on trade also suffers from endogeneity (Melitz and Toubal, 2014). Linguistic proximity between languages should decrease transaction costs in a similar way, by facilitating translation and enhancing trust.

Empirically, trust is difficult to measure and the results from the literature are ambiguous. While several authors find positive and significant effects on trade (den Butter and Mosch, 2003; Guiso et al., 2009), others do not (Spring and Grossmann, 2016). However, the literature has a more unified view on the effect of cultural proximity on trade, although it is at least as hard to measure as informal trust (see Felbermayr and Toubal, 2010; Campbell, 2010; Melitz and Toubal, 2019). There are also hints to substitution effects between informal and formal trust. Yu et al. (2015) find that the role of (informal) trust for trade is smaller when the rule of law functions better.

Egger and Lassmann (2015) control for communication ability to estimate the cultural effect of native language on trade. I control for the channel of informal trust by including variables that account for common religion, common legal systems and colonial past in my regressions.

2.3 The Gravity Equation of Trade

2.3.1 The Development of the Gravity Equation

The gravity equation of trade, first estimated by Tinbergen (1962), assumes that trade can be explained in a similar way as the gravity force between two objects, which rises proportionally with the mass of the objects and inversely with the distance between these objects. Tinbergen takes the economic size of a country, usually measured as GDP, as 'masses' and the geographic distance between (the capitals or main cities of) these countries as 'distance'.

This simple empirical model had surprisingly high explanatory power but lacked theoretical underpinnings for meaningful interpretations. Anderson (1979) and Bergstrand (1985) are early attempts for a theory of gravity. Anderson introduced a first economic model of gravity under the assumption of product differentiation by place of origin, the 'Armington assumption' (Armington, 1969). Because this approach excluded prices, it was criticized by Bergstrand, who developed a model in a Heckscher-Ohlin-framework.

It took about two decades until the importance of the gravity equation was admitted by the 'mainstream' trade economics. One reason for the admission was the 'mystery of missing trade' introduced by Trefler (1995): The Heckscher-Ohlin-Vanek model predicts much higher trade in factor services than is observed. Leamer and Levinsohn (1995) emphasized the role of distance for trade as described in the gravity equation. In the same year, McCallum (1995) used a gravity estimation to reveal the still surprisingly high border effect between the United States and Canada. To put in a nutshell, distance and the gravity equation of trade was accepted as a way to identify and explain several puzzles in trade economics.

What followed was an increase in theoretical and empirical work on the gravity equation. Anderson and Van Wincoop (2003) expanded the work of Anderson and tackled Krugman (1995) critique that bilateral distance is all that matters in the gravity equation, ignoring the relative distance to all other countries. The result was the 'structural gravity equation' which included 'multilateral resistance terms' to capture the remoteness of a country pair to all other countries. Redding and Venables (2004) introduced an easier way to estimate the MR-terms, i.e. by importer(-time) and exporter(-time) fixed effects. Thus, structural gravity was equipped with solid micro-foundations and relatively easy to estimate.

2.3.2 A Model of Structural Gravity

Eaton and Kortum (2002) established a link to the existing trade theory by deriving a gravity equation from a Ricardian model along the line of Dornbusch et al. (1977). Instead of the ad-hoc assumption of product differentiation by country, differences in technology are the drivers of trade in this model. In the following, I shortly describe their gravity model, which leads to the same results as the demand side model of Anderson and Van Wincoop (2003).

This section follows by large Eaton and Kortum (2002). They consider a world consisting of $i = 1, ..., N$ countries. As in Dornbusch et al. (1977), there is a continuum of goods, $l \in [0, 1]$, where country i's productivity in producing good l is denoted with $z_i(l)$. Consumers preferences are assumed to be homothetic and identical across countries. Consumers from country j, by choosing their consumption quantities $q(l)$, maximize the constant elasticity of substitution (CES) utility function:

$$U_j = \left[\int_0^1 q(l)^{\frac{\sigma-1}{\sigma}} \mathrm{d}l \right]^{\frac{\sigma}{\sigma-1}}. \tag{2.1}$$

The elasticity of substitution among different goods l is given by σ. Assuming constant returns to scale, the costs of producing one unit of good l in country i and delivering it to importer country j is given by

$$p_{ij}(l) = \frac{c_i}{z_i(l)} t_{ij}, \tag{2.2}$$

where c_i denotes the input costs in country i and $t_{ij} > 1$ the iceberg trade costs from exporter i to importer j. $p_{ij}(l)$ is what consumers from j pay under assumed perfect competition for good l from country i. However, since consumers can choose from all N countries in the world, the price they pay for good l is $p_j(l) = \min\{p_{ij}(l); i = 1, ..., N\}$.

Country i's efficiency in the production of good l is a realization of a random variable Z_i that is drawn independently for each l from its country-specific probability distribution $F_i(z) = Pr[Z_i \leq z]$. Country i's efficiency is drawn from a Fréchet distribution

$$F_i(z) = e^{-A_i z^{-\theta}}, \tag{2.3}$$

with $A_i > 0$ and $\theta > 1$. Eaton and Kortum (2002) interpret A_i as country i's state of technology, thus reflecting absolute advantage. θ reflects comparative advantages by governing the variation within the distribution. A lower value of θ leads to more heterogeneity and hence a higher incentive to trade.

Following equation 2.2, the cost of a good from country i in country j is the realization of the random variable $P_{ij} = c_i t_{ij} / z_i$ and the lowest price is the realization of $P_j = \min\{P_{ij}; i = 1, ..., N\}$. Replacing z in equation 2.3 using equation 2.2, the distribution of prices is given by $G_{ij}(p) = Pr[P_{ij} \leq p] = 1 - e^{-[\sum_{j=1}^{N} A_i c_i^{-\theta} t_{ij}^{-\theta}] p^{\theta}}$. Therefore, the distribution of prices for which a country j actually buys, $G_j(p) = Pr[P_j \leq p] = 1 - \prod_{j=1}^{N}[1 - G_{ij}(p)]$, simplifies to

$$G_j(p) = 1 - e^{-[\sum_{i=1}^{N} A_i c_i^{-\theta} t_{ij}^{-\theta}] p^{\theta}}. \tag{2.4}$$

This price distribution yields the probability that country i provides good l at the lowest price to country j,

$$\pi_{ij} = \frac{A_i c_i^{-\theta} t_{ij}^{-\theta}}{\sum_{k=1}^{N} A_k c_k^{-\theta} t_{kj}^{-\theta}}, \tag{2.5}$$

which is also the fraction of goods importer j obtains from country i. Multiplying 2.5 with total expenditures of country j, E_j, gives the exports from i to j,

$$X_{ij} = \frac{A_i c_i^{-\theta} t_{ij}^{-\theta}}{\sum_{k=1}^{N} A_k c_k^{-\theta} t_{kj}^{-\theta}} E_j. \tag{2.6}$$

In equilibrium and at delivered prices, the sum of exports from i including to itself, $\sum_{j=1}^{N} X_{ij}$, equal output in i, Y_i.

Anderson and Yotov (2016, pp. 58) show that from this supply side model, one can easily derive the structural gravity equations from Anderson and Van Wincoop (2003):

$$X_{ij} = \frac{Y_i E_j}{Y} \left(\frac{t_{ij}}{\Pi_i P_j} \right)^{-\theta} \tag{2.7}$$

$$\Pi_i^{-\theta} = \sum_{j=1}^{N} \left(\frac{t_{ij}}{P_j} \right)^{-\theta} \frac{E_j}{Y} \tag{2.8}$$

$$P_j^{-\theta} = \sum_{i=1}^{N} \left(\frac{t_{ij}}{\Pi_i} \right)^{-\theta} \frac{Y_i}{Y}, \tag{2.9}$$

where $\theta = 1 - \sigma$, with σ being the elasticity of substitution between all goods in the model of Anderson and Van Wincoop. The theoretical gravity equation 2.7 can be decomposed in a 'size term', which describes the hypothetical level of trade in a frictionless world, and a 'trade cost term' that captures the effects of trade barriers. P_j and Π_i are the structural inward and outward multilateral resistance terms.

2.3.3 General Equilibrium Analysis using Structural Gravity

The effect of changes in trade costs on trade between countries i and j can be calculated as partial equilibrium effects, holding output, expenditures and multilateral resistance terms constant. Taking into account that these variables are also dependent on trade costs, general equilibrium trade and welfare effects can be estimated. This is due to the properties of the multilateral resistance terms and given an estimate of the elasticity of trade with respect to trade costs, σ. However, for theory-consistent and meaningful estimates of multilateral resistance terms, one has to include internal trade (Head and Mayer, 2014).

Baier et al. (2019) derive a simple general equilibrium model, starting from equation 2.6. The model focuses only on trade in final goods. There is just one sector, which best suits aggregated trade. Trade values are normalized by holding total nominal output in the sample constant. Baier et al. assume that labor is the single factor of production and input costs in country i equal wage in country i, $c_i = w_i$. Output is defined as $Y_i \equiv L_i w_i = \sum_{j=1}^{N} X_{ij}$. Expenditures and output of countries i can diverge because of trade imbalances D_i, such that $E_i = Y_i + D_i$. Then, from equation 2.6 it follows that

$$L_i w_i = \sum_{j=1}^{N} \frac{A_i w_i^{-\theta} t_{ij}^{-\theta}}{\sum_{k=1}^{N} A_k w_k^{-\theta} t_{kj}^{-\theta}} (L_j w_j + D_j) \quad \forall i. \tag{2.10}$$

The system of equations in 2.10 can be solved 'in changes', using the 'hat algebra' introduced by Dekle et al. (2007), where $\hat{x} = x'/x$ denotes the difference between the counterfactual, x', and the baseline scenario, x. Given an initial change in trade costs, $\hat{t}_{ij}$, the 'equilibrium in changes' can be written as

$$\hat{w}_i Y_i = \hat{w}_i^{-\theta} \sum_{j=1}^{N} \frac{\pi_{ij} \hat{t}_{ij}^{-\theta}}{\hat{P}_j^{-\theta}} (\hat{w}_j Y_j + D_j) \quad \forall i, \tag{2.11}$$

where $\hat{P}_j^{-\theta} = \sum_{i=1}^{N} \pi_{ij} \hat{w}_j^{-\theta} \hat{t}_{ij}^{-\theta}$. To compute full endowment general equilibrium effects, all that is needed are initial trade shares, π_{ij}, output and expenditure levels, Y_i and E_j respectively, and a set of changes in trade barriers, $\hat{t}_{ij}$.

Difference in welfare between baseline and counterfactual scenario is defined as

$$\hat{W}_i = \hat{E}_i / \hat{P}_i, \tag{2.12}$$

where $\hat{E}_i = (\hat{w}_i Y_i + D_i)/E_i$.

Difference in bilateral exports are given by

$$\hat{X}_{ij} = \frac{\hat{w}_i^{-\theta} \hat{t}_{ij}^{-\theta}}{\hat{P}_j^{-\theta}} \hat{E}_j. \tag{2.13}$$

I make use of this simple model in section 6.4.3 to estimate the trade and welfare effects of a change in spoken language in the sample, using the partial effects obtained in section 6.4.2. For the computation in Stata, I use the `ge_gravity` command by Baier et al. (2019).

Chapter 3

Data and Descriptive Analysis

3.1 Trade Data

My source of data on international bilateral trade in goods is the 2020 version of *CEPII's BACI* database. It contains trade data between over 200 entities[1] and more than 5000 products at HS92 6-digit level between 1995 and 2018. The database is built from *UN Comtrade* data, but corrects for various inconsistencies. Most importantly, it enlarges the country coverage by estimating mirror trade flows, i.e. reported CIF (cost, insurance and freight) imports from country i to j are reported FOB (free-of-board) exports from country j to i (Gaulier and Zignago, 2010). My largest sample on international trade in goods contains 207 countries between 1996 and 2016. Some countries from the original *BACI* trade data have been dropped either because data on explanatory variables is missing or because they dissolved during the observed time span (e.g., Serbia and Montenegro split up in 2006).

The highly disaggregated international trade data enables me to construct measures of the extensive and intensive (product) margin of trade, following Hummels and Klenow (2005). The extensive margin is the number of the up to 5,000 HS-6-product categories traded from exporting to importing country, while the intensive margin is the average trade value by product category. By construction, exports equal the product of extensive and intensive margin. Literature interprets the extensive margin of trade as fixed costs of trade, or entry costs into a market (Dutt et al., 2013). I investigate the effect of language on both margins in section 4.3.3.

In gravity literature, it is common now to include domestic trade for several reasons. First, it is consistent with theory, which includes a country's trade with itself (Yotov et al., 2016). Second, I can account for trade diversion from domestic to international trade (Dai et al., 2014). Third, it enables me to consistently estimate the multilateral resistance terms by importer and exporter fixed effects with a Pseudo-Poisson maximum

[1]For convenience, I call them 'countries', although some of them do not represent independent states.

likelihood estimator (Fally, 2015).

Such internal trade has to be constructed from gross production data, which is for most countries only available for the manufacturing sector. Hence, the literature focuses on trade in manufacturing goods. I use *CEPII's TradeProd* data set for the analysis of international and intra-national trade, which reports data from 1980 to 2006. It consists of international manufacturing trade data from *BACI* and data on gross production from *Worldbank's Trade, Production and Protection* data set from Nicita and Olarreaga (2007) and complements it with data from *OECD* and *UNIDO Indstat*.

I use *BACI* and *UNIDO's Indstat 2* database in the version of 2020 to extend the internal trade data for the period from 2006 to 2018 and add some data for the period between 2000 and 2006. The freely available Indstat 2 database reports data on gross production from 2000 to 2018 by ISIC 3 2-digit code for 174 countries, although there are gaps in the data. I use the *WITS concordance tables* to match manufacturing trade data from *BACI*, reported in HS92 6-digit code, to 23 ISIC 3 2-digit sectors. I construct domestic trade by sector by subtracting total exports by country and sector from gross production. I exclude the ISIC sector 'Recycling', since there is no trade reported for this sector. Finally, to combine my constructed data with the *TradeProd* data, I merge the 22 ISIC 3 2-digit sectors and the 28 ISIC 2 2-digit sectors to the 8 sectors usually used in the gravity literature (Bergstrand et al., 2015; Anderson and Yotov, 2016).[2] Data sometimes differs for the overlap between 2000 and 2006, but a correlation of .999 between *TradeProd* and my data for this period is reassuring. The small differences can be attributed to corrections in newer versions of the *Indstat 2* and *BACI* data on production and trade. Additionally, while *Indstat 2* is reported on ISIC 3, *TradeProd* is reported on ISIC 2. The differences between the versions can lead to minor differences in aggregated internal trade. If there is an overlap, I always chose the data from my constructed data set because *BACI* and *Indstat 2* is corrected *ex-post* and therefore more reliable.

I face the same problems as Nicita and Olarreaga (2007) when they constructed the *Trade, Production and Protection* data set: for some observations, there is no data on internal trade, or it is not positive. This can be due to incomplete or wrong data on gross production if small firms are not covered or production is allocated to the wrong sector. Additionally, there could be discrepancies between the year of production and the year of export. The same problem occurs in *CEPII's TradeProd* data. To handle this issue, I follow in large parts Baier et al. (2019). First, I replace single missing sectors by linear interpolation between years. If internal trade is non-positive for up to three sectors, I replace them by the average expenditure share on domestic products in the respective

[2] The industries are (1) Food, Beverages, and Tobacco Products; (2) Textile, Apparel, and Leather Products; (3) Wood and Wood Products; (4) Paper and Paper Products; (5) Chemicals, Petroleum, Coal, Rubber, and Plastic Products; (6) Other Non-metallic Products; (7) Basic Metal Products; (8) Fabricated Metal Products, Machinery, Equipment. The category 'Other manufacturing' is included in category (8).

year. In some years, there is no data on gross production at all. If the gap is only one year, I linearly inter- and extrapolate aggregated data from adjacent years. Because of the gaps in reported gross production, the coverage of the final data set depends on the chosen period. In 2016, the data includes a maximum of 106 countries.

My source for international trade in services is the *OECD-WTO Balanced Trade in Services Statistics*. The data set provides annual data from 1995-2012, covering 191 economies, broken down for the 11 main EBOPS 2002 service categories. To develop this data set, the *OECD* and *WTO* have leveraged all available official data, and combined these with estimates using derivations, backcasting techniques, interpolation, and predictions derived from regression models. As a result, the data is different from the reported statistics, like in the case of *CEPII's BACI* database (Fortanier et al., 2017).

For the empirical analysis in chapter 4, I use several different data sets. First, I compare different estimation methods for the gravity equation in section 4.2.1. I use balanced cross-country data of 104 countries in the year 2016 on international and domestic trade.

In section 4.3.1, I use a set of international trade in goods from 1996 to 2016. I choose this period because the language data I use has been collected within these 20 years. It contains 207 countries and therefore can draw a broad picture of international trade. I can compare the results with those of the former literature which does not use internal trade data, e.g. Melitz and Toubal (2014). In section 4.3.3, I distinguish between extensive and intensive (product) margin, using the same data set on international trade.

The third data set is a worldwide set of international trade in services for 184 countries from 1996 to 2012, used in section 4.4. Although trade in services seems to be an intuitive choice for trade data analysis when it comes to language and culture, given the importance of communication for services and the growing relevance of trade in services due to technological progress in the last decades, the literature has so far focused mainly on trade in goods.

Another data set contains intra- and international trade data on manufacturing goods from 1996 to 2016. Domestic trade data can be consistently constructed for 78 countries over this period, which capture about 80 percent of worldwide international trade in manufacturing goods.

I construct a last data set for section 5.2. I extend the sample range of intra- and international trade in manufacturing goods as far as possible. I track 55 countries from 1982 to 2012, using data in 6 year intervals to compare effects over time. I choose the years such that the number of countries is maximized. Trade between these countries make up between two thirds and 85 percent of worldwide trade in manufacturing goods, depending on the year.

3.2 Language Data and Variable Construction

3.2.1 Native and Spoken Language worldwide

CEPII provides the most complete data set on native (L1 speakers) and foreign (L2 speakers) languages by country in the gravity literature so far, constructed by Melitz and Toubal (2014). I update and expand their data with new and updated sources. The main source is *Ethnologue*, an annual reference publication of *SIL International* that provides statistics and other information on the living languages of the world. Unfortunately, while the data on native language is the most exact available, data on foreign language is only listed for each country if this language is spoken as a mother tongue as well or if the language is an official language. Therefore, I rely on additional sources for spoken language: national censuses and surveys, the *Arabbarometer*, the *Caucasusbarometer* and new versions of the *Eurobarometer* on languages from 2010 and 2012. I compare the data between these sources, the data from Melitz and Toubal, also updated and reported in Ginsburgh et al. (2017), and the data from the *CIA factbook*. I choose the most reliable and reasonable data, knowing full well that in some cases, it is nothing but a rough estimate and some surveys might be outdated.

I take into account more languages than Melitz and Toubal, especially in African countries. Often, similar languages form a dialect continuum, where many, but sometimes not all, dialects are mutually intelligible. For European languages, such as German or Italian, such differences in dialects are seldom taken into account in surveys. Thus, I am not able to tell apart different dialects of these languages. For other languages, surveys distinguish between dialects, although many linguists consider them as one and the same language or parts of a dialect continuum, e.g. Macedonian and Bulgarian or BCMS, which stands for Bosnian-Croatian-Montenegrin-Serbian and is sometimes dubbed Serbo-Croatian. In such cases, which are especially frequent in Africa, I rely on descriptions in *Ethnologue* and linguistic distances computed by the *Automated Similarity Judgment Program* (ASJP) to judge if two languages are mutually intelligible or not. I am fully aware of the fact that such language classifications can be ambiguous. Therefore, I use an additional measure of linguistic proximity to control for similarities in languages, in the case I wrongly classified some languages.

I construct the same language measures as Melitz and Toubal, i.e. common native (CNL) and common spoken language (CSL) and two measures of linguistic proximity, $LP0$ and $LP1$, comparable to Melitz and Toubals 'linguistic proximity (ASJP)' and 'common language' measure, respectively. I compare these measures to a dummy variable that equals one if two countries have a common official language (COL), the most frequently used language variable in the gravity literature.

There are 7117 known living languages in the world, according to *SIL International*.

language	L1 + L2 speakers (in millions)	L1 speakers (in millions)	number of countries where language is spoken
English	1,357	430	134
Chinese	1,345	1,342	25
Hindi-Urdu	997	584	19
Spanish	531	440	61
Arabic	395	368	54
French	312	98	80
Bengali	281	279	9
Malay	278	79	7
Russian	269	165	41
Portuguese	239	222	21
Punjabi	173	173	5
German	165	93	52

Table 3.1: World languages by speakers and countries

Many of them are spoken by a relatively small number of people, globally speaking. In my data set on native and spoken languages, I only take into account languages that are spoken by more than one percent of the population in at least two countries. Additionally, to measure the linguistic proximity between countries, I also include languages native to at least 4 percent of the population in only one country. Thus, I end up with 195 different languages in my data set. They are listed in table A.1 in appendix A.

Of the 195 languages in the data, several are outstanding in their function as *lingua franca*. Table 3.1 lists the largest languages in the world by number of native and foreign language speakers (L1 and L2 speakers). Of course, the numbers are only estimates. However, it is affirming that they are quite similar to the estimates of *SIL International*.[3] In the third column, I report the estimated number of native speakers (L1 speakers) only. In the last column, I state the number of countries in which the language is spoken according to my data.

With these estimates, I can draw a broad picture of world languages. Indo-European colonial languages, such as English, Spanish and French, are wide spread *linguae francae* and often spoken as foreign language. As a result, they are of high importance for international communication. Speaking English potentially connects an individual to people in 134 countries in the world. Chinese and Hindi-Urdu, despite the high number of speakers, are concentrated on only some large countries. Therefore, their influence on international trade might be limited.

Figure 3.1 shows the spread of English and English Creole and Pidgin languages in the world. For each country in the dataset, it represents the percentage of speakers (again, L1 plus L2). The data is very detailed for European and Arabian countries and

[3]To construct these numbers, I use the percentage of speakers from my data and multiply it with the population of every country in 2015. I only report languages with more than 150 million speakers worldwide. Hindi and Urdu are aggregated to one language, as well as all Chinese dialects. Furthermore, I count all English, French and Portuguese Pidgin and Creole languages as their respective source language for the calculations in table 3.1.

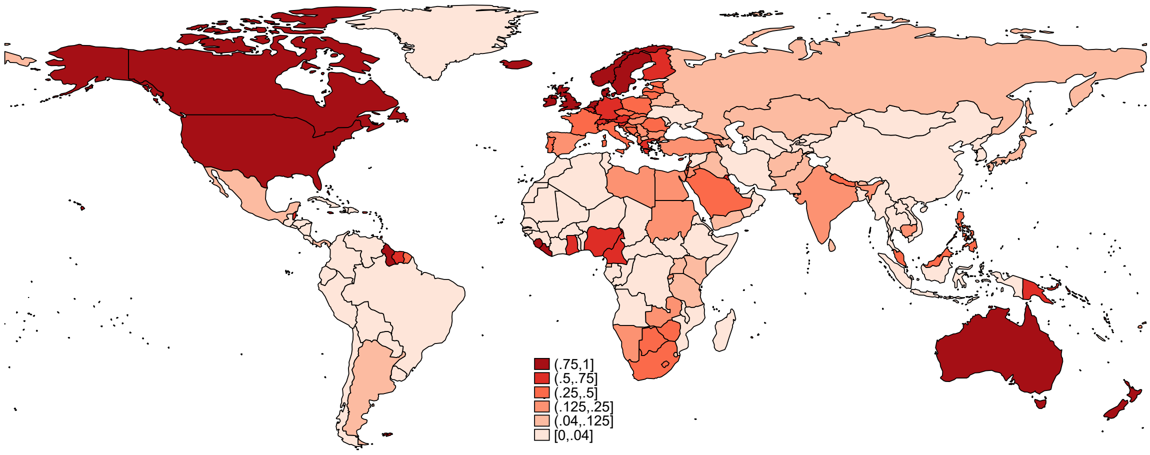

Figure 3.1: Fraction of English speakers worldwide

former British colonies, but might underestimate the number of speakers in countries such as South Korea, were no surveys or reliable estimates on foreign language skills are available. Nevertheless, the map depicts the most important insights on the spread of English: apart from English-speaking countries, English is widely spoken in Germanic countries in Northern and Central Europe. Also in other parts of Europe, English is spoken by a substantial part of the population. English and English Creole and Pidgin languages are commonly spoken in former British and U.S.-American dependencies all over the world, such as India, Malaysia, Nigeria and South Africa. The *Arabbarometer* reveals that English is quite common in Eastern Arabic countries too.

Despite the globally spread knowledge in English, many parts of the world communicate mainly in other international languages. Figure 3.2 presents the percentage of speakers of French and French Creole in the world. Taking a look at Africa, it can be seen that foreign language borders are drawn along the borders of former colonial empires. The colonial languages prevail in spite of policies that are aimed at reducing their incluence. For example, French is no longer an official language in Algeria and the country is not part of the *Organisation internationale de la Francophonie*, French is still spoken by more than half of the population and is still widely used in media, business and as a language of instruction at universities.

Other world languages are regionally important *linguae francae*, as shown by figures in the appendix A. Spanish connects Ibero-America and Spain, and an Spanish speaking minority in the U.S. (see figure A.1), Russian is widespread in Eastern Europe and Central Asia (figure A.2), German in Northern, Central and Eastern Europe, but also in Georgia and Kazakhstan (figure A.3) and Arabic as mainly native language in the Arabian world (figure A.4). Hence, each region of the world has typically one prominent language, but no language is spoken by a substantial part of the population in all countries of the world. It is therefore not surprising that Melitz and Toubal (2014, p. 361) conclude that "[...] all that really matters is a common language, whatever the language may be."

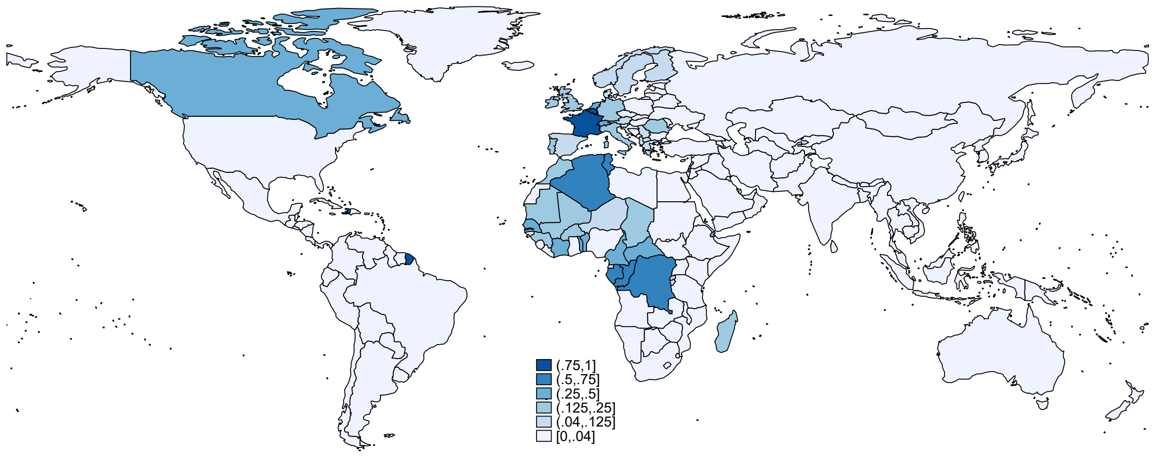

Figure 3.2: Fraction of French speakers worldwide

3.2.2 Intercommunication Distances

I construct five different common language variables to measure linguistic proximity between country pairs. Three of these variables fall into the category of 'intercommunication distances' (Ginsburgh and Weber, 2020, p. 369), i.e. common official, common native and common spoken language. The first variable is the usual common language dummy that equals one if two countries share a common official or widely used language, dubbed COL. I update *CEPII's GeoDist* data set by adding some smaller official languages and relatively new official languages, e.g. the Berber languages in the Maghreb. Furthermore, I introduce the Creole language Papiamento, which is spoken in the Caribbean and listed as Spanish in the data set. I consider 109 official languages, although there are more with regional status, e.g. in India, which are not relevant for international trade since they have an official status in only one country worldwide. The correlation between *CEPII*'s version and mine is .88 for the 207 countries in the whole sample and slightly higher for the smaller samples I use in the empirical part as well.

COL is a measure easily to construct and requires only few, easily available data. On the other hand, it captures linguistic relationships only vaguely. More nuanced measures have been introduced by Melitz and Toubal (2014): Fractional variables that measure the possibility that two randomly assigned people from the populations of the country pair speak the same language. They distinct between two measures: one that only takes into account mother tongues, 'common native language' (CNL), and one that considers foreign language skills as well, 'common spoken language' (CSL).

To construct those variables, one needs data on native and spoken language for all countries in the sample. Both CNL and CSL are constant over time for the worldwide samples. Time-varying data on native and spoken language exists to my knowledge only for a few countries. I further investigate the causes and effects of changing language skills in chapter 6. There, I also describe my panel data set on common language, which is restricted to 32 countries.

Given the data, the construction of a constant CNL and CSL variable is relatively easy. For each language l and exporter i, I multiply the percentage of (native) speakers in the population, L_{il}, with the percentage of (native) speakers of language l in importer's country j, L_{jl}. Then, $\alpha_{ijl} = L_{il}L_{jl}$ is the probability that two individuals drawn randomly from the population speak the same (native) language l. I could now sum up over all languages and receive α_{ij}. In some cases though and especially for CSL, the sum would exceed one, because people can speak more than one language. Since there is no meaningful interpretation for a probability beyond one, some kind of normalization is needed. Melitz and Toubal (2014) pick the language for which α_{ijl} is highest, lets say $max(\alpha)_{ij}$, and compute common language, native or spoken, as $CL_{ij} = max(\alpha)_{ij} + (\alpha_{ij} - max(\alpha)_{ij}))(1 - max(\alpha)_{ij})$. I refine this measure by iteratively calculating CL_{ij} as follows:

$$
\begin{aligned}
CL_{ij,1} &= \alpha_{ij,1} \\
CL_{ij,2} &= CL_{ij,1} + (1 - CL_{ij,1})\alpha_{ij,2} \\
CL_{ij,3} &= CL_{ij,2} + (1 - CL_{ij,2})\alpha_{ij,3} \\
&\;\;\cdots \\
CL_{ij} &= CL_{ij,l-1} + (1 - CL_{ij,l-1})\alpha_{ij,l}
\end{aligned}
$$

For one or two common languages, and thus in most cases, both methods are the same. Even for the rare case that there are three or more common languages for a country pair, e.g. CSL for Belgium and the Netherlands, the measure can never exceed one. In addition, one does not have to assign $max(\alpha)_{ij}$. The measure is always the same, irrespective of the sequence in which the languages l are added.

However, this normalization does not exactly represent the potential language overlap between two or more languages. 'Language Overlap' I define here as the percentage of the population speaking two or more languages that are relevant for the country pair, e.g. Dutch, French, English and German for BEL-NLD. Communication between two individuals needs only one common language, the other languages are redundant. Since I do not have data on the individual level for all country pairs, I have to estimate the language overlap. My method assumes an average overlap, although for most pairs every size of the language overlap is possible, from a total overlap to no overlap at all.[4]

[4] Using the *Eurobarometer* surveys, I construct the percentage of speakers out of data from around 1000 individuals per country. I test my normalization for the afore mentioned country pair BEL-NLD and construct a dummy variable that is one if two individuals from Belgium and the Netherlands speak the same language for each of the about a million possible interactions in this sample. The mean of this dummy over the million observations gives the actual common spoken language I like to capture by CSL. The thus calculated value of CSL is 81,9 percent. My measure estimates CSL as 89,3 percent,

In general, there are many zeros in CNL and CSL. Since CNL and CSL are products of the percentages of speakers, many different combinations can lead to the same value of CNL and CSL. E.g., a value of CSL of 5 percent can be the product of a hundred percent of the population in country i and five percent in country j speaking a common language, or a product of ten percent in i and fifty percent in j. The CNL and CSL measures cannot capture differences of that kind. I experimented with an alternative measure that equals the minimum of the percentage of speakers in both countries. However, this measure performed poorly relative to the CNL and CSL variable described above.

3.2.3 Linguistic Proximity

So far, the constructed variables cover common languages, but do not account for similarities between different languages. In the literature, there are two approaches to account for linguistic distance (or proximity) between languages. Either one distinguishes languages according to their language family and their smaller phylogenetic 'branches' or one uses a distance measure computed by comparative linguistic, usually the *Levenshtein distance* (LD). The first method uses a language tree and assigns a value to two languages according to their 'distance' on the tree. English, for example, is part of the West-Germanic languages, as well as German. Danish, however, is a North-Germanic language, and therefore more distinct from English than German. The main issue with this method is that within certain language families, the similarities are larger than within others. E.g., the Slavic languages are more alike than the Germanic ones. To get a more nuanced picture of language similarities, I therefore construct my linguistic proximity variables using the *Levenshtein distance*.

The LD is defined as the minimum number of successive changes necessary to convert one word of one language into another word of a different language with the same meaning, e.g. the English word 'ear' into the German word 'Ohr' needs two changes. I use the LDND, the so-called *normalized LD divided*, which corrects for word length and chance similarity. To calculate the LD, a word list of at least 28 words for each language is required. The database of the *Automated Similarity Judgment Program* (ASJP) provides word lists and a program to calculate the LDND. I consider 195 different languages that are either spoken in two countries or by at least four percent in any country. Further, there has to be an entry for the language in the ASJP database with at least 28 words. The LDND ranges from 0 to 105, where 0 means all entries in the word lists are the same, i.e. the languages are the same. The higher the value, the more distinct are languages. Mutually intelligible languages not necessarily have a score of zero, because

which suggests an underestimation of the language overlap. If I simply sum up over all languages, $\alpha_{BEL,NLD} = 1.56$. For another country pair, Belgium and France, the corresponding values are 0.825, 0.837 and 1.03, respectively. Given the high computational effort needed, I rather stick to the calculation as described in the main text.

some words can be slightly different without hindering mutual understanding. Therefore, I use the lowest value of LDND in my data set (23.29) as floor instead of zero. To make a comparison with the other language variables easier, I follow Melitz and Toubal (2014) and invert the scale and normalize it to the range of 0 to 1. Thus, I receive a measure of linguistic proximity instead of linguistic distance.

After calculating the linguistic proximity between languages, I have to calculate the linguistic proximity between countries. Following the literature, I calculate the primary language(s) for each countries, according to their largest native languages. I normalize the primary languages such that they sum up to one. E.g., for the U.S., the primary languages are English (.86) and Spanish (.14) and for the UK, the only primary language is English with a value of one. Then, for each language in each country pair, I compute the linguistic proximity. Because both the proximity between languages and the sum of the primary languages neither exceed one nor is lower than zero, the measure of linguistic proximity ranges from 0 to 1. I construct two variables, $LP0$ and $LP1$. $LP0$ serves as an additional variable to count for linguistic proximity besides a common official, native or spoken language. Thus, it only measures linguistic links between different languages and is zero for same languages. $LP0$ is comparable to Melitz and Toubal (2014) LP(ASJP) variable. $LP1$ assumes a linguistic proximity of one for same languages and therefore is closest to Melitz and Toubal's aggregate language index.[5]

Table 3.2 presents the correlations between the five constant language variables for the 207 countries in the sample. The correlations between CNL, CSL and $LP1$ are high. This is not surprising, since CNL is a sub-sample of CSL and $LP1$ is constructed using information on native languages. In conclusion, it is not recommended to use these variables in the same regression because of potential multicollinearity. COL is modestly correlated with CNL, CSL and $LP1$. However, I would be cautious combining it with the other variables. $LP0$ shows no strong correlation with any variable but $LP1$. Therefore, it seems to be suited for its purpose to control for other linguistic linkages. Nevertheless, $LP0$ has a critical relation to CNL: For high values of CNL, such as the pair U.S.-UK, $LP0$ has to be low by design. The low negative correlation between $LP0$ and CNL is due to the fact that for about 75 percent of the observations, CNL is zero, while $LP0$ is not. $LP1$ functions as a remedy to this potential issue and combines CNL and $LP0$.

[5] For the pair UK and U.S., $LP0$ for Spanish and English is $0.14 * 1 * 0.2 = 0.028$, with 0.2 being the inverted and normalized LDND. For $LP1$, I add the common primary language English with weight one, which gives me a value of $0.028 + 0.86 = .888$.

	COL	CNL	CSL	$LP0$	$LP1$
COL	1				
CNL	0.39	1			
CSL	0.47	0.63	1		
$LP0$	0.06	-0.05	0.12	1	
$LP1$	0.38	0.81	0.60	0.49	1

Table 3.2: Correlations between language variables

	COL	CNL	CSL	$LP0$	$LP1$
COL	1				
CNL	0.45	1			
CSL	0.53	0.64	1		
$LP0$	-0.20	-0.30	0.01	1	
$LP1$	0.39	0.88	0.67	0.14	1

Table 3.3: Correlations for alternative language classification

3.2.4 Alternative Language Classification

I count Creole and Pidgin languages[6] as distinct from their respective source language. In the following, I present a different language classification, which counts Creole and Pidgin languages as their respective source language, as it is done in *CEPII*'s language data set and Melitz and Toubal (2014).

I consider several Creole and Pidgin languages in my data that origin from English, French and Portuguese, as well as Afrikaans, a Dutch Creole language. If I follow Melitz and Toubal and treat Pidgin, Creole and source languages as mutually intelligible, all language variables except for COL change. I keep only Papiamento as separate language, which is mainly a mixture of Spain and Portuguese, but also influences by Dutch. Therefore, it is not possible to assign it to a single source language.

Creole or Pidgin languages and their respective source languages, e.g. Haitian Creole and French, are, although linguistically close to each other, usually not mutually intelligible. According to the ASJP database, the LDND between Haitian Creole and French is 49, about the same LDND as German and Dutch, two distinct languages. Afrikaans is the closest to its source language, Dutch, with an LDND of 35. These LDND scores are clearly higher than for languages that are considered to be the same, such as Bosnian and Croatian (15) and Catalan and Valencian (19). Creole and Pidgin languages are not only often sufficiently different from their respective source language, but from each other as well. The LDND for Haitian and Seychellois Creole is 58, for example. Thus, from a linguistic point of view, it might be wrong to subsume all Creole and Pidgin languages with a common source languages as one and equal to their respective source language.

Correlations between the language variables are of course affected by this alternative

[6]Sometimes, Creole and Pidgin are distinguished on the ground that Creole languages can be native languages and Pidgin cannot. Since *Ethnologue* reports native speakers for Pidgin languages as well, I do not follow this distinction.

classification, as shown in table 3.3. The correlation of $LP0$ with COL and CNL is more negative and lower for CSL and $LP1$, compared to table 3.2. Many very similar languages in overseas territories and former colonies are counted as the same and thus increase CNL and CSL, but less so linguistic proximity, since they are quite close to their source language. As a result, mean and variance of CNL and CSL are slightly higher, while they are lower for $LP0$. The afore mentioned negative relation between CNL and $LP0$ is more pronounced. The correlation between *CEPII*'s prox2 and $LP0$ is .77 and higher than for my classification, where it is only .57.

Since Creole and source languages are usually not mutually intelligible, I stick to my original classification. However, it is important to note that the classification of languages is neither a trivial nor an unambiguous task. In section 4.3.2, I use the alternative language classification to investigate the difference to mine in the estimation results.

3.3 Control Variables

The standard gravity variables are from *CEPII's Gravity* database. I update their data on colonial past by adding new data from `www.worldstatesmen.org`, the main source of *CEPII's Gravity* data set (Mayer and Zignago, 2011). I construct a dummy variable that equals one if two countries have been in a colonial relationship after 1945 ($COLPOST45$) or are currently in a colonial relationship ($COLCUR$, used in section 5.2) and another variable that equals one if two countries had the same colonizer after 1945 ($SIBPOST45$). Additionally, I construct a dummy ($EMPIREBEFORE45$) that equals one if two countries belonged to the same (colonial) empire between 1815 (after the Congress of Vienna) and 1945, which I use in section 6.5. I add data on *CEPII*'s other gravity variables ($CONTIG$, $COMLEG$, $COMCUR$, $GATT/WTO$ and EU) as well. $CONTIG$ is a dummy variable that equals on if two countries are contiguous, i.e. the share a border. The variable $COMLEG$ is constructed out of two variables from CEPII and equals one if countries share common legal origins, before or after transition. $COMCUR$, also a dummy, equals one if two countries use the same currency. $GATT/WTO$ and EU equal one if both countries are members of the WTO (General Agreement on Tariffs and Trade before 1995) or of the European Union, respectively. Data on regional trade agreements (RTA) are from *Mario Larch's Regional Trade Agreements Database* from Egger and Larch (2008). Since new members of the European Union usually signed a trade agreement with the EU before their accession, RTA and EU are distinct variables in a panel estimation.

For the logarithm of geographic distance ($LNDIST$), I use *CEPII*'s population weighted bilateral distances. For some country pairs, data is missing. I fill those gaps by following the construction of *CEPII*'s distance measure (Mayer and Zignago, 2011). I use data on population and location of up to 25 most populated cities per country from the *GeoNames* geographical database on `www.geonames.org`, just as they do.[7] For each country pair, I calculate the greater circle distance between each possible city pair. Then, I construct geographic distance between countries as the population weighted average between the calculated distances of all city pairs. For internal distance, I use the same method, but use the greater circle distances between the cities of the same country. The correlation between *CEPII*'s data and my data is almost one. I follow Eaton and Kortum (2002) and assume a non-constant distance elasticity. Hence, I split the distance variable into six intervals.[8]

To control for other cultural influences, I use a fractional common religion variable ($RELIG$), which represents the probability that two randomly drawn individuals from two countries have the same religious affiliation. The definition of 'same religious affiliation' is difficult, since major religions, such as Christianity, Islam or Buddhism, are subdivided into many different families and denominations. Although different religion families share many common norms and ideas, conflicts have often arisen between them. Thus, the cultural and historical differences between these subdivisions might be of higher importance for economic relations than their common beliefs and practices. Therefore, I use the latter definition and count, e.g., two catholic Christians as members of the same religion, but not a catholic and a protestant.

My main source of religious affiliation, the *World Religion Data* from Maoz and Henderson (2013), divides the world religions roughly into several subdivisions. In my data set, Christianity is divided into Catholic, Orthodox, Protestant and Others. Islam is divided into Sunni, Shia and Others and Buddhism into Mahayana (North-Eastern), Theravada (Southern) and Others. There is no subdivision for Hinduism and Judaism. I also include smaller religions such as Taoism, Shinto or Sikh.

Data and estimates on bilateral migration stock is from the *UN Population Division, Trends in International Migration Stocks* from 2015, and supplemented by the *Worldbank's Bilateral Migration Matrix*. UN's data set includes estimates in five year intervals, starting in 1990. The *Bilateral Migration Matrix* reports estimates based on various sources for 2013 and 2017. The data set includes bilateral migration between 202 countries in the period from 1996 to 2016. However, more than half of the entries are zeros.

Table 3.4 presents the summary statistics of the explanatory variables used in my empirical analysis for the data on 207 countries from 1996-2006. Each of the 255,852 observations in the data presents one country pair in a single year. The means of CNL and CSL are relatively low because they are zero for many country pairs, for about 75

[7] I use only data from cities with more than 1000 inhabitants or which are administrative centers. For many small countries, especially islands, there are less than 25 cities that fulfill these requirements. For those countries that are merged in *CEPII's BACI* trade data set, e.g. Belgium-Luxembourg, I calculate distances as if they where one country. I.e., Luxembourg is then counted as one of the major cities in the constructed country Belgium-Luxembourg.

[8] Given the maximum distance of 20000 km, the intervals are: [0 km, 625 km), [625 km, 1250 km), [1250 km, 2500 km), [2500 km, 5000 km), [5000 km, 10000 km), [10000 km, 20000 km).

Variable	Range	Mean	Std. Dev.	Min	Max
$LNDIST$		8.844	0.759	4.013	9.897
$CONTIG$	$\{0, 1\}$	0.013	0.112	0	1
$COMLEG$	$\{0, 1\}$	0.366	0.482	0	1
$COLPOST45$	$\{0, 1\}$	0.007	0.083	0	1
$SIBPOST45$	$\{0, 1\}$	0.118	0.322	0	1
$GATT/WTO$	$\{0, 1\}$	0.457	0.498	0	1
RTA	$\{0, 1\}$	0.145	0.352	0	1
$COMCUR$	$\{0, 1\}$	0.011	0.104	0	1
EU	$\{0, 1\}$	0.011	0.106	0	1
$RELIG$	$[0, 1]$	0.155	0.200	0	0.980
COL	$\{0, 1\}$	0.179	0.383	0	1
CNL	$[0, 1]$	0.027	0.127	0	1
CSL	$[0, 1]$	0.115	0.216	0	1
$LP0$	$[0, 1)$	0.155	0.085	0	0.888
$LP1$	$(0, 1]$	0.180	0.144	0.047	1

Table 3.4: Summary statistics of exogenous variables

percent for CNL and about 40 percent for CSL, respectively. Additionally, the values are larger than 0.5 for only a small part of the observations. Naturally, the mean of CSL is larger than the mean of CNL since $CSL \geq CNL$ for all observation. $LP0$ never equals one by construction, since this would mean that everyone in two countries speaks the same language, a case that cannot be captured by $LP0$ since it only takes into account different languages. On the other hand, $LP1$ is never zero because either there is at least some linguistic proximity between different languages in two countries or a small part of people from two countries speak the same mother tongue.[9]

I report the correlations between exogenous variables for the sample of 207 countries in the years 1996 to 2016 in table A.2 in appendix A. They are small to modest, but the negative correlation between $LNDIST$ and many other variables is worth mentioning. Geographic proximity does not only influence trade, but also economic and political interaction (RTA, EU, $COMCUR$) and the spread of language, culture and religion. There is also a certain degree of correlation between language, religion and history variables. In many cases, a former colony kept the hegemons language as official language. E.g., in the French colonial empire, Catholicism as French's state religion and the French language and culture spread over the same countries.

[9] Actually, there is one possibility where $LP0$ would equal one. For Niue and Tavaluan, the highest ASJP value, linguistic proximity is normalized to one. Hence $LP0$ would equal one if all people of one country speak Niue and everyone in another country speaks Tavaluan. The same is true for the minimum of $LP1$, which would equal zero if everyone would speak Ukrainian in one country and Kabiye in another one. Obviously neither of these cases is empirically relevant.

Chapter 4

Re-Estimation of the Role of Language for Trade

4.1 Introduction

In the previous chapters, I gave a short overview over the literature on language and trade and the gravity equation of trade, and I presented my data. Now, I proceed with the econometric analysis in this chapter. I recapitulate some of the previous empirical findings on the effect of language on trade and investigate some new hypotheses.

The literature presented in section 2.1 found mixed results regarding the significance of language. The chosen method seems to be crucial, since Melitz and Toubal (2014) find a highly significant, positive and large effect for one-step OLS, but not for PPML or GPML. The results also seem to be sensitive to the inclusion of domestic trade in the gravity equation. Anderson and Yotov (2016) find no effect of language for most manufacturing sectors, using internal trade and a two-step CANOVA approach proposed by Egger and Nigai (2015). Consequently, the role of language for trade needs to be clarified, using the most recent theoretical and empirical findings.

Besides the method used, there are other possible reasons for the mixed results. One might be the measure of intercommunication distances and linguistic proximity. Maybe a simple dummy, the most commonly used variable for language, captures information on (ethno-)linguistic ties poorly. Thus, I test the fractional measures presented in section 3.2 and compare them to a common language dummy, which they have so far not superseded in the empirical literature on trade.

This chapter is structured as follows. In section 4.2, I present the different econometric methods and investigate how the estimation results for a language variables are affected by the choice of method. Then, I choose the best suited method based on theory and empirical results and present the regression model for the subsequent sections. In section 4.3, I estimate the impact of the different language variables in a gravity estimation with international trade in all goods in a sample covering almost all countries of the world between 1996 and 2016. This approach is closest to Melitz and Toubal (2014), therefore it is possible to directly compare my results to their findings to either confirm or dismiss them. Then, I study the impact of language on the extensive and intensive product margins of trade to determine if language impacts trade via the fixed or the variable costs of trade (Chaney, 2008; Dutt et al., 2013). In section 4.4, I also estimate the effect of language on international trade in services. Finally, I use both intra- and international trade for a theory-consistent estimation of international trade costs in section 4.5. In this section, I further investigate the results on sectoral level, since Anderson and Yotov (2016) find significant results of a language dummy for only three out of eight sectors. Again, I compare the fractional language variables to the standard dummy variable to see if they perform better. Next, I focus on the impact of world languages and consider the role of migration for the language-trade-relationship. Thereafter, I try to detect a decreasing marginal effect of language on trade, as proposed in section 2.2.

4.2 Empirical Approach

4.2.1 Method Comparison

To re-estimate the effect of language on trade, I use the structural gravity equation described in section 2.3. The first suspect regarding the ambiguous results for language on trade, summarized in section 2, is the estimation method. Melitz and Toubal (2014) found large discrepancies between various estimators proposed by the literature, i.e. OLS, Pseudo-Poisson maximum likelihood (PPML) and Gamma PML (GPML). Anderson and Yotov (2016) find no significant effect of language, using the two step CANOVA approach proposed by Egger and Nigai (2015). In the following, I compare results for OLS, PPML and GPML estimator in one-step and two-step procedures. For the example of common official language, I show that the method has a critical impact on the resulting estimate of the effect of language on trade.

Gravity regressions have usually been estimated with OLS by taking the log-normal form of the gravity equation instead of the multiplicative form. This method was criticized by Santos Silva and Tenreyro (2006), since the conditional expectation of the logarithm of the error term in such an equation depends on the variance. Hence if the variance of a multiplicative equation depends on the regressors, i.e. heteroscedasticity is prevailing, the expected value of the logarithm of the error term will depend on the explanatory variables as well and the estimated coefficients will be biased. While earlier papers circumvent this problem with NLS, Santos Silva and Tenreyro (2006) propose a Pseudo Poisson Maximum Likelihood (PPML) estimator. It's 'pseudo' because one does not have to assume a restrictive Poisson distribution. The correct estimate of the mean is sufficient for consistent, asymptotically normal estimators. The same is true for the gamma Pseudo (or Quasi-)ML (GPML) estimator, which was introduced as alternative by Santos Silva and Tenreyro. Another advantage of the PPML and GPML estimator is the possible inclusion of zeros, which are common in trade. In a Monte Carlo simulation, they show that PPML and GPML are robust to various assumption about the variance, while OLS and NLS perform rather poorly under heteroscedasticity.

Another advantage of PPML has been pointed out by Fally (2015). OLS estimation procedures that are consistent with structural gravity, such as those proposed by Anderson and Van Wincoop (2003) and Head and Mayer (2014), are quite complex, since the inward and outward multilateral resistance terms, P_i and Π_i, require certain equilibrium constraints on output and expenditure, Y_i and E_j. Fally (2015) shows that for PPML, these adding-up-constraints are automatically satisfied by importer(-time) and exporter(-time) fixed effects. For PPML, fitted output and expenditure equal observed output and expenditure, i.e., $Y_i = \hat{Y}_i = \sum_j \hat{X}_{ij}$ and $E_j = \hat{E}_j = \sum_i \hat{X}_{ij}$.[1] Consistent data on domestic trade is needed to fulfill these conditions, since they constitute a considerable part of Y_i and E_j.[2] For the same reason, it is important that the sample includes a large fraction of worldwide trade. Domestic trade has to be constructed out of gross production data, as described in 3.1.

The results of a PPML gravity estimation are usually quite distinct from those of an OLS estimation. In a Monte Carlo simulation, Head and Mayer (2014) demonstrate that PPML is severely biased under mis-specification. In their simulation, the low distance elasticity of -.7 does only occur if the distance elasticity is not constant, and does not disappear with increasing sample size. PPML puts more weight on large trade flows than GPML and OLS, leading to a lower estimate of the distance elasticity for PPML if the effect of distance is non-constant, i.e. lower for large trade flows (Fally, 2015).

Egger and Nigai (2015) propose an explanation for and a remedy to this problem. The same properties that lead to the advantageous results shown by Fally are the reason for the bias under mis-specification. They demonstrate that the usual parameterized approach leaves a significant part of trade costs unexplained. Because the multilateral

[1] Furthermore, he shows that PPML is the only estimator that fulfills these conditions. That is because PPML's moment condition leads to $\sum_j \hat{X}_{ij} = \sum_j X_{ij}$. Contrary to that, for OLS it must hold that $\sum_j \ln(\hat{X}_{ij}) = \sum_j \ln(X_{ij})$, but because of Jensen's Inequality, $\ln(\sum_j \hat{X}_{ij}) \neq \ln(\sum_j X_{ij})$ and thus $\sum_j \hat{X}_{ij} \neq \sum_j X_{ij}$. The same problem arises for GPML, since the moment condition and variance to mean ratio of OLS and GPML are (approximately) the same (Head and Mayer, 2014). In appendix B, I report the deviance of fitted output to observed output for one-step OLS and GPML for the sample used in this section.

[2] E.g., gross production in the U.S. in 2016 is five times larger than total exports, which leads to domestic trade being four times total exports. As a result, the estimated importer and exporter fixed effects and the estimated international trade costs change substantially if internal trade is included. Without domestic trade, U.S.' total exports would be somewhat smaller than Germany's total exports, although U.S.' gross production is 2.5-times larger. Not including internal trade therefore distorts multilateral trade resistance and actual trade costs such that they are underestimated for relatively less open economies, as for the U.S. in the above example.

resistance terms are a function of the trade costs and PPML with fixed effects 'forces' the data to fit, a wrong estimate of the trade cost terms lead to wrong estimates of the multilateral resistance terms by fixed effects and therefore to biased estimates that are not consistent with the theory of structural gravity.

Egger and Nigai (2015) propose a two-step CANOVA approach as solution. First, they decompose the data into multilateral resistance terms, estimated by importer(-time) and exporter(-time) fixed effects, and trade cost terms estimated by country-pair (time) fixed effects, using the adding-up properties of PPML. The estimation with pair fixed effects leaves a smaller (or even no) part of the bilateral trade costs unexplained, compared to a parametric regression. A saturated CANOVA approach uses all available degrees of freedom to estimate (time-variant) directional trade cost terms, which results in a full decomposition, while an unsaturated CANOVA approach does not. The former can only be used with data on domestic trade, i.e $(T) \times N \times N$ observations. In this section and also some subsequent sections, I use domestic trade, but I have concerns about singletons due to frequent zeros of trade, which can cause separation if I perform a full decomposition (Correia, 2015; Correia and Guimarães, 2019). I drop the observations that might cause separation, which leaves me with less than $(T) \times N \times N$ observations that are necessary for a saturated approach. Therefore, I always perform an unsaturated CANOVA estimation in this chapter by either estimating symmetric trade cost terms in cross-country regressions or estimating asymmetric, but constant trade costs with panel data.

In the second step, Egger and Nigai (2015) regress the estimated trade cost terms on the standard gravity variables. Egger and Nigai, as well as other authors (Anderson and Yotov, 2016; Kharel, 2019) use PPML in the second step. In this section, I estimate the second step with OLS, PPML and GPML, since theory does neither suggest nor exclude any structure of the bilateral trade costs t_{ij}. If the mis-specification bias is solved by the two-step approach, at least the distance elasticity should be similar between PPML and GPML. OLS might still be biased due to heteroscedasticity in estimated trade costs Head and Mayer (2014, p. 177).

Next, I compare the results for one-step and the two-step procedures and also the three different estimators, i.e. OLS, PPML and GPML. I use international and internal trade as dependent variable, as described in section 3.1. To reduce the number of fixed effects for computational reasons, I restrict my sample in this section to one year, 2016. In this year, I am able to construct domestic trade for 106 countries.

$$\log X_{ij} = \nu_i + \zeta_j + \beta_{COL} COL_{ij} + \beta_k K_{ij} + \epsilon_{ij} \tag{4.1}$$

$$X_{ij} = \exp\left(\nu_i + \zeta_j + \beta_{COL} COL_{ij} + \beta_k K_{ij} + \epsilon_{ij}\right) \tag{4.2}$$

The log-linearized one-step regression model, described in equation 4.1, is used for the OLS estimator, whereas the exponential model, 4.2, is used for PPML and GPML. I regress X_{ij} on the common official language dummy, COL_{ij}, which is the most used language variable in gravity literature, and a set of explanatory variables, K_{ij}. K_{ij} contains constant geographical variables ($LNDIST$ and $CONTIG$), political variables (RTA, WTO and $COMCUR$) and cultural or historical variables ($COMLEG$, $COLPOST45$, $SIBPOST45$ and $RELIG$), described in 3.3. I do not include EU though, since EU membership is already included as membership in a preferential trade agreement in RTA. Multilateral resistance terms are estimated by exporter and importer fixed effects, ν_i and ζ_j.

For the single step estimates, I include a dummy, $DOMESTIC$, that equals one for domestic trade to control for any differences between internal and international trade. Additionally, I estimate the effects of distance and religion separately for domestic trade, since both are non-zero for observations $i = i$. Since for OLS, the dependent variable is $\log X_{ij}$, 25 observations with no trade are dropped from the regression. This small difference in observations has no significant impact on the results.

$$X_{ij} = \exp\left(\mu_i + \pi_j + \delta_{ij} + e_{ij}\right) \tag{4.3}$$

$$\log \hat{\delta}_{ij} = \nu_i + \zeta_j + \beta_{COL} COL_{ij} + \beta_k K_{ij} + \epsilon_{ij} \tag{4.4}$$

$$\hat{\delta}_{ij} = \exp\left(\nu_i + \zeta_j + \beta_{COL} COL_{ij} + \beta_k K_{ij} + \epsilon_{ij}\right) \tag{4.5}$$

The first step of the CANOVA approach is described in model 4.3. I decompose trade, X_{ij}, by exporter fixed effects, μ_i, importer fixed effects, π_j, and symmetric country pair fixed effects, δ_{ij}. Since this is an unsaturated approach, there is an error term, e_{ij}, included. I estimate the first step with PPML, which can correctly decompose trade according to Egger and Nigai (2015). The Imputed R^2 for the first step is almost one, hence the unexplained part of trade is negligible.

I follow Anderson and Yotov (2016) and drop internal trade in the second step of the CANOVA approach. Since trade costs are estimated relative to domestic trade, internal trade costs $\exp(\delta_{ii}) = 0 \forall i$.[3] Then, I include importer and exporter fixed effects that account for country-specific trade costs in the second step. These country fixed effects differ from the fixed effects that represent inward and outward multilateral resistance terms in the first step, since the former are zero for domestic trade and the latter are not (Egger and Nigai, 2015, footnote 18).[4]

[3] I use the `ppmlhdfe` command in Stata 16.1, which works somewhat differently than the `ppml` commands The estimated country-pair fixed effects are not zero for internal trade, so I have to normalize them *ex post*. After normalization, the estimated trade costs terms from `ppmlhdfe` equal those from `ppml`.

[4] Alternatively, one can keep the domestic trade observations and set the importer and exporter fixed

In the second step, I regress estimated trade costs, $\hat{\delta}_{ij}$ for PPML and GPML in model 4.5 and $\log \hat{\delta}_{ij}$ for OLS in model 4.4, on the same variables as in the one-step regressions, except for $DOMESTIC$ and the separate estimates for intra-national distance and religion. Country pairs with zeros of trade in both directions and other observations that could cause separation are dropped in the second step.

Table 4.1, columns (1)-(3) reports the one step estimates with OLS, PPML and GPML, respectively. The results for OLS in column (1) are in line with the literature, with a distance elasticity of about one for all intervals. The effects of the standard gravity variables are all significant. The PPML result for distance in column (2) is a bit larger than in Anderson and Van Wincoop (2003) or Fally (2015). This is presumably due to use of distance intervals, which surprisingly reveal a decreasing distance elasticity for PPML. In the third column, I report the results for GPML. For most variables, the coefficients are similar to OLS, while PPML results differ strongly from both OLS and GPML. This hints to the mis-specification bias for PPML found by Head and Mayer (2014). The coefficient of COL for PPML is smaller compared to OLS and GPML, but still significant, in line with Fally (2015, table 1). The high R^2 for PPML is due the already mentioned fact that PPML 'forces' the data to fit by its adding-up constraint.

Columns (4)-(6) report the results for the second stage of the CANOVA approach. The distance elasticity is again about one for OLS in column (4), but reduces slightly. For PPML in column (5), distance elasticity is now constant and also slightly larger. In column (6), the distance elasticity for GPML is smaller than in column (3), closer to the result for PPML, but increasing with distance. Except for the effect of a WTO membership, which reduces for all two-step procedures, the coefficients in the OLS regression are almost unchanged. GPML results are more different now from OLS than in the one-step regressions. The results for PPML change for almost all variables. A common currency has a significant negative impact now, a common legal origin is positive and significant. The coefficients of the colonial variables and regional trade agreements are similar to those for GPML in column (6). However, COL has no impact in column (5).

PPML is quite sensitive to the inclusion of internal trade. If I exclude domestic trade, the results change for most variables, as shown in table B.1 in appendix B. The coefficient of COL is not much affected for OLS and GPML. For PPML, however, the coefficient of COL turns insignificant and even slightly negative in the one-step estimation in column (3), confirming the PPML results of Melitz and Toubal (2014). The distance elasticity decreases to the well known result of about 0.7. In columns (4)-(6), I exclude domestic trade in the first step. The effect of COL for PPML is now positive and significant. Again, OLS and GPML are not affected much by the exclusion of internal trade.

Which of the estimators is the proper one to use? The OLS results are astonishingly

effects to zero for internal trade in the second step (Egger and Nigai, 2015). The results are exactly the same.

	One-step procedures			Two-step procedures		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	PPML	GPML	OLS	PPML	GPML
	$\ln(X_{ij})$	X_{ij}	X_{ij}	$\hat{\delta}_{ij}$	$\exp(\hat{\delta}_{ij})$	$\exp(\hat{\delta}_{ij})$
COL	0.54	0.23	0.53	0.56	0.01	0.53
	(0.07)***	(0.11)**	(0.08)***	(0.07)***	(0.07)	(0.07)***
$LNDIST[0,625]$	-1.04	-0.95	-0.96	-1.01	-0.92	-0.80
	(0.11)***	(0.19)***	(0.12)***	(0.09)***	(0.09)***	(0.09)***
$LNDIST]625,1250]$	-1.05	-0.89	-1.05	-1.01	-0.92	-0.88
	(0.10)***	(0.17)***	(0.10)***	(0.08)***	(0.08)***	(0.08)***
$LNDIST]1250,2500]$	-1.08	-0.90	-1.09	-1.05	-0.94	-0.93
	(0.09)***	(0.16)***	(0.09)***	(0.08)***	(0.07)***	(0.08)***
$LNDIST]2500,5000]$	-1.08	-0.86	-1.10	-1.03	-0.93	-0.96
	(0.08)***	(0.14)***	(0.09)***	(0.07)***	(0.07)***	(0.07)***
$LNDIST]5000,10000]$	-1.09	-0.86	-1.11	-1.05	-0.94	-0.98
	(0.08)***	(0.13)***	(0.08)***	(0.06)***	(0.06)***	(0.06)***
$LNDIST]10000,20000]$	-1.09	-0.83	-1.10	-1.05	-0.91	-0.96
	(0.07)***	(0.13)***	(0.08)***	(0.06)***	(0.06)***	(0.06)***
$LNDIST\_INTRA$	-0.65	-0.16	-1.65			
	(0.24)***	(0.07)**	(0.42)***			
$CONTIG$	0.64	0.51	0.69	0.66	0.40	0.76
	(0.11)***	(0.17)***	(0.13)***	(0.11)***	(0.07)***	(0.11)***
$GATT/WTO$	0.98	1.30	0.58	-0.05	0.72	-0.27
	(0.21)***	(0.11)***	(0.25)**	(0.19)	(0.22)***	(0.16)*
RTA	0.56	0.15	0.53	0.57	0.36	0.46
	(0.04)***	(0.07)**	(0.05)***	(0.04)***	(0.06)***	(0.04)***
$COMCUR$	-0.43	0.14	-0.35	-0.49	-0.38	-0.27
	(0.08)***	(0.10)	(0.10)***	(0.07)***	(0.07)***	(0.07)***
$COMLEG$	0.20	0.01	0.21	0.23	0.17	0.23
	(0.04)***	(0.06)	(0.04)***	(0.03)***	(0.03)***	(0.03)***
$COLPOST45$	0.97	-0.10	0.77	0.99	0.91	0.82
	(0.14)***	(0.24)	(0.15)***	(0.12)***	(0.08)***	(0.12)***
$SIBPOST45$	1.18	0.31	0.84	1.10	0.83	0.80
	(0.09)***	(0.15)**	(0.09)***	(0.08)***	(0.08)***	(0.07)***
$RELIG$	0.51	0.63	0.54	0.48	0.72	0.69
	(0.09)***	(0.19)***	(0.10)***	(0.08)***	(0.09)***	(0.08)***
$RELIG\_INTRA$	3.18	2.08	2.27			
	(1.04)***	(0.24)***	(1.42)			
$DOMESTIC$	1.07	-1.58	7.88			
	(1.59)	(1.11)	(2.59)***			
Observations	10,211	11,236	11,236	10,582	10,582	10,582
Imputed R^2	0.850	0.997	0.813	0.765	0.797	0.709
CNL	0.94	0.46	0.90	1.09	0.40	0.99
	(0.14)***	(0.14)***	(0.15)***	(0.11)***	(0.14)***	(0.13)***
CSL	1.03	0.50	0.86	0.93	0.76	0.89
	(0.09)***	(0.14)***	(0.11)***	(0.08)***	(0.10)***	(0.09)***
$LP1$	1.13	0.71	1.12	1.12	0.61	1.08
	(0.12)***	(0.15)***	(0.14)***	(0.10)***	(0.11)***	(0.12)***

Results for importer and exporter fixed effects are excluded for brevity. The lower panel reports the results for other language variables, excluding results for covariates for brevity. Robust standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 4.1: Method comparison

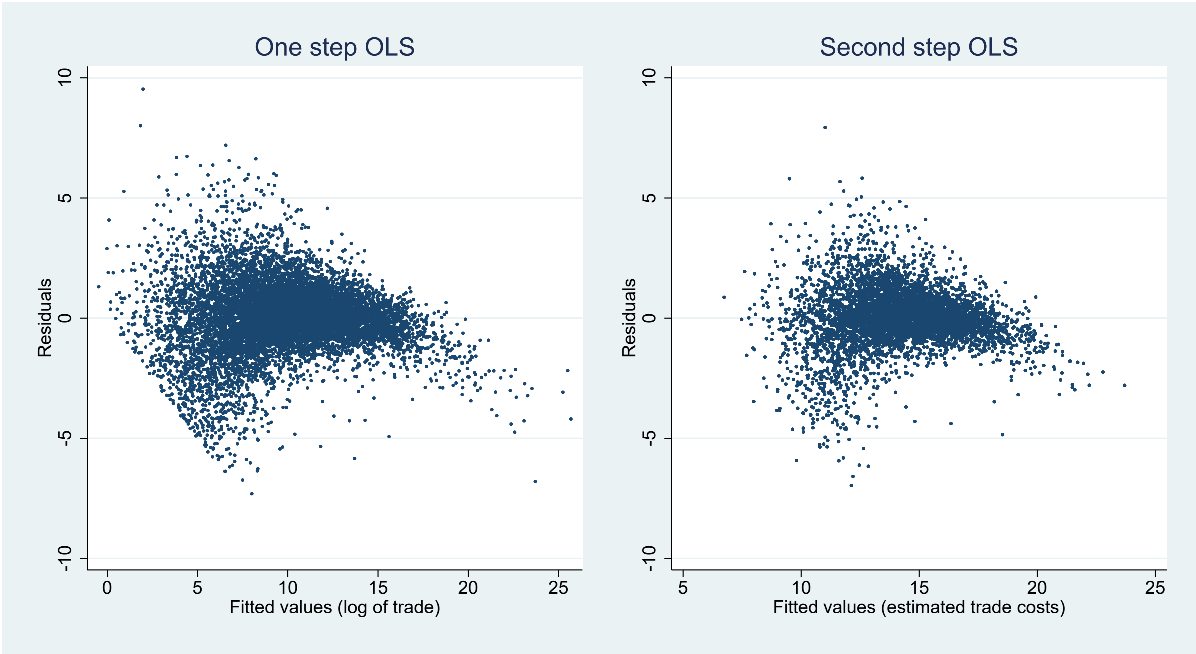

Figure 4.1: Heterogeneity in trade data

robust to method and the inclusion of domestic trade. A Breusch-Pagan test[5] however clearly rejects the assumption of homoscedasticity for both one-step and two-step OLS regressions with a p-value of less than 0.0001. Under these circumstances, OLS would be inconsistent (Santos Silva and Tenreyro, 2006). Figure 4.1 illustrates the heteroscedasticity of the trade data. The variance is clearly larger for small trade values (costs) than for larger values. Furthermore, it can be seen that OLS underestimates large trade observations. The seemingly cut-off part in the left panel results from the fact that, because of log-linearization, exports, i.e. fitted values plus residuals, have to be larger than zero in the OLS regression.

(Head and Mayer, 2014, pp. 175) show that a (one-step) PPML underestimates the impact of distance in case of a model mis-specification, as in column (2), and Egger and Nigai (2015) show that trade cost estimates are biased in a one step PPML. Therefore, I rule out a one-step PPML as well. The GPML results in columns (3) and (6) are not biased due to heteroscedasticity. Nevertheless, GPML does not possess the preferable features of PPML described by Fally (2015), i.e. that multilateral resistance terms can be directly estimated by importer and exporter fixed effects in a one-step procedure. Therefore, an estimation method as in column (3) might not be appropriate. Results for GPML in column (6) sometimes differ significantly from those in column (3), suggesting that a one-step GPML estimator probably fails to decompose trade correctly. Thus,

[5]Santos Silva and Tenreyro (2006) and Head and Mayer (2014) use a Park-like test, which is sometimes criticized because the null hypothesis must be stronger than homoscedasticity and using OLS residuals can cause the F statistic to deviate from the F distribution (Wooldridge, 2012, p. 288).

and because of the theoretical arguments put forward by Egger and Nigai, I prefer the two-step estimation for GPML and PPML over one-step estimations.

The coefficients for PPML and GPML in columns (5) and (6) differ substantially for some variables, such as COL or $GATT/WTO$. To decide between both methods, I take a look at the Imputed R^2:[6] PPML clearly outperforms GPML in the two-step regression. I also compare the degrees of freedom adjusted deviance, which is remarkably lower for PPML (0.004) than for GPML (1.405). This is also true for the estimates without internal costs in table B.1, with a df-adjusted deviance of 0.517 for PPML and 1.401 for GPML. Thus, I follow Egger and Nigai (2015) and use their CANOVA approach with PPML in both steps. Nevertheless, the divergent results for GPML might be of concern for future research.

For the regularly used common language dummy, the result of this section is apparently unfavorable: A common official language does not increase trade at all in the two-stage CANOVA regression with PPML. Anderson and Yotov (2016) draw the same conclusion. They explain this result with the emerging vertical disintegration of manufacturing and the increasing trade between the global North and South over the last decades, which both led to the decreasing importance of linguistic linkages. This explanation is puzzling, since the most recent literature on language and trade investigate the same time period, but finds significant results. I have shown that the reason for the different results lies in the methodology. The usage of the PPML estimator, a two stage CANOVA approach and the inclusion of domestic trade all alter the result for the often used common language dummy.

I re-estimate the regressions with each of the alternative variables proposed by Melitz and Toubal (2014) separately, instead of COL, and report them in the lower panel of table 4.1. I omit the results for the covariates and do not report the Imputed R^2, since the results are similar to those presented in the upper panel. Each language variable has a positive and significant impact on trade, independent of the estimation method. The coefficients from the PPML regressions are nevertheless smaller than those estimated with OLS and GPML. Without domestic trade, CNL, CSL and $LP1$ are insignificant in a one-step PPML regression, just as COL (see lower panel of table B.1 in appendix B). This again confirms the PPML results of Melitz and Toubal. I further study and interpret the various measures of common language in a larger panel data set in the next sections.

[6] I follow Santos Silva and Tenreyro (2006) and use the square of the correlation between trade (cost terms) and fitted values.

4.2.2 Regression Model

In the further sections 4.3, 4.4 and 4.5, I use the unsaturated two-step CANOVA approach to estimate the effects of language on trade, using panel data from 1996 to 2016 (2012 for trade in services in section 4.4). Contrary to Melitz and Toubal (2014), who use consecutive trade data from 1998-2007, I use 4-year intervals. Fixed effects estimation applied to data pooled over consecutive years is sometimes criticized because dependent and independent variables cannot fully adjust in a single year's time (Trefler, 2004; Cheng and Wall, 2005).

$$X_{ij,t} = \exp\left(\mu_{i,t} + \pi_{j,t} + \delta_{ij} + \beta_z Z_{ij,t} + \epsilon_{ij,t}\right) \tag{4.6}$$

The model of the first step is presented in 4.6. I regress exports between exporter i and importer j in year t, $X_{ij,t}$, on a set of exporter-time ($\mu_{i,t}$), importer-time ($\pi_{j,t}$) and asymmetric country-pair fixed effects, δ_{ij}. I include a set of time-varying explanatory variables, $Z_{ij,t}$, that control for trade policy changes over time. $Z_{ij,t}$ consists of dummies that equal one if a regional trade agreement is in place (RTA) or both countries are members of the WTO (WTO), the European Union (EU) or a currency union ($COMCUR$). Additionally, I include one lag of EU and RTA to account for 'phasing-in' effects (Baier and Bergstrand, 2007).

Since bilateral trade can be relatively volatile compared to other economic measures, such as GDP, I estimate average trade costs over the period by constant, directional country-pair fixed effects, δ_{ij}. I estimate $2NT$ importer-time and exporter-time fixed effects and $N(N-1)$ asymmetric, but constant country-pair fixed effects for international trade. In the regressions that include domestic trade, these pair fixed effects are estimated relative to internal trade.

I follow the suggestion of Egger (2004) and split the time-varying variables into two components, a time-varying (within) part and a time-invariant (between) part. For the first step, I use only the difference to the first period, 1996, which represents the time-varying part. Hence, apart from the lagged variables, the time-invariant effect of already existing memberships in GATT, currency unions, free trade agreements and the European Union is captured in the second step. The first step results are unaffected by this procedure, whereas the estimated trade cost terms would differ. As a result, the coefficients of $GATT/WTO$, $COMCUR$, FTA and EU would be downward biased and the estimated coefficients of the other variables would be affected as well.

$$\hat{\delta}_{ij} = \exp\left(\nu_i + \zeta_j + \beta_{Lang} Lang_{ij} + \beta_k K_{ij} + \epsilon_{ij}\right) \tag{4.7}$$

In a second step, described in equation 4.7, I regress the estimated constant asymmetric pair fixed effects, $\hat{\delta}_{ij}$, on a set of importer and exporter fixed effects, my constant language variables, $Lang_{ij}$, and the same set of gravity variables from equations 4.5, K_{ij}. Following Anderson and Yotov (2016), I include regional trade agreements and GATT/WTO membership before 1996 as explanatory variables. To avoid multicollinearity between the language variables, I estimate their respective effect separately.

4.3 International Trade in Goods

4.3.1 Melitz and Toubal (2014) Revisited

Melitz and Toubal (2014) introduced new measures of common language and linguistic proximity and test them on panel data on international trade in goods, using consecutive years from 1998 to 2007 in one-step OLS, PPML and GPML regressions. Solely their OLS results are significant and robust. In this section, I re-evaluate their findings with the two step CANOVA approach and the model presented in section 4.2 and the updated language variables from section 3.2. Melitz and Toubal include international trade in all goods categories between 195 countries. For most of those countries, internal trade cannot be constructed due to missing data on gross domestic production. Since I want to directly compare Melitz and Toubal's results to mine, I use only international trade data in all goods categories between 207 countries in the period between 1996 and 2016.

With the $N = 207$ countries and $T = 6$ time periods (1996, 2000, 2004, 2008, 2012 and 2016), the sample contains $TN(N-1) = 255,852$ observations in the first step. The `ppmlhdfe` command's algorithm drops $62,112$ observations that are either singletons or separated by a fixed effect. The latter are dropped since they could cause non-existence of the Maximum Likelihood estimator (Correia and Guimarães, 2019). These observations are usually zeros of trade in all T in a uni-directional country pair. As a result, the estimation uses $193,740$ observations to estimate $32,290$ directional trade costs terms for the second step.

Table 4.2, column (1), reports the result for the time-varying variables in the first step estimation. The estimated coefficients can be interpreted as average partial effects (Baier and Bergstrand, 2007). Only membership in the European Union has a significant impact on trade. In section 4.5, I show that the effect of regional trade agreements turns positive and significant once I include domestic trade. The imputed R^2 is close to one, hence the bias due to unobservable trade costs should be very small and the estimated pair fixed effects, $\hat{\delta}_{ij}$, should resemble the actual constant directional trade cost terms.

In the second step, I regress the estimated trade costs terms on my language measures and the controls. Table 4.3 displays the results for the language variables COL, CNL, CSL, $LP0$ and $LP1$, respectively. I compare my results to table 3 and table 5 (for $LP1$) in Melitz and Toubal (2014).

In column (1), the coefficient of COL is highly significant. Since the coefficients

	(1) $X_{ij,t}^{All,Inter}$	(2) $X_{ij,t}^{All,ExtMargin}$	(3) $X_{ij,t}^{All,IntMargin}$
$GATT/WTO_t$	0.08	0.10	-0.37
	(0.07)	(0.03)***	(0.27)
$COMCUR_t$	-0.03	0.04	0.03
	(0.03)	(0.01)***	(0.10)
RTA_t	0.05	-0.04	0.04
	(0.03)	(0.01)***	(0.08)
RTA_{t-4}	-0.01	-0.05	0.10
	(0.03)	(0.01)***	(0.09)
EU_t	0.13	-0.02	0.32
	(0.04)***	(0.02)	(0.12)**
EU_{t-4}	0.07	-0.00	0.10
	(0.03)***	(0.01)	(0.10)
Observations	193,740	193,740	193,740
Imputed R^2	0.993	0.986	0.910

Results for importer-time, exporter-time and asymmetric country-pair fixed effects are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 4.2: International trade in goods, first step

display semi-elasticities, a common official language on trade is *ceteris paribus* associated with $(\exp(0.54) - 1) \times 100 = 72$ percent more trade. The effect is larger than in the meta-analysis of Egger and Lassmann (2012), the OLS estimate of 51 percent in Melitz and Toubal (2014) and the estimate for the smaller sample in 2016, reported in appendix B.

In column (2) of table 4.3, the positive coefficient of CNL is not significant. The significant effect of CSL in column (3) can be interpreted in the following way: A ten percentage points higher probability that two randomly drawn people from both populations speak the same language *ceteris paribus* is correlated with $(\exp(0.46) - 1) \times 10 = 5.8$ percent more trade. If I control for linguistic proximity between different languages in (4) and (5), the effects of CSL and CNL slightly increase and both are significant, although $LP0$ itself has no significant effect on trade. Interestingly, adding linguistic proximity in Melitz and Toubal (2014) decreased the impact of CNL and CSL in a one-step PPML estimation, while the opposite was true for their OLS estimates.

In this respect, my results are in line with Melitz and Toubal's OLS estimation, except for the insignificance of $LP0$. Therefore, they seem to confirm the interpretation given by Melitz and Toubal (2014, p. 356): "[T]he importance of native language only emerges once we recognize gradations in linguistic proximity between different native languages and we cease to suppose a sharp cleavage between the presence and absence of a CNL." So the fact that CNL is about 70 percent for the pair UK-U.S. relative to less than 5 percent for UK-DE might not be important for trade. Only by taking into account that German is a language similar to English (both are West Germanic languages), the

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: $\exp(\hat{\delta}_{ij}^{All})$						
COL	0.54					
	$(0.10)^{***}$					
CNL		0.31		0.38		
		(0.23)		$(0.18)^{**}$		
CSL			0.39		0.46	
			$(0.20)^{**}$		$(0.21)^{**}$	
$LP0$				0.26	0.34	
				(0.69)	(0.73)	
$LP1$						0.61
						$(0.22)^{***}$
$LNDIST[0,625]$	-0.61	-0.57	-0.57	-0.56	-0.57	-0.55
	$(0.14)^{***}$	$(0.14)^{***}$	$(0.14)^{***}$	$(0.14)^{***}$	$(0.14)^{***}$	$(0.15)^{***}$
$LNDIST]625,1250]$	-0.65	-0.61	-0.61	-0.61	-0.61	-0.59
	$(0.13)^{***}$	$(0.13)^{***}$	$(0.13)^{***}$	$(0.13)^{***}$	$(0.13)^{***}$	$(0.13)^{***}$
$LNDIST]1250,2500]$	-0.69	-0.65	-0.66	-0.65	-0.66	-0.64
	$(0.12)^{***}$	$(0.12)^{***}$	$(0.12)^{***}$	$(0.12)^{***}$	$(0.12)^{***}$	$(0.12)^{***}$
$LNDIST]2500,5000]$	-0.75	-0.71	-0.71	-0.71	-0.71	-0.70
	$(0.11)^{***}$	$(0.11)^{***}$	$(0.11)^{***}$	$(0.11)^{***}$	$(0.11)^{***}$	$(0.12)^{***}$
$LNDIST]5000,10000]$	-0.72	-0.69	-0.69	-0.69	-0.69	-0.68
	$(0.11)^{***}$	$(0.10)^{***}$	$(0.11)^{***}$	$(0.11)^{***}$	$(0.11)^{***}$	$(0.11)^{***}$
$LNDIST]10000,20000]$	-0.77	-0.74	-0.74	-0.74	-0.74	-0.73
	$(0.09)^{***}$	$(0.09)^{***}$	$(0.09)^{***}$	$(0.09)^{***}$	$(0.10)^{***}$	$(0.10)^{***}$
$CONTIG$	0.45	0.48	0.46	0.47	0.45	0.45
	$(0.13)^{***}$	$(0.13)^{***}$	$(0.14)^{***}$	$(0.12)^{***}$	$(0.12)^{***}$	$(0.13)^{***}$
$GATT/WTO$	0.72	0.71	0.72	0.72	0.73	0.71
	$(0.30)^{**}$	$(0.31)^{**}$	$(0.32)^{**}$	$(0.31)^{**}$	$(0.32)^{**}$	$(0.30)^{**}$
RTA	0.63	0.65	0.64	0.65	0.63	0.64
	$(0.12)^{***}$	$(0.12)^{***}$	$(0.12)^{***}$	$(0.12)^{***}$	$(0.13)^{***}$	$(0.12)^{***}$
$COMCUR$	0.38	0.52	0.53	0.53	0.55	0.52
	(0.26)	$(0.26)^{**}$	$(0.26)^{**}$	$(0.25)^{**}$	$(0.25)^{**}$	$(0.25)^{**}$
$COMLEG$	-0.15	-0.05	-0.07	-0.06	-0.08	-0.07
	(0.10)	(0.09)	(0.09)	(0.10)	(0.10)	(0.09)
$COLPOST45$	0.70	0.81	0.77	0.81	0.76	0.80
	$(0.16)^{***}$	$(0.17)^{***}$	$(0.17)^{***}$	$(0.17)^{***}$	$(0.17)^{***}$	$(0.17)^{***}$
$SIBPOST45$	0.43	0.58	0.53	0.57	0.52	0.57
	$(0.14)^{***}$	$(0.16)^{***}$	$(0.16)^{***}$	$(0.15)^{***}$	$(0.15)^{***}$	$(0.15)^{***}$
$RELIG$	0.70	0.77	0.74	0.74	0.70	0.63
	$(0.22)^{***}$	$(0.27)^{***}$	$(0.26)^{***}$	$(0.22)^{***}$	$(0.22)^{***}$	$(0.21)^{***}$
Observations	32,290	32,290	32,290	32,290	32,290	32,290
Imputed R^2	0.781	0.775	0.775	0.768	0.765	0.776

Results for importer and exporter fixed effects are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 4.3: International trade in goods, second step

difference in CNL becomes significant.[7]

To a certain degree, the same is true for CSL, because CSL includes CNL. On the other hand, learning a foreign language is easier if this language is similar to the mother tongue. Ginsburgh et al. (2017) confirm that foreign language knowledge is higher for

[7] $LP0$ is .43 between the United Kingdom and Germany, while it is only .03 between the United Kingdom and the United States.

countries whose main languages are more alike. As a result, CSL already reflects part of $LP0$. Therefore, it performs better than CNL by itself and is not affected as much as CNL if $LP0$ is included.

$LP1$ in column (6) directly measures linguistic proximity without separating common languages from distinct ones. *Ceteris paribus*, a ten percentage points higher linguistic proximity increases trade by $(\exp(0.61)-1)\times 10 = 8.4$ percent. The effect is higher than those of CNL and CSL, which might be explained by the extent of $LP1$: It captures not only linguistic, but ethnic, historical and cultural linkages. This is also reflected by the reduced impact of the other cultural variable, $RELIG$. Both the spread of language and religion is governed by similar influences, mainly geography and history, as can be seen in the modest correlation for $LNDIST$, $LP1$ and $RELIG$ in table A.2.

Compared to the OLS result of Melitz and Toubal (2014, table 5, col. 1), the effect of $LP1$ is smaller. The same is true for CNL and CSL compared to Melitz and Toubal (2014, table 3). In section 4.2.1, I have shown that this is most likely due to the estimation method. Following Santos Silva and Tenreyro (2006) and Head and Mayer (2014), the OLS estimates could be inconsistent and biased upwards because of heteroscedasticity in a log-linear model.

Interestingly, the distance elasticity is non-constant and around 0.7, in contrast to the CANOVA regression without internal trade in the appendix B to the method comparison from section 4.2.1. The coefficients of all other controls have the expected sign, a reasonable magnitude and are significant, except for $COMLEG$. In column (1), the effects of colonial linkages and common currency are smaller than in the other regressions. Obviously, this is due by the fact that most former colonies kept their respective colonial language as official language, although only part of the population is able to communicate in it and even fewer people speak it as mother tongue. Furthermore, former French colonies in Western and Central Africa all still use the CFA Franc, which was/is bound to the franc/Euro. Thus, COL and $COMCUR$ are more correlated with the colonial past than the other language variables, and COL might capture part of their effect on trade.

4.3.2 Results for an Alternative Language Specification

As explained in section 3.2.4, Melitz and Toubal (2014) use a different language classification, where Creole and Pidgin languages are counted as their respective source language. In this section, I show that this alternative classification has a strong effect on the empirical outcomes. In the first stage, nothing changes. Table 4.4 presents the estimates of the second stage for international trade in all goods. The results can be directly compared to table 4.3. COL, however, does not change with the language classification. I do not report results for control variables, since they are similar to those in table 4.3.

The effect of common native language in column (2) does not change much in magni-

	(1)	(2)	(3)	(4)	(5)
Dependent variable: $\exp(\hat{\delta}_{ij}^{All})$					
CNL_SOURCE	0.38		0.52		
	$(0.17)^{**}$		$(0.21)^{**}$		
CSL_SOURCE		0.72		0.78	
		$(0.15)^{***}$		$(0.15)^{***}$	
LP_SOURCE			0.49	0.39	
			(0.41)	(0.37)	
$LP1\_SOURCE$					0.67
					$(0.24)^{***}$
Observations	32,290	32,290	32,290	32,290	32,290
Imputed R^2	0.775	0.771	0.774	0.770	0.776

Results for importer and exporter fixed effects are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 4.4: International trade in goods, second step, alternative language classification

tude, but is estimated precisely now. Adding $LP0$ in column (3) again increases the effect of CNL, now even to $(\exp(0.52)-1)*10 = 6.8$ percent for a ten percentage points higher CNL. A remarkable change in magnitude happens to CSL. In column (4), a ten percentage points higher CSL is, *ceteris paribus*, associated with $(\exp(0.78)-1)*10 = 11.8$ percent higher trade. Since $LP1$ is almost the same for both classifications, the estimated effect in (5) is similar to the one in table 4.3. The effect of $LP0$ increases, but is still not significant at the five percent level.

The reason for the better performance of CNL and CSL can be explained by the simultaneous presence of source and Creole/Pidgin language in former colonies. According to my data, in those countries only a few, if any, speak the former colonial language as mother tongue. The respective Creole languages are more common as native languages. E.g., CNL is zero between the United Kingdom and Nigeria, but in the alternative language classification, CNL is about .19, since in 2005 some estimated 30 million people spoke Nigerian Pidgin as mother tongue in Nigeria. Additional 60 million Nigerians spoke English as a foreign language, which leads to a CSL of .45 for UK and Nigeria in my original classification. If I add the 30 million Pidgin speakers, CSL raises to two thirds.

Despite the better performance of CNL and CSL, I do not doubt the classification of Pidgin and Creole languages as languages of their own in my data set for the reasons I have already given in section 3.2. There might be some reasons to doubt the numbers reported in *Ethnologue*. The gradations of Creole languages, local dialects and the source language is sometimes difficult to determine. E.g. for Nigeria, it is hard to distinguish English speakers from those who speak a nativized English dialect and those who speak a Nigerian Pidgin. The sharp distinction between nativized Nigerian Pidgin and English, which is only spoken as secondary language, most likely does not represent the more complex reality. In this respect, the estimates from table 4.3 present a lower bound and those from 4.4 an upper bound for the importance of common native and spoken language for international trade in goods.

In conclusion, I can confirm Melitz and Toubal (2014) results. Language, however measured, plays a significant role for international trade in goods. One critique is that neither them nor I use internal trade and therefore, the results are not consistent with theory. Furthermore, they might be biased due to mis-specification in the first step, resulting from the omission of internal trade. I tackle this issue in section 4.5.

4.3.3 The Extensive and Intensive Product Margin of Trade

Rauch (1999) suggests that common language is of particular importance in the contact phase of trade, as described in section 2.2. To test this hypothesis, I measure the impact of language on fixed trade costs by distinguishing between extensive and intensive product margin of trade in this section.

Evenett and Venables (2002) document a reduction of zero trade observations from 1970 to 1997, which I can confirm for the period of 1996 to 2016 (see table 4.7 in the next section). This observation can be explained by decreasing fixed entry costs into a foreign market (Hummels and Klenow, 2005) or by growing networks of trade (Chaney, 2014). To explain zeros of trade by fixed costs, Rubinstein et al. (2008) estimate the impact of gravity variables on the probability that two countries trade with each other in a probit model. They conclude that cultural variables, such as common language and religion, mainly affect fixed costs of trade, but not variable costs.

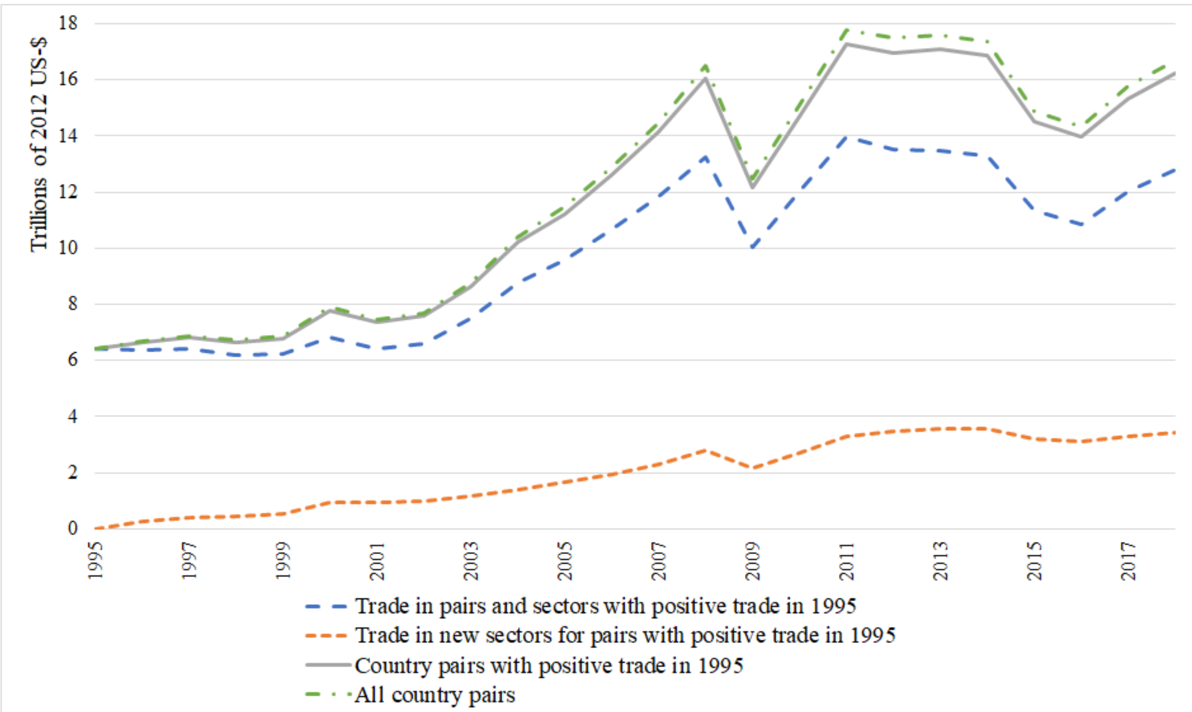

Figure 4.2: Intensive and extensive product margins from 1995 to 2017

The impact of a reduction in fixed trade costs has been studied theoretically by several papers (Melitz, 2003; Bernard et al., 2003; Chaney, 2008). Chaney demonstrates in a Krugman (1980) model of international trade with firm heterogeneity, that a change in fixed costs does solely affect the extensive margin of trade. Empirically, Hummels and Klenow (2005, p. 718) "[...] find that the extensive margin accounts for 62 percent of the greater exports of larger economies." Kehoe and Ruhl (2013), using U.S. import data, show that the extensive margin contributes to trade growth for countries that underwent trade policy or technology changes. Dutt et al. (2013) investigate the effect of WTO membership on extensive and intensive margin and conclude, in line with Chaney, that WTO raises the extensive margin of trade and therefore reduces fixed costs, while the intensive margin is negatively affected.

Dutt et al. (2013, fig. 1) show for the period from 1970 to 2000 that trade between country pairs that already traded before 1970 grow mainly along the extensive margin, while the intensive margin stayed relatively constant. Unfortunately, the figure does not include trade for the huge trade boost in the beginning of the new century. Figure 4.2 re-does this exercise for trade values between 1995 and 2018, measured in constant 2012 U.S. dollars.[8] The gray, solid line displays total trade between country pairs that already traded in 1995. Like Dutt et al., I divide the trade growth between these pairs into trade in old sectors already traded in 1995, represented by the blue, dashed line, and trade in new sectors, which is portrayed by the orange line with short dashes. Until the turn of the millennium, the trends are in line with Dutt et al. and trade in new sectors drives growth, while trade in previously traded sectors stays constant. The main driver of the large trade boost in the new century, though, is trade in old sectors. However, this trade sectors are hit hard by the trade collapse in 2009 and later in 2015, when trade fell due to oil price shocks and economic slowdown in emerging economies (WTO, 2016). Trade in new sectors is less affected, and constantly grows at a smaller rate. Additionally, I display trade growth for all country pairs, including those that did not trade in 1995, by the green line with dots and dashes. Trade growth with new partners, i.e. the difference between the green and the gray, solid, line, are rather small. This is in line with the findings for trade before 1995 in Rubinstein et al. (2008, fig. 2). This is still puzzling, given that in the mid-90s, there was no trade for almost 45 percent of all country pairs worldwide. By 2012, however, this number fell to less than 30 percent. Growth at the extensive margin thus also captures the increasing trade integration over the past decades. Trade in new sectors with old and new partners combined grew by almost 4 trillions of 2012 U.S. dollars, accounting for about 38 percent of global trade growth.

To estimate the impact of language on the trade margins, I use the same sample of 207 countries between 1996 and 2016 as in section 4.3.1. I divide it into extensive and

[8] *CEPII's BACI* trade data is in nominal U.S. dollars. I deflate the data using the U.S. GDP deflator from the *U.S. Bureau of Economic Analysis.* (U.S. Bureau of Economic Analysis, Gross domestic product (implicit price deflator), retrieved from *FRED, Federal Reserve Bank of St. Louis*; `https://fred.stlouisfed.org`, on November 22, 2020.)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: $\exp(\hat{\delta}_{ij}^{All,ExtMargin})$						
COL	0.42					
	(0.04)***					
CNL		0.47		0.58		
		(0.07)***		(0.07)***		
CSL			0.47		0.52	
			(0.06)***		(0.06)***	
$LP0$				0.46	0.32	
				(0.13)***	(0.13)**	
$LP1$						0.54
						(0.07)***
$LNDIST[0,625]$	-0.63	-0.59	-0.60	-0.58	-0.60	-0.59
	(0.07)***	(0.07)***	(0.07)***	(0.07)***	(0.07)***	(0.07)***
$LNDIST]625,1250]$	-0.63	-0.59	-0.60	-0.59	-0.61	-0.59
	(0.06)***	(0.06)***	(0.06)***	(0.06)***	(0.06)***	(0.06)***
$LNDIST]1250,2500]$	-0.67	-0.63	-0.64	-0.63	-0.64	-0.63
	(0.05)***	(0.05)***	(0.05)***	(0.05)***	(0.05)***	(0.05)***
$LNDIST]2500,5000]$	-0.68	-0.65	-0.65	-0.64	-0.65	-0.65
	(0.05)***	(0.05)***	(0.05)***	(0.05)***	(0.05)***	(0.05)***
$LNDIST]5000,10000]$	-0.69	-0.66	-0.66	-0.65	-0.66	-0.65
	(0.05)***	(0.05)***	(0.04)***	(0.05)***	(0.04)***	(0.05)***
$LNDIST]10000,20000]$	-0.70	-0.67	-0.68	-0.66	-0.68	-0.67
	(0.04)***	(0.04)***	(0.04)***	(0.04)***	(0.04)***	(0.04)***
$CONTIG$	0.29	0.32	0.31	0.32	0.31	0.30
	(0.06)***	(0.06)***	(0.06)***	(0.06)***	(0.06)***	(0.06)***
$GATT/WTO$	0.24	0.23	0.21	0.23	0.21	0.23
	(0.06)***	(0.06)***	(0.06)***	(0.06)***	(0.06)***	(0.06)***
RTA	0.22	0.23	0.20	0.23	0.20	0.22
	(0.03)***	(0.03)***	(0.03)***	(0.03)***	(0.03)***	(0.03)***
$COMCUR$	0.49	0.58	0.57	0.60	0.58	0.58
	(0.10)***	(0.10)***	(0.10)***	(0.10)***	(0.10)***	(0.10)***
$COMLEG$	0.02	0.09	0.07	0.08	0.07	0.08
	(0.03)	(0.02)***	(0.02)***	(0.03)***	(0.03)***	(0.02)***
$COLPOST45$	0.87	0.96	0.92	0.95	0.91	0.96
	(0.09)***	(0.10)***	(0.10)***	(0.10)***	(0.10)***	(0.10)***
$SIBPOST45$	0.45	0.55	0.51	0.54	0.50	0.54
	(0.05)***	(0.05)***	(0.05)***	(0.05)***	(0.05)***	(0.05)***
$RELIG$	0.41	0.43	0.39	0.38	0.36	0.38
	(0.05)***	(0.05)***	(0.05)***	(0.05)***	(0.05)***	(0.05)***
Observations	32,290	32,290	32,290	32,290	32,290	32,290
Imputed R^2	0.434	0.434	0.438	0.436	0.439	0.435

Results for importer and exporter fixed effects are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 4.5: International trade in goods, second step, extensive product margin

intensive margin, as described in section 3.1. Extensive margin simply counts sectors with positive trade by country pair, while intensive margin is the average trade by sector and country-pair. I use the same model as before, but now with the respective margins as dependent variable instead of exports.

The results for the first step CANOVA regression with PPML are presented in columns

(2) and (3) in table 4.2. WTO membership increases the extensive margin of trade significantly, while the coefficient for the intensive margin is negative, confirming the results of Dutt et al. (2013). A common currency does also affect the extensive margin, but has no impact on the intensive margin of trade. Interestingly, regional trade agreements decrease the extensive margin, which partly contradicts Kehoe and Ruhl (2013) regarding trade policy. However, technology changes and other trade enhancing policy changes might have been even stronger for countries that yet did not form a preferential trade agreement. The intensive margin of trade is solely affected by an EU accession.

In the second step, I use the respective estimated trade cost term by margin and perform the same regressions as in table 4.3 in section 4.3.1 for both margins. I present the results for average cross-country differences over two decades in the extensive margin in table 4.5. All language variables are significant and positive in all regressions. The coefficient of COL for the extensive margin in column (1) is slightly lower than for trade, while CSL is already significant in column (2). CSL in column (3) is of the same size as CNL, an both coefficients increase slightly if $LP0$ is included in columns (4) and (5). The effect of $LP1$ is somewhat smaller than for trade, but still highly significant.

All control variables are significant as well, except for common legal origin in column (1). The distance elasticity is comparable to table 4.3, but adjacency has a smaller effect. The extensive margin is larger between countries that were already part of the GATT or an RTA in 1996, but the coefficients are considerably smaller than for trade.

The results for the intensive margin are displayed in table 4.6. The language variables' coefficients are close to zero and insignificant, except for $LP0$. Dutt et al. (2013, table 1) estimate the impact of a common language dummy in a one-step OLS regression and find similar results. However, their dummy for common spoken language[9] shows inconclusive results, compared to my fractional variable, CSL.

The intensive margin is mainly driven by the geographical variables, but the distance elasticity is lower. Furthermore, former colonies trade more intensively with their respective former colonizers. A WTO membership before 1996 has a significant negative impact on the intensive margin of trade, in line with the argument of Dutt et al. (2013) that the intensive margin should be lower after a WTO accession, while the extensive margin increases, i.e. trade is more diversified. Preferential trade agreements and common currency have only a marginally significant positive impact in most of the regression. The Imputed R^2 for the two margins are considerably smaller than for trade, in particular for the intensive margin.

In both stages, the estimates for the extensive and intensive margins do not sum up to the coefficients for trade, since trade is their product, not their sum as in the log-linearized OLS estimations by Dutt et al. (2013). Furthermore, PPML is a highly

[9]The dummy is from Melitz (2008) and equals one if a language is spoken by at least 9 percent of the population in both countries.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: $\exp(\hat{\delta}_{ij}^{All,IntMargin})$						
COL	0.00					
	(0.05)					
CNL		0.03		0.11		
		(0.15)		(0.18)		
CSL			0.05		0.08	
			(0.08)		(0.08)	
$LP0$				0.35	0.32	
				(0.19)*	(0.15)**	
$LP1$						0.15
						(0.12)
$LNDIST[0,625]$	-0.42	-0.41	-0.41	-0.41	-0.42	-0.41
	(0.07)***	(0.07)***	(0.07)***	(0.07)***	(0.07)***	(0.07)***
$LNDIST]625,1250]$	-0.42	-0.42	-0.42	-0.41	-0.42	-0.41
	(0.06)***	(0.06)***	(0.06)***	(0.06)***	(0.06)***	(0.06)***
$LNDIST]1250,2500]$	-0.41	-0.41	-0.41	-0.41	-0.41	-0.40
	(0.06)***	(0.06)***	(0.06)***	(0.06)***	(0.06)***	(0.06)***
$LNDIST]2500,5000]$	-0.40	-0.40	-0.40	-0.40	-0.40	-0.39
	(0.05)***	(0.05)***	(0.05)***	(0.05)***	(0.05)***	(0.05)***
$LNDIST]5000,10000]$	-0.39	-0.38	-0.38	-0.38	-0.38	-0.38
	(0.05)***	(0.05)***	(0.05)***	(0.05)***	(0.05)***	(0.05)***
$LNDIST]10000,20000]$	-0.39	-0.39	-0.39	-0.38	-0.39	-0.38
	(0.05)***	(0.04)***	(0.05)***	(0.04)***	(0.05)***	(0.05)***
$CONTIG$	0.20	0.20	0.19	0.19	0.19	0.19
	(0.07)***	(0.07)***	(0.07)***	(0.07)***	(0.07)***	(0.07)***
$GATT/WTO$	-0.31	-0.31	-0.32	-0.31	-0.32	-0.31
	(0.06)***	(0.06)***	(0.06)***	(0.06)***	(0.06)***	(0.06)***
RTA	0.07	0.07	0.07	0.07	0.07	0.07
	(0.04)*	(0.04)*	(0.04)*	(0.04)*	(0.04)	(0.04)*
$COMCUR$	0.25	0.25	0.25	0.26	0.26	0.25
	(0.13)*	(0.13)*	(0.13)*	(0.13)**	(0.13)**	(0.13)*
$COMLEG$	-0.01	-0.01	-0.02	-0.02	-0.02	-0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
$COLPOST45$	0.20	0.20	0.19	0.19	0.19	0.19
	(0.09)**	(0.09)**	(0.09)**	(0.09)**	(0.09)**	(0.08)**
$SIBPOST45$	0.06	0.06	0.06	0.06	0.05	0.06
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
$RELIG$	0.12	0.11	0.10	0.08	0.08	0.08
	(0.06)*	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Observations	32,290	32,290	32,290	32,290	32,290	32,290
Imputed R^2	0.155	0.155	0.155	0.156	0.156	0.156

Results for importer and exporter fixed effects are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 4.6: International trade in goods, second step, intensive product margin

non-linear estimation procedure. This might explain why the estimates for $LP0$ are significant for both margins, but not for total trade in table 4.3.

All language variables apart from $LP0$ affect solely the extensive margin of trade. Following Chaney (2008), this indicates that a common language, but not necessarily linguistic proximity, reduce the fixed costs of trade. This result and the positive impact of religion on extensive, but not on intensive margin, confirm the results of Rubinstein et al. (2008). For future research, it would be interesting to extend the network theory of trade by Chaney (2014) by common language to test the hypothesis of Rauch (1999) described in section 2.2.

4.4 International Trade in Services

4.4.1 Results for Aggregated Worldwide Trade in Services

In this section, I study the effect of language on trade in services. The data set contains 184 countries from 1996 to 2012. Some countries, mostly small territories, are not in the data set on service trade. Additionally, Belgium and Luxembourg and the Southern African Customs Union are represented as one country in *CEPII*'s data on trade in goods, but are reported separately in trade in services.

Year	Total trade (trillions of 2012 U.S.-$)		Percentage of positive trade observations	
	trade in goods	trade in services	trade in goods	trade in services
1996	6.65	1.77	55.1	99.9
2000	7.83	1.92	63.8	99.9
2004	10.31	2.64	68.6	99.9
2008	16.31	3.98	71.4	99.9
2012	17.37	4.28	72.8	100

Table 4.7: Worldwide total trade in goods and services

The data is quite different from the data set on trade in goods, as can be seen in table 4.7. The value of worldwide trade in services in 2012 was about 4.3 trillion U.S. dollars, compared to traded goods worth more than 17 trillion U.S. dollars in 2012. Both sectors have seen a tremendous growth in international trade. Trade in services has grown by 142 percent between 1996 and 2012, and trade in goods by 161 percent.

An important feature of the data set on trade in services is that it contains almost no zeros, contrary to the data on trade in goods. This results from the different methodologies used to estimate missing information by Fortanier et al. (2017). The originally reported data, without estimated values, contains about 90 percent non-positive bilateral trade data. Thus, it should be kept in mind that, other than in the data on trade in goods, most of the values are estimates.

In the econometric analysis, I proceed in the same manner as in the previous section and include the same explanatory variables, as described in 4.2.2. Table 4.8 reports the results for the first step estimation. Additionally to EU, $GATT/WTO$ has a significant effect on trade, which can be attributed to GATS, the *General Agreement on Trade in Services*. Again, RTA has no effect on trade. At this point, the difference in zero-trade observation is crucial. For trade in goods, a quarter of the (asymmetric) country pairs

	(1)
	$X_{ij,t}^{Srv,Inter}$
$GATT/WTO_t$	0.20
	(0.06)***
$COMCUR_t$	0.07
	(0.04)*
RTA_t	0.00
	(0.02)
RTA_{t-4}	-0.03
	(0.02)
EU_t	0.30
	(0.04)***
EU_{t-4}	0.04
	(0.04)
Observations	168,325

Results for importer-time, exporter-time and asymmetric country-pair fixed effects are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 4.8: International trade in services, first step

never trade and therefore I cannot estimate their respective trade costs. For trade in services, I have trade costs estimates for almost all observations.

Table 4.9 reports the results for trade in services in the same way as in table 4.3. The effect of COL in column (1) in table 4.9 is highly significant, but considerably lower than for trade in goods. Nordås (2018) used a common language dummy in a PPML regression on international trade in services between 30 reporter and 63 partner countries between 2000 and 2013. My estimate is similar to his, although slightly higher.

CNL has a significant effect in columns (2) and (4) that is close to the estimates for trade in goods. Significance and magnitude of CSL are clearly higher for trade in services. *Ceteris paribus*, trade is $(\exp(0.61) - 1) * 10 = 8.4$ percent higher for a CSL is 10 percentage points higher. This difference is plausible, because direct communication is presumably more important for most services than for trade in goods.

Interestingly, both in column (4) and (5), $LP0$ is significant for trade in services, contrary to trade in goods. This might reflect the importance of linguistic and cultural linkages rather than direct communication, that boost trade in cultural services, such as movies, music, books and related royalties. Such cultural goods can be translated easily, so that speaking the same language is not necessary to consume them. In column (6), $LP1$ is significant as well, but the effect is smaller than for trade in goods.

The impact of some covariates differ as well. A common legal origin has a positive and significant effect now. The estimated coefficients for the political variables $GATT/WTO$, RTA and $COMCUR$ are lower than in table 4.3. Furthermore, the coefficient of $RELIG$

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: $\exp(\hat{\delta}_{ij}^{Srv})$						
COL	0.34					
	(0.03)***					
CNL		0.32		0.41		
		(0.08)***		(0.08)***		
CSL			0.53		0.61	
			(0.06)***		(0.06)***	
$LP0$				0.39	0.51	
				(0.15)***	(0.15)***	
$LP1$						0.50
						(0.07)***
$LNDIST[0, 625]$	-0.59	-0.56	-0.56	-0.56	-0.56	-0.55
	(0.05)***	(0.06)***	(0.06)***	(0.06)***	(0.06)***	(0.06)***
$LNDIST]625, 1250]$	-0.61	-0.58	-0.57	-0.57	-0.58	-0.57
	(0.05)***	(0.05)***	(0.05)***	(0.05)***	(0.05)***	(0.05)***
$LNDIST]1250, 2500]$	-0.63	-0.60	-0.60	-0.60	-0.60	-0.59
	(0.04)***	(0.04)***	(0.05)***	(0.04)***	(0.04)***	(0.04)***
$LNDIST]2500, 5000]$	-0.65	-0.62	-0.61	-0.61	-0.61	-0.61
	(0.04)***	(0.04)***	(0.04)***	(0.04)***	(0.04)***	(0.04)***
$LNDIST]5000, 10000]$	-0.64	-0.61	-0.61	-0.61	-0.61	-0.60
	(0.04)***	(0.04)***	(0.04)***	(0.04)***	(0.04)***	(0.04)***
$LNDIST]10000, 20000]$	-0.65	-0.62	-0.61	-0.61	-0.61	-0.61
	(0.03)***	(0.04)***	(0.04)***	(0.04)***	(0.04)***	(0.04)***
$CONTIG$	0.61	0.63	0.60	0.63	0.59	0.61
	(0.05)***	(0.05)***	(0.05)***	(0.05)***	(0.05)***	(0.05)***
$GATT/WTO$	0.25	0.25	0.23	0.25	0.23	0.25
	(0.04)***	(0.04)***	(0.04)***	(0.04)***	(0.04)***	(0.04)***
RTA	0.25	0.25	0.24	0.24	0.23	0.24
	(0.03)***	(0.03)***	(0.03)***	(0.03)***	(0.03)***	(0.03)***
$COMCUR$	0.17	0.26	0.27	0.27	0.28	0.26
	(0.07)**	(0.07)***	(0.07)***	(0.07)***	(0.07)***	(0.07)***
$COMLEG$	0.10	0.18	0.15	0.17	0.14	0.17
	(0.02)***	(0.02)***	(0.02)***	(0.02)***	(0.02)***	(0.02)***
$COLPOST45$	1.14	1.23	1.13	1.23	1.12	1.22
	(0.11)***	(0.12)***	(0.12)***	(0.12)***	(0.11)***	(0.12)***
$SIBPOST45$	0.16	0.23	0.19	0.23	0.18	0.23
	(0.04)***	(0.04)***	(0.04)***	(0.04)***	(0.04)***	(0.04)***
$RELIG$	0.18	0.21	0.13	0.18	0.09	0.14
	(0.05)***	(0.05)***	(0.05)**	(0.05)***	(0.05)*	(0.05)***
Observations	33,665	33,665	33,665	33,665	33,665	33665
Imputed R^2	0.691	0.673	0.669	0.675	0.674	0.674

Results for importer and exporter fixed effects are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 4.9: International trade in services, second step

is smaller and sometimes even insignificant. Contrary to that, the effect of a colonial linkage after 1945 is larger than for trade in goods.

4.4.2 Results for Separate Service Sectors

So far, I have estimated the aggregated effect of language on trade, both in goods and in services. However, aggregated trade in services subsumes rather distinct types of trade, such that the impact of any of the gravity variables usually differs by sector (Nordås, 2018). Thus, a look on the individual sectors should be enlightening. I split aggregate trade in services into 11 service sectors, which are quite different from each other, both in type and size.[10] I deal with the differences between the sectors further below.

The structural gravity model is separable, i.e. bilateral expenditures both at the aggregate and the sectoral level are separable from output and expenditure at the country level. Thus, for each sector k, one can estimate a separate gravity equation, as demonstrated by Anderson and Van Wincoop (2004):

$$X_{ijk,t} = \frac{Y_{ik,t}E_{jk,t}}{Y_k, t}\left(\frac{t_{ijk,t}}{P_{jk,t}\Pi_{ik,t}}\right)^{1-\sigma_k}. \tag{4.8}$$

Equation 4.8 shows such a sectoral structural gravity equation. It is similar to the structural gravity on aggregate level, but bilateral trade costs $t_{ijk,t}$ and the multilateral resistance terms, $P_{jk,t}$ and $\Pi_{ik,t}$, are sector-specific. This implies that equation 4.8 can be estimated for each sector in the same way as described in section 4.2 for aggregated trade. The exporter and importer fixed effects are then exporter-product and importer-product fixed effects. Sectoral bilateral trade costs are estimated by asymmetric country-pair-product fixed effects in 11 separate first-step regressions, each for one service sector.

Already the results for the first step, reported in table C.1 in appendix C, vary by sector. New WTO memberships increased trade only in three sectors - Travel, Communication, and Finance. The EU accessions significantly raised service trade in almost all sectors. From the number of observations it can be seen that on disaggregated level, there are more zeros of trade, especially in the cultural sectors in columns (8) and (10) and in the construction sector.

Table 4.10 reports the results of the second step of this series of two-step CANOVA estimations with PPML. Each column represents one service sector, while the rows report the estimated effect and imputed R^2 for the four separately estimated language variables COL, CNL, CSL and $LP1$. I use the same set of covariates as in 4.9, but do not report them for readability of the table. Consequently, table 4.10 shows the results of 44 separate

[10] The sectors are: (1) Transportation, (2) Travel, (3) Communication Services, (4) Construction, (5) Insurance Services, (6) Finance Services, (7) Computer and Information Services, (8) Royalties and License Fees, (9) other Business Services, (10) Personal, Cultural and Recreational Services and (11) Government Services including Services not elsewhere specified.

second-step CANOVA estimates. Since the number of observations is the same within each column, they are reported only once at the end of the table.

Except for CNL and $LP1$ in column (1), transportation services, all language variables have a positive and significant effect on each service sector. Transportation might not need much complex communication or is less sensitive to cultural proximity, which is especially related to CNL and $LP1$.

Travel, or tourism, makes up the largest part of international trade in services. It counted for about a quarter of worldwide trade in services in 2012. According to my estimates in column (2), a common official language has the largest effect on the travel sector, increasing trade ceteris paribus by $(\exp(0.48) - 1) \times 100 = 62$ percent. In the third row, one can see that an increase of ten percentage points in the probability to meet someone in the partner country who speaks the same language increases trade in travel services ceteris paribus by 10.5 percent. These findings are in line with Accetturo et al. (2019), who find a positive correlation between the share of German speaking population and the share of tourists from German countries in the Italian region of Southern Tyrol on municipality level. The large effect is no surprise, since direct communication and translation are often essential for a trip to a foreign country. Additionally, cultural proximity enhances trust and influences consumer preferences (Disdier and Mayer, 2007).

The coefficient for CNL is largest for insurance and financial services and royalties and license fees, in columns (5), (6) and (8), respectively. For royalties, the impact of COL, CSL and $LP1$ is relatively large too. A sizable part of royalties come from cultural goods such as books and music that are written or sung in a specific language. Naturally, it is easier to export such goods to countries where many people speak the same language and have a similar culture and therefore, similar preferences. In particular, this might be true for a common mother tongue, since it is easier to, e.g., read a book in one's native language. Furthermore, preferences for goods secured by trade marks, copyright, licenses etc. are probably similar between linguistically and culturally close countries.

Considerable effects of the language variables can also be seen in insurance and financial services, columns (5) and (6), respectively. In a highly globalized world with fragmented production, these services are essential for cross-border economic activities. However, it seems that cultural and linguistic proximity are nevertheless highly relevant for these sectors. Nordås (2018) shows as well that trade in finance and insurance services are significantly higher for countries that share a common language.

Although not reported in table 4.10, the covariates also differ by sector. I report the full regression tables for the estimates with CSL in table C.2 in the appendix C. The coefficient for the lowest distance interval, for example, ranges from -0.2 for insurance services to -0.7 in travel and construction and almost -0.8 for transport services. The impact of contiguity varies in a similar way. This partly confirms the findings of Nordås (2018), who finds no effect of distance and contiguity for insurance and financial services

	(1) TRANSP	(2) TRAVEL	(3) COMMUN	(4) CONSTR	(5) INSUR	(6) FINANCE	(7) IT	(8) RYLTIES	(9) OTHBUS	(10) CULTURE	(11) GMNT
Dependent variable: $\exp(\hat{\delta}_{ijk}^{Srv})$											
COL	0.25	0.47	0.20	0.40	0.34	0.22	0.27	0.33	0.20	0.25	0.23
	(0.07)***	(0.05)***	(0.05)***	(0.06)***	(0.05)***	(0.05)***	(0.07)***	(0.11)***	(0.05)***	(0.06)***	(0.04)***
Imputed R^2	0.839	0.733	0.527	0.534	0.199	0.170	0.675	0.232	0.540	0.175	0.398
CNL	0.14	0.51	0.30	0.62	0.74	0.60	0.50	0.68	0.25	0.44	0.31
	(0.17)	(0.13)***	(0.11)***	(0.16)***	(0.11)***	(0.12)***	(0.14)***	(0.30)**	(0.16)	(0.12)***	(0.09)***
$LP0$	0.30	-0.22	-0.13	0.41	0.60	0.04	0.72	0.22	-0.17	0.46	0.35
	(0.20)	(0.24)	(0.22)	(0.25)	(0.23)***	(0.24)	(0.28)***	(0.41)	(0.29)	(0.20)**	(0.15)**
Imputed R^2	0.846	0.728	0.529	0.528	0.206	0.172	0.674	0.226	0.550	0.176	0.392
CSL	0.48	0.74	0.44	0.52	0.56	0.69	0.52	0.59	0.49	0.40	0.41
	(0.16)***	(0.10)***	(0.09)***	(0.11)***	(0.08)***	(0.11)***	(0.11)***	(0.15)***	(0.11)***	(0.11)***	(0.08)***
$LP0$	0.51	-0.08	-0.02	0.28	0.41	-0.02	0.72	0.08	-0.01	0.36	0.35
	(0.20)**	(0.23)	(0.20)	(0.23)	(0.22)*	(0.23)	(0.27)***	(0.34)	(0.25)	(0.18)**	(0.15)**
Imputed R^2	0.836	0.718	0.528	0.532	0.208	0.175	0.676	0.232	0.554	0.180	0.396
$LP1$	0.25	0.70	0.41	0.76	0.77	0.57	0.72	0.69	0.43	0.56	0.37
	(0.16)	(0.10)***	(0.10)***	(0.15)***	(0.11)***	(0.12)***	(0.13)***	(0.26)***	(0.14)***	(0.12)***	(0.09)***
Imputed R^2	0.844	0.725	0.526	0.530	0.206	0.171	0.671	0.231	0.549	0.176	0.392
Observations	33,417	33,512	32,544	25,299	28,574	30,168	27,506	20,944	33,435	24,257	33,393

Results for importer-product and exporter-product fixed effects, as well as for control variables, are excluded for brevity.
Robust standard errors, clustered by country pair, in parentheses. * $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 4.10: International trade in services, second step, by sector

and a high sensitivity to distance of above -0.4 for construction and telecommunications. However, all distance variables are on average higher and always significant in my regressions.

4.5 Intra- and International Trade in Manufactured Goods

4.5.1 Theory-Consistent Estimation of the Language Effect on Aggregate Trade

For now, I have focused on international trade only. In this section, I include internal trade, as it has been done frequently in the recent literature since Baier and Bergstrand (2007). In gravity theory, consumers can choose from domestic products as well. As described in section 4.2.1, its inclusion ensures theoretical consistency. Country i's estimated total output $Y_{i,t}$ and total expenditures $E_{i,t}$ as well as the inward and outward multilateral resistance terms, $P_{i,t}$ and $\Pi_{i,t}$ respectively, are now correctly estimated by the exporter-time and importer-time fixed effects in the first stage (Fally, 2015). Empirically, the estimation of international trade relative to domestic trade accounts for diversion effects from the home market to foreign markets (Dai et al., 2014).

Using internal trade data comes at the cost of a smaller sample and a restriction on the manufacturing sector, as explained in section 3.1. As in section 4.3, I use the years from 1996 to 2016 in 4 year intervals. The number of countries shrinks to 78, but they capture about 80 percent of worldwide manufacturing trade. Nevertheless, I win domestic trade that is on average twice to three times as large as total international exports.

Already in the first step, differences can be noticed, as can be seen in table 4.11. To distinguish between the impact of the smaller sample size, the focus on manufacturing trade and the inclusion of internal trade, I use only international trade in all good categories in column (1), international trade in manufacturing goods in column (2) and lastly include internal trade in column (3). I will come back to column (4) later in section 4.5.4. Already in the first column, the effects of a membership in a regional trade agreement and the WTO are significant, in contrast to the larger sample in column (1) in table 4.2. These differences can be attributed to the reduction in sample size. Column (2) shows that using only trade in manufactured goods does not change much, except for WTO, which is smaller in size and insignificant again.

In column (3), I estimate all international trade cost terms relative to internal trade cost terms by setting $\delta_{ii} = 0 \forall i$, as explained in section 4.2.2. All variables have a significant effect on trade now, which is also larger compared to column (2). The coefficient of $COMCUR$ even changes sign. The effect of a regional trade agreement is lower than esti-

	(1) $X_{ij,t}^{All,Inter}$	(2) $X_{ij,t}^{Man,Inter}$	(3) $X_{ij,t}^{Man,Intra}$	(4) $X_{ij,t}^{Man,Intra}$
$GATT/WTO_t$	0.20	0.12	0.16	0.10
	(0.11)*	(0.10)	(0.05)***	(0.05)*
$COMCUR_t$	-0.05	-0.06	0.27	0.25
	(0.03)	(0.03)*	(0.08)***	(0.07)***
RTA_t	0.09	0.10	0.13	0.09
	(0.03)***	(0.03)***	(0.04)***	(0.04)**
RTA_{t-4}	0.00	0.02	0.09	0.05
	(0.03)	(0.03)	(0.04)**	(0.04)
EU_t	0.11	0.07	0.44	0.30
	(0.04)***	(0.04)*	(0.05)***	(0.05)***
EU_{t-4}	0.08	0.05	0.33	0.27
	(0.03)***	(0.03)**	(0.05)***	(0.05)***
$LNMIGR_t$				0.25
				(0.03)***
Observations	35,598	35,544	36,012	35,082

Results for importer-time, exporter-time and asymmetric country-pair fixed effects are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 4.11: Trade in manufacturing goods, first step

mated by the literature (e.g. Baier et al. (2019) estimate a coefficient of 0.293 for RTAs). However, usually the literature investigates an earlier time period, whereas my data includes the finance crisis and the rather sluggish development in global trade thereafter. Additionally, the most profitable trade agreements might have been negotiated and signed first and latter agreements are less trade enhancing. The differences in the results of the first step can thus be mainly attributed to the inclusion of internal trade. Firstly, PPML now correctly estimates the multilateral resistance terms by the exporter and importer fixed effects (Fally, 2015) and secondly, trade diversion from internal to international trade is considered (Dai et al., 2014).

The estimated trade costs terms, $\hat{\delta}_{ij}$, differ substantially from those without domestic trade. For the same sample, the correlation between the estimated trade cost term with and without domestic trade is only 0.34.[11] Not surprisingly, the results for the second step, reported in table 4.12, are quite different as well. In the second step, I drop $COMCUR$ as explanatory variable, because it is zero for all country pairs except for two in the first period, 1996.

Contrary to my previous results on international goods trade in column (1) in table 4.12, COL has no significant effect. This confirms my own results for 106 countries in 2016

[11] I compare the estimated trade cost terms for manufacturing trade in the sample of 207 countries to those estimated for the 78 countries in this sample. The correlation is almost one. Thus, reducing the sample size from about 190,000 positive observations to only 35,000 in the first step has almost no impact on estimated δ_{ij}, since the 78 countries account for most of the world trade and hence total exports are only scarcely affected. The impact of internal trade though is large, because it is often larger than a country's total international exports, as explained in section 4.2.1.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: $\exp(\hat{\delta}_{ij}^{Man})$						
COL	0.04					
	(0.09)					
CNL		0.21		0.58		
		(0.19)		(0.20)***		
CSL			0.47		0.49	
			(0.13)***		(0.13)***	
$LP0$				0.85	0.55	
				(0.20)***	(0.18)***	
$LP1$						0.52
						(0.16)***
$LNDIST[0,625]$	-0.64	-0.63	-0.61	-0.62	-0.64	-0.60
	(0.12)***	(0.12)***	(0.12)***	(0.11)***	(0.11)***	(0.12)***
$LNDIST]625,1250]$	-0.65	-0.63	-0.62	-0.62	-0.63	-0.60
	(0.11)***	(0.11)***	(0.11)***	(0.10)***	(0.10)***	(0.11)***
$LNDIST]1250,2500]$	-0.69	-0.67	-0.66	-0.66	-0.67	-0.64
	(0.10)***	(0.10)***	(0.10)***	(0.09)***	(0.09)***	(0.10)***
$LNDIST]2500,5000]$	-0.67	-0.66	-0.64	-0.64	-0.65	-0.63
	(0.09)***	(0.09)***	(0.09)***	(0.09)***	(0.08)***	(0.09)***
$LNDIST]5000,10000]$	-0.71	-0.69	-0.68	-0.68	-0.69	-0.67
	(0.09)***	(0.09)***	(0.08)***	(0.08)***	(0.08)***	(0.08)***
$LNDIST]10000,20000]$	-0.69	-0.67	-0.65	-0.65	-0.67	-0.64
	(0.08)***	(0.08)***	(0.08)***	(0.08)***	(0.07)***	(0.08)***
$CONTIG$	0.46	0.45	0.45	0.46	0.47	0.44
	(0.10)***	(0.10)***	(0.10)***	(0.09)***	(0.09)***	(0.10)***
$GATT/WTO$	0.63	0.63	0.51	0.61	0.50	0.62
	(0.14)***	(0.14)***	(0.14)***	(0.14)***	(0.14)***	(0.14)***
RTA	0.23	0.24	0.23	0.24	0.23	0.25
	(0.07)***	(0.07)***	(0.07)***	(0.07)***	(0.07)***	(0.07)***
$COMLEG$	0.20	0.19	0.18	0.20	0.21	0.17
	(0.05)***	(0.05)***	(0.05)***	(0.05)***	(0.05)***	(0.05)***
$COLPOST45$	0.64	0.63	0.51	0.56	0.48	0.57
	(0.17)***	(0.17)***	(0.17)***	(0.16)***	(0.16)***	(0.16)***
$SIBPOST45$	0.57	0.59	0.55	0.58	0.53	0.59
	(0.16)***	(0.16)***	(0.15)***	(0.15)***	(0.15)***	(0.15)***
$RELIG$	0.40	0.39	0.28	0.27	0.21	0.32
	(0.13)***	(0.13)***	(0.13)**	(0.13)**	(0.12)*	(0.13)**
Observations	5,924	5,924	5,924	5,924	5,924	5,924
Imputed R^2	0.761	0.760	0.766	0.769	0.772	0.764

Results for importer and exporter fixed effects are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 4.12: Trade in manufacturing goods, second step

in section 4.2.1 and those of Anderson and Yotov (2016). The effect of CNL in column (2) is still not significant without $LP0$, as in the estimation for international trade in all goods in table 4.3, column (2). The impact of CSL in column (3) is slightly larger than in table 4.3, while its significance increases. The coefficient of $LP0$ is now significant both in columns (4) and (5), in contrast to the result in table 4.3. Furthermore, the impact of $LP0$ is smaller together with CSL. This can be explained by better foreign language skills for country pairs whose populations' mother tongues are linguistically more similar to each other (Ginsburgh et al., 2017). A ten percentage points higher value of common spoken language is correlated with an increase in trade of $(\exp(0.49) - 1) * 10 = 6.3$ percent, all else equal. The effect of $LP1$ in column (6) is about the same magnitude as in the larger sample in section 4.3. Overall, the combination of CSL and $LP0$ seems to capture most of the variance, regarding the Imputed R^2.

There are several possible reasons for the differences between these results and the results in section 4.3.1. First, I focus on manufacturing goods here, which are usually more heterogeneous goods (Melitz and Toubal, 2014). Another likely reason is the smaller sample size, which focuses on relatively large, advanced and well-linked countries. The third reason is the inclusion of domestic trade, which changes the estimated trade costs terms tremendously. To distinguish between the effects, I estimate the same second-step regressions as in the above table with trade cost terms from the first step regressions in columns (1) and (2) in table 4.11. I present the respective results in tables D.1 and D.2 in appendix D.

The differences between table 4.3 to table D.1 capture the impact of the sample size. The coefficient for COL is smaller, while the impact of all other language variables, in particular $LP0$, increases and is now highly significant. The results for trade in all goods in table D.1 do not differ much from those for manufacturing goods in table D.2. Comparing tables D.2 and 4.12, it can be seen that the inclusion of domestic trade diminishes the coefficients and significance of all language variables except for $LP0$. The strongest reduction occurs to common native language.

As a result, I can pin down the reason for the insignificance of the language measure in Anderson and Yotov (2016). It is not the considered time period, but the inclusion of internal trade. However, they do not use aggregated, but sectoral data, which I investigate in the next section. Their explanation might still hold true: Maybe language was of more importance in earlier years, when globalization and vertical disintegration of manufacturing trade was weaker than in recent decades. I further investigate this hypothesis in section 5.2.

In conclusion, there is still an impact of language on trade when internal trade is included, although its magnitude is smaller than estimated with international trade only. Surprisingly, the so far most used measure of language, COL, does not influence trade. Other measures, such as CNL, CSL and $LP1$, are better suited to capture the role of language for trade. The common language dummy does not discriminate between the spread of a language within a country and hence only inaccurately captures (ethno-)linguistic ties and similarities between countries.

4.5.2 Results for Separate Manufacturing Sectors

Section 4.4.2 has shown that a sectoral view on trade reveals informative insights. Here, I take a closer look on the individual manufacturing sectors. Melitz and Toubal (2014) already found that a common language is more important for heterogeneous goods, using the Rauch (1999) classification of goods. Anderson and Yotov (2016) estimates the impact of a language dummy by industry sector, but finds significant and positive effects only for three out of eight sectors. I follow them and divide aggregated trade into 8 industries, according to the UN 2-digit International Standard Industrial Classification (ISIC).[12]

The sample is, however, smaller for some sectors than for aggregate trade, because for some countries it is not possible to construct internal trade for each sector. Additionally, there are more zeros of trade for some sectors than for others, leading to a varying number of observations by sector. International trade volumes in the sample differ substantially by sector. With a trade value of 5.9 trillion current U.S.-$ in 2012, the machinery sector is the largest manufacturing trade sector and more than twice as large as the second largest sector, chemicals. Trade in each of the other sectors is worth less than a ninth of the machinery sector.

I estimate first and second step CANOVA regressions for each sector separately, as in section 4.4.2. The results for the first step regressions are reported in table C.3 in appendix C. As for trade in services, results and the number of observations vary by sector. A WTO membership had a significant positive impact on most industries, with the exception of Textiles, where the impact is negative. Generally, none of the explanatory variables had a positive and significant effect on trade in the textile sector. For all other manufacturing industries, joining a currency union, a regional trade agreement or the European Union had a positive impact, often significantly so.

The results in table 4.13 of the second-step estimation are reported in the same way as in table 4.10: For each sector, I perform four separate regressions for each of the language variable of interest and report the respective estimate. Results for the control variables in each sector are again reported in the appendix, in table C.4.

COL is only significant for the sectors food, wood, and machinery. This partly confirms the results of Anderson and Yotov (2016), in the sense that a common language

[12] The industries are (1) Food, Beverages, and Tobacco Products; (2) Textile, Apparel, and Leather Products; (3) Wood and Wood Products; (4) Paper and Paper Products; (5) Chemicals, Petroleum, Coal, Rubber, and Plastic Products; (6) Other Non-metallic Products; (7) Basic Metal Products; (8) Fabricated Metal Products, Machinery, Equipment. The ISIC category 'Other manufacturing' is included in category (8).

	(1) FOOD	(2) TEXTILE	(3) WOOD	(4) PAPER	(5) CHEMICALS	(6) MINERALS	(7) METALS	(8) MACHINERY
Dependent variable: $\exp(\hat{\delta}_{ijk}^{Man})$								
COL	0.39	0.15	0.55	0.13	0.14	0.07	0.18	0.32
	(0.14)***	(0.11)	(0.17)***	(0.17)	(0.20)	(0.22)	(0.22)	(0.10)***
Imputed R^2	0.846	0.704	0.669	0.872	0.534	0.907	0.507	0.570
CNL	1.16	0.57	0.60	0.97	0.65	-0.21	0.10	1.00
	(0.34)***	(0.31)*	(0.37)*	(0.40)**	(0.35)*	(0.38)	(0.33)	(0.23)***
*LP*0	0.67	0.27	0.52	1.20	1.07	0.64	0.52	0.77
	(0.44)	(0.29)	(0.48)	(0.40)***	(0.31)***	(0.46)	(0.33)	(0.26)***
Imputed R^2	0.855	0.708	0.662	0.874	0.534	0.908	0.506	0.583
CSL	0.59	0.32	0.58	1.04	0.23	-0.27	-0.05	0.85
	(0.23)***	(0.19)	(0.24)**	(0.27)***	(0.31)	(0.41)	(0.25)	(0.16)***
*LP*0	-0.23	-0.02	0.28	0.77	0.71	0.77	0.45	0.26
	(0.37)	(0.26)	(0.40)	(0.36)**	(0.33)**	(0.38)**	(0.32)	(0.22)
Imputed R^2	0.845	0.705	0.661	0.880	0.531	0.911	0.506	0.589
*LP*1	0.82	0.45	0.52	1.01	0.69	-0.01	0.24	0.81
	(0.28)***	(0.24)*	(0.31)*	(0.30)***	(0.27)**	(0.32)	(0.25)	(0.19)***
Imputed R^2	0.849	0.708	0.663	0.876	0.534	0.907	0.504	0.582
Observations	5,504	5,657	5,136	5,020	5,610	4,999	5,043	5,793

Results for importer-product and exporter-product fixed effects, as well as for control variables, are excluded for brevity.
Robust standard errors, clustered by country pair, in parentheses. * $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 4.13: Trade in manufacturing goods, second step, by sector

dummy is only significant for a minority of sectors. They find a significant and positive effect only for paper, machinery and basic metals. For the latter, however, none of my language variables has a significant effect, while for paper and paper products (including books), COL has no impact. The different results might be due to their smaller sample size in the slightly earlier time period 1990-2002 in Anderson and Yotov (2016).

The coefficient of CNL are at least marginally significant for all sectors but minerals and basic metals. CSL and $LP1$ do not have an effect either. Probably, these are less heterogeneous goods that do not need complex communication.

CNL, CSL and $LP1$ have a highly significant and comparatively large impact for food and manufacturing, as COL. The possible interpretation for both might be different. The large impact on trade in food products could come from similar consumption preferences. Such common preferences are better captured by mother tongue and linguistic proximity. On the other hand, trade in parts and accessories of complex machinery and equipment might need a high level of communication. That could be the reason why CSL performs better for this industry, compared to food products.

Contrary to COL, the other language variables have a large and significant effect on trade in paper and paper products, as one would expect, since translation and advertisement of books should induce costs. The high effect of $LP1$ on this sector might be explained by relatively easy and therefore cheap translation into linguistically similar languages. Furthermore, for very close languages, such as the Scandinavian ones, it is often not necessary to translate books, e.g. from Danish to Swedish.

Also at sectoral level, common language and linguistic distance are relevant for trade, although not in all sectors and if so, not to the same extend. For the largest sector, machinery, the impact of all language measures is highly significant and noticeably larger than for total manufacturing trade. Overall, the fractional measures CNL, CSL and $LP1$ again perform better than a common official language dummy.

4.5.3 The Impact of World Languages

In this smaller sample of internal and international trade, Creole and Pidgin languages occur seldom. Therefore, the results for the alternative language classification used in section 4.3.2 would not differ much from those in table 4.12. However, from section 3.2.1, one could suspect that only some languages, i.e. world languages spoken in many different countries around the world, drive the results for common native and, in particular, common spoken language.

To test for this hypothesis, I split both measures into two variables. One variable, CNL_WORLD and CSL_WORLD, respectively, subsumes only the six most widely spread languages, namely English, French, Spain, German, Russian and Arabic, and another variable aggregates all other languages, which I dub CNL_OTHER

Dependent variable: $\exp(\hat{\delta}_{ij}^{Man})$	(1)	(2)	(3)	(4)
CNL_WORLD	0.66			
	(0.21)***			
CNL_OTHER	0.36			
	(0.44)			
CSL_WORLD		0.42		
		(0.13)***		
CSL_OTHER		0.51		
		(0.28)*		
$CNL\_ENGLISH$			0.72	
			(0.42)*	
$CNL\_NO\_ENGLISH$			0.52	
			(0.21)**	
$CSL\_ENGLISH$				-0.06
				(0.21)
$CSL\_NO\_ENGLISH$				0.54
				(0.15)***
$LP0$	0.85	0.59	0.85	0.62
	(0.20)***	(0.18)***	(0.20)***	(0.20)***
Observations	5,924	5,924	5,924	5,924
Imputed R^2	0.770	0.771	0.769	0.772

Results for importer and exporter fixed effects, as well as for control variables, are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 4.14: Trade in manufacturing goods, second step, world languages

and CSL_OTHER, respectively. Furthermore, I investigate the impact of English, the most widely spoken language in the world.

The results for the language variables are presented in table 4.14, where I exclude the control variables, since they do not differ significantly from table 4.12. In column (1), the world languages' effect for common native language is highly significant and of a similar magnitude as CNL in column (4) in table 4.12. The other languages have a positive, yet not significant coefficient. Hence, the six main languages are the drivers of CNL. Taking into account foreign language skills in column (2), all languages matter and the impact of the world languages and other languages are similar. Speaking a world language thus has no larger impact on trade than any other language, in line with the results of Melitz and Toubal (2014). Nevertheless, the world languages' effect is more significant in this sample.

English is clearly the most spread language in the world. However, gravity literature so far has shown that English neither drives the language effect nor is it more effective, i.e. has a larger coefficient (Melitz, 2018). However, these results were not estimated consistent with theory, but with an OLS estimator. Therefore, I re-estimate a separate impact of English on trade.

In columns (3) and (4), I divided the language variables into English and non-English languages. For common native language, English has a marginally significant, but clearly larger effect on trade than other languages. However, the effect vanishes for common spoken language. In both regressions, the other languages, now including also other world languages, significantly impact on trade. Hence, English as a foreign language has no particular effect on trade.

The large effect of CNL_WORLD and the significant impact of $CNL\_ENGLISH$ might be due to the sample, in which countries with English (and other world languages) as native languages are over-represented, but parts of the world where these languages are not spoken as mother tongue are excluded. In a robustness test, I use the sample from section 4.3.1, with international trade only, but all countries in the world. The results are presented in table D.3 in appendix D. There, neither the world languages nor English on its own have an impact on trade, both for common native and common spoken language, confirming Melitz (2018).

4.5.4 Language, Migration, and Trade

Migration is driven by similar variables as trade, i.e. distance, historical factors, common culture and language, since all this factors influence costs and benefits of migration. Adserà and Pytliková (2015) show that also common language and linguistic proximity can explain patterns of international migration. In addition, migration increases trade via networks and demand for foreign goods. As a result, the effect of the language variables might be upward biased if migration is excluded as explanatory variable. Melitz and Toubal (2014) show this with an OLS regression. In this section, I re-evaluate their findings with updated data and the most recent advances in estimation methodology.

Both immigrants and emigrants can have a positive effect on bilateral trade, and Melitz and Toubal (2014) show that their impact on trade is similar. I sum up the stock of immigrants in country i from country j and the stock of emigrants from i in j at time t for each country pair. In line with the literature, I take the natural logarithm of this total stock of migrants to depict a declining effect of migrants on trade. In consequence, all observations without migration in either way are dropped, thus I loose 1,333 observations for the second step.[13]

I use the stock of migrants already in the first step, since I have time-varying data on migration. The cross-country differences in the number of bilateral migrants is already captured by the constant asymmetric country-pair fixed effects. Again, only the variation over time will be captured in the first step regression. Because the migration variables are measured in natural logarithms, the relevant difference will be $LNMIGR_t - LNMIGR_{t-l}$, with l being the lag length. This is a first order Taylor approximation of the growth rate

[13]Taking the log of the sum of immigrants and emigrants reduces this problem. If I would have used the log of the immigrant stock and the log of the emigrant stock separately, I would have lost about 2,000 additional directional trade cost estimates for the second step.

of $MIGR_t$, $g_{MIGR} = (MIGR_{t-l}/MIGR_t) - 1$. Alternatively, the estimated coefficient of $LNMIGR$ can be interpreted as the average partial effect of total migration.

The results for the first step are reported in table 4.11, column (4). The estimated coefficients of the political variables are similar to those in column (3), but slightly lower. The estimated effect for total migration is significant at the one percent level and of considerable size. The coefficient can be directly interpreted as elasticity: A one percentage point increase in migrants stock between two countries *ceteris paribus* results in an increase in trade of 0.25 percent.

In the second step, I control for the already existing stock of total migrants at the beginning of the time period in 1996. The outcomes are reported in table 4.15. The effect of migration is lower compared to the one estimated in the first step. However, the effects might not be directly comparable, because in the first step I estimated the effect of a *change* in migration stock and here, I estimate the effect of the difference in*levels*. There are many possible reasons for the weaker effect in the cross-country results of the second step. Migrants, living for a longer time in their destination country, might have less contact to their origin country relative to newly arrived migrants. The former do not play a role in the first step regression, while the latter are not accounted for in the second step. Maybe ease in travel or communication over borders due to technical innovations has increased the gains for trade from migrant networks.

In the first two columns, COL and CNL have no effect on trade. Nevertheless, CNL is again significant if I add $LP0$ in column (4). For COL, CNL and CSL, the size of the coefficient shrinks compared to the respective results in table 4.12. The effect of linguistic proximity, however, remains the same.

It seems that the language variables captured some of the effects of migrant networks on trade that enhance trust and exchange of information. Although the coefficients are somewhat smaller, direct communication, expressed via CSL, and (ethno-)linguistic links, represented by $LP1$, played a significant role for trade in the observed period. However, a common official language is again not related to higher bilateral exports.

The control variables in all regressions are affected by migration as well. The effects of distance, colonial linkages and religion decrease and the latter even drop insignificant. The correlation between $LNMIGR$ and the other covariates is low to modest, so there is no hint to multicollinearity. But migration is influenced by all these variables, particularly the above mentioned. Migration between parts of a former colonial empire is easier and more likely, e.g. between India, Nepal and the UK. Thus, the effect of colonial past on trade might only prevails because of migration networks.

Dependent variable: $\exp(\hat{\delta}_{ij}^{Man,Migr})$	(1)	(2)	(3)	(4)	(5)	(6)
COL	-0.14					
	(0.10)					
CNL		0.03		0.48		
		(0.21)		(0.22)**		
CSL			0.35		0.37	
			(0.15)**		(0.15)**	
$LP0$				0.97	0.73	
				(0.17)***	(0.17)***	
$LP1$						0.52
						(0.16)***
$LNMIGR$	0.14	0.14	0.13	0.14	0.14	0.13
	(0.01)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***
$LNDIST[0,625]$	-0.56	-0.55	-0.53	-0.54	-0.55	-0.52
	(0.11)***	(0.12)***	(0.12)***	(0.10)***	(0.10)***	(0.12)***
$LNDIST]625,1250]$	-0.57	-0.56	-0.54	-0.54	-0.55	-0.52
	(0.10)***	(0.11)***	(0.11)***	(0.09)***	(0.09)***	(0.11)***
LNDIST]1250,2500]	-0.60	-0.59	-0.58	-0.57	-0.58	-0.56
	(0.09)***	(0.10)***	(0.10)***	(0.09)***	(0.08)***	(0.10)***
$LNDIST]2500,5000]$	-0.60	-0.58	-0.57	-0.56	-0.57	-0.55
	(0.09)***	(0.09)***	(0.09)***	(0.08)***	(0.08)***	(0.09)***
$LNDIST]5000,10000]$	-0.61	-0.59	-0.58	-0.57	-0.58	-0.56
	(0.08)***	(0.08)***	(0.08)***	(0.07)***	(0.07)***	(0.08)***
$LNDIST]10000,20000]$	-0.58	-0.57	-0.55	-0.54	-0.56	-0.53
	(0.08)***	(0.08)***	(0.08)***	(0.07)***	(0.07)***	(0.08)***
$CONTIG$	0.33	0.31	0.31	0.33	0.34	0.29
	(0.10)***	(0.10)***	(0.10)***	(0.09)***	(0.09)***	(0.10)***
$GATT/WTO$	0.84	0.86	0.76	0.86	0.74	0.88
	(0.18)***	(0.18)***	(0.18)***	(0.17)***	(0.17)***	(0.18)***
RTA	0.22	0.22	0.22	0.23	0.22	0.24
	(0.08)***	(0.08)***	(0.07)***	(0.08)***	(0.08)***	(0.07)***
$COMLEG$	0.20	0.18	0.16	0.19	0.20	0.14
	(0.05)***	(0.06)***	(0.05)***	(0.05)***	(0.05)***	(0.05)***
$COLPOST45$	0.24	0.22	0.16	0.15	0.09	0.19
	(0.17)	(0.17)	(0.17)	(0.15)	(0.15)	(0.17)
$SIBPOST45$	0.13	0.14	0.15	0.13	0.10	0.16
	(0.20)	(0.20)	(0.20)	(0.19)	(0.19)	(0.19)
$RELIG$	0.28	0.28	0.20	0.15	0.11	0.21
	(0.14)**	(0.14)**	(0.14)	(0.13)	(0.13)	(0.14)
Observations	4,501	4,501	4,501	4,501	4,501	4,501
Imputed R^2	0.782	0.779	0.782	0.792	0.793	0.783

Results for importer and exporter fixed effects are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 4.15: Trade in manufacturing goods, second step, including migration

4.5.5 Decreasing Marginal Effect of Language

In theory, the effect of a common language should diminish with the percentage of speakers in the population. As described in section 2.2, for effective translation, it is sufficient that only a small part of the population speaks a foreign language. Thus, the effect of CNL and CSL should be higher for smaller values. Furthermore, it could be the case that countries with low CNL, CSL, and also $LP1$ are still mainly in the contact phase of trade, where common language and culture are larger restrictions.

With a fractional variable, such as CNL, CSL and $LP1$, an empirical test of this hypothesis is possible. In this section, I deviate from the assumption that the language elasticity of trade is constant in the same way as Eaton and Kortum (2002) for the distance elasticity. I split each of the aforementioned fractional variables into three intervals, resembling their respective distribution over the sample. I choose the intervals [0, .125), [.125, .5) and [.5,1) for CNL and CSL. For $LP1$, I use the intervals [0, .25), [.25, .5) and [.5,1), to match the different distribution.

In this section, I use the same sample as presented in section 4.5.1. The first step decomposition is the same as in table 4.11, column (3). In the second step, I replace CNL, CSL and $LP1$ with the respective intervals. The results for the language variables are reported in table 4.16. In columns (1) and (2), I present the results for CNL and CSL together with $LP0$. Column (3) shows the estimation results for $LP1$. In columns (4)-(6), I regress trade costs on the language intervals, but control for migration stocks in the first and second step, just as in the previous section. The number of observations decreases again because of country-pairs without migrants in either direction. In all regressions, I exclude further control variables for brevity.

CNL in column (1) has a stunningly large effect for the lowest interval: a difference of only one percentage point of CNL is correlated with a 29.6 percent higher trade, all else equal. The high effect might be caused by small minorities and migrant groups that foster trade via their networks in foreign countries (Rauch and Trindade, 2002). Therefore, I control for the stock of migrants in column (4): Now, the coefficient for the first interval decreases strongly and becomes insignificant. The highest interval is robust to the inclusion of migration and presumably drives the result for CNL in column (4) in table 4.15. The middle interval is insignificant both in column (1) and (4). Common native language hence only affects trade via migrants and language minorities and for countries with a high value of CNL. A steadily diminishing effect of language cannot be observed.

Lets turn to CSL in column (2). Here, the pattern is as presumed: The effect of CSL diminishes with the magnitude of CSL, hinting to a decreasing marginal effect of common spoken language on trade. Contrary to common native language, the middle interval is positive and significant. However, if I control for migration in column (5), all coefficients decrease and lose significance.

For linguistic proximity in column (3), I find incidence for a decreasing marginal effect with weaker and therefore more plausible estimated coefficients in the lowest interval. However, the interpretation of a decreasing marginal effect of linguistic proximity is less straightforward than for CNL or CSL and the effect could be driven by the CNL-component.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: $\exp(\hat{\delta}_{ij}^{Man})$						
$CNL]0,.125]$	3.42			0.56		
	(1.33)***			(1.28)		
$CNL].125,.5]$	-0.19			-0.45		
	(0.37)			(0.47)		
$CNL].5,1]$	0.69			0.56		
	(0.21)***			(0.23)**		
$CSL]0,.125]$		3.82			1.82	
		(0.89)***			(0.97)*	
$CSL].125,.5]$		1.16			0.34	
		(0.27)***			(0.32)	
$CSL].5,1]$		0.68			0.41	
		(0.15)***			(0.17)**	
$LP1]0,.25]$			1.15			0.77
			(0.69)*			(0.63)
$LP1].25,.5]$			0.64			0.56
			(0.34)*			(0.32)*
$LP1].5,1]$			0.65			0.57
			(0.22)***			(0.22)***
$LP0$	0.74	0.63		0.86	0.72	
	(0.19)***	(0.19)***		(0.17)***	(0.17)***	
$LNMIGR$				0.13	0.14	0.13
				(0.02)***	(0.02)***	(0.01)***
Observations	5,924	5,924	5,924	4,501	4,501	4,501
Imputed R^2	0.772	0.773	0.764	0.798	0.802	0.792

Results for importer and exporter fixed effects, as well as for control variables, are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 4.16: Trade in manufacturing goods, second step, intervals for language variables

In conclusion, I find hints for a decreasing marginal effect of common language, but they become weaker if I control for migration. Again, a causal interpretation is not possible. It cannot be said if a common spoken language lead to migration and to more trade, or if migration and trade induced higher foreign language skills.

Chapter 5

Language and Trade in a Historical Perspective

5.1 Introduction

In this chapter, I take on a historical perspective on common language and trade in two, distinct ways. I try to clarify the changing role of language and culture for trade in section 5.2. Anderson and Yotov (2016), after finding a positive and significant effect of a common language dummy for only some manufacturing sectors, argued that "manufactures trade has grown between North and South, enhanced by the vertical disintegration of manufacturing, both weakening the influence of common language relative to its effect on aggregate trade found in previous studies" (Anderson and Yotov, 2016, p. 287). Thus, they suggest that official language was more relevant for trade in the past. Baier et al. (2018) estimate the gravity equation of trade between 1986 and 2006 with a one-step PPML estimator. Using only international trade, they find a decreasing effect of a common language dummy over time. However, if they include internal trade, no such trend is observable. I investigate the impact of language on trade with a two-step CANOVA approach by Egger and Nigai (2015) for over 50 countries between 1982 and 2012.

In section 5.3, I control for past trade with a new method by Frensch and Fidrmuc (2020) and estimate the impact of common language and linguistic proximity solely on contemporaneous trade costs. Although I controlled for cultural and historical factors that might be correlated with language in chapter 4, the estimated coefficients cannot, and should not, be interpreted causally. Most studies conclude that a common language facilitates trade, but because of probable endogeneity bias, hesitate to interpret these effects causally. Reversed causality is an issue, especially regarding foreign language skills. Furthermore, long lasting international relations between countries could have led to both more trade and higher foreign language skills. Hence, the correlation between language and trade that gravity literature measures might be nothing but a relic of past trade relations.

If trade is determined by the past, as Campbell (2010) has shown, historical relations between linguistically similar countries might prevail, but are not of relevance anymore for today's trade decisions. Head and Mayer ponder about the too large effects of distance and language on trade, "compared to any reasonable accounting of the costs" (Head and Mayer, 2014, p. 189). Controlling for historical trade costs might solve this issue.

5.2 The Changing Effect of Language and Culture on Trade

I extend the sample range of internal and international trade in manufacturing goods as far as possible. As mentioned in section 3.1, I am able to track 55, mostly developed, countries from 1982 to 2012. Trade between these countries make up between two thirds and 85 percent of worldwide trade, depending on the year. I use data in 6 year intervals to compare effects over time. I chose the years such that the number of countries I can track is maximized.

I use the same method as in section 4.2.1 for each of the 6 observations in the respective years 1982, 1988, 1994, 2000, 2006 and 2012 for the same 55 countries. In the first step, I decompose trade data with exporter, importer and symmetric country-pair fixed effects. Since I estimate each year separately, there are no time-varying explanatory variables included in the first step. Singletons are often zeros of trade in both directions, which are more frequent in earlier years. Thus, in the second step, the number of observations increases over time, as zeros of trade occur less frequently.

The model in the second step is similar to the ones in the previous chapters. I drop $GATT/WTO$ from the list of explanatory variables because for the later years, all countries in the sample are members of the WTO and therefore no effect can be estimated. I also include a variable that captures the effect of being currently a colony, $COLCUR$, to capture changes in the colonial status, e.g. for Macao. Furthermore, I do not regress trade on common spoken language. Foreign language skills might have changed over time in either direction and to different extents, therefore CSL cannot be interpreted for observations in earlier years. Although there were changes in common native language for some countries as well, which also influence linguistic proximity measures, I assume CNL, $LP0$ and $LP1$ to be constant over time. The official languages of the countries in the sample have not changed over this period of time.

Table 5.1 reports the results for the six selected years between 1982 and 2012. In the upper panel, I present the estimates for the regressions that include $LP1$ as language variable. In the lower panels, I report the results for CNL and $LP0$ as well as for COL. There, I do not report the covariates' results, because they are similar to the ones in the

Dependent variable:	(1) $\exp(\hat{\delta}_{ij}^{Man,1982})$	(2) $\exp(\hat{\delta}_{ij}^{Man,1988})$	(3) $\exp(\hat{\delta}_{ij}^{Man,1994})$	(4) $\exp(\hat{\delta}_{ij}^{Man,2000})$	(5) $\exp(\hat{\delta}_{ij}^{Man,2006})$	(6) $\exp(\hat{\delta}_{ij}^{Man,2012})$
$LP1$	0.06	0.08	0.13	0.19	0.29	0.53
	(0.15)	(0.14)	(0.15)	(0.19)	(0.15)*	(0.19)***
$LNDIST[0,625]$	-0.77	-0.68	-0.58	-0.39	-0.44	-0.45
	(0.06)***	(0.06)***	(0.07)***	(0.08)***	(0.07)***	(0.08)***
$LNDIST]625,1250]$	-0.79	-0.69	-0.61	-0.41	-0.44	-0.44
	(0.06)***	(0.06)***	(0.06)***	(0.08)***	(0.07)***	(0.07)***
$LNDIST]1250,2500]$	-0.80	-0.68	-0.62	-0.45	-0.49	-0.50
	(0.05)***	(0.06)***	(0.06)***	(0.07)***	(0.06)***	(0.07)***
$LNDIST]2500,5000]$	-0.79	-0.68	-0.62	-0.44	-0.51	-0.52
	(0.05)***	(0.05)***	(0.05)***	(0.07)***	(0.06)***	(0.06)***
$LNDIST]5000,10000]$	-0.81	-0.69	-0.63	-0.49	-0.55	-0.55
	(0.05)***	(0.05)***	(0.05)***	(0.06)***	(0.05)***	(0.06)***
$LNDIST]10000,20000]$	-0.82	-0.69	-0.62	-0.50	-0.56	-0.55
	(0.05)***	(0.05)***	(0.05)***	(0.06)***	(0.05)***	(0.06)***
$CONTIG$	0.25	0.48	0.33	0.50	0.37	0.38
	(0.08)***	(0.08)***	(0.08)***	(0.12)***	(0.10)***	(0.10)***
RTA	0.35	0.63	0.54	0.36	0.25	0.40
	(0.11)***	(0.09)***	(0.07)***	(0.08)***	(0.06)***	(0.10)***
$COMLEG$	0.34	0.27	0.27	0.19	0.20	0.15
	(0.05)***	(0.04)***	(0.04)***	(0.06)***	(0.05)***	(0.05)***
$COMCUR$	-0.63	-0.10	-0.33	-0.26	-0.29	-0.36
	(0.23)***	(0.19)	(0.17)**	(0.09)***	(0.08)***	(0.09)***
$COLPOST45$	0.87	0.79	0.83	0.33	0.38	0.30
	(0.16)***	(0.12)***	(0.12)***	(0.17)*	(0.16)**	(0.17)*
$COLCUR$	-0.94	-1.53	-1.23	0.56	-0.06	-0.69
	(0.79)	(0.72)**	(0.60)**	(0.33)*	(0.28)	(0.32)**
$SIBPOST45$	0.39	0.35	0.03	0.37	0.09	0.22
	(0.18)**	(0.15)**	(0.14)	(0.32)	(0.15)	(0.15)
$RELIG$	0.15	0.24	0.34	0.46	0.78	0.83
	(0.09)	(0.09)***	(0.09)***	(0.14)***	(0.14)***	(0.15)***
Observations	2,436	2,584	2,684	2,724	2,750	2,742
Imputed R^2	0.940	0.940	0.940	0.941	0.932	0.915
CNL	0.01	0.10	0.19	0.25	0.33	0.64
	(0.16)	(0.16)	(0.17)	(0.23)	(0.17)*	(0.23)***
$LP0$	-0.60	-0.64	-0.55	-0.32	-0.24	0.26
	(0.17)***	(0.17)***	(0.19)***	(0.24)	(0.18)	(0.22)
Imputed R^2	0.943	0.945	0.944	0.942	0.935	0.916
COL	0.33	0.26	0.13	0.20	0.21	0.12
	(0.07)***	(0.07)***	(0.07)*	(0.10)**	(0.08)***	(0.09)
Imputed R^2	0.944	0.942	0.939	0.941	0.933	0.914

Results for importer and exporter fixed effects, as well as for control variables in the lower panels, are excluded for brevity. Robust standard errors, clustered by country pair, in parentheses. * $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 5.1: Change in bilateral trade costs in 30 years, 1982-2012

upper panel. I also do not report the number of observations again, since they are the same for each column.

The first row reports the effect of $LP1$ on trade. While the impact was not significant before 2006, its magnitude slightly increased over time. In 2012, the impact is large and highly significant. To further disentangle the effect, I decompose $LP1$ into its components, CNL and $LP0$, in the middle panel. It can be seen that both the effect of a common mother tongue and linguistic proximity increase over time. A common native language has a significant and positive impact only in 2006 ans 2012. $LP0$ was negative between 1982 and 2006 and turned positive, but insignificant in 2012. $LP1$'s effect seems to be driven mostly by CNL, since both coefficients are similar to each other. I conclude that a common native language and linguistic proximity, plausibly linked with common culture, became more important for trade over time.

In the last panel, I report the estimate for COL. The effect of a common official language on trade slightly decreased over time, but stays significant except for 2012. This seems to contradict the results in section 4.5. The difference most likely lies in the sample size. However, I cannot find a decreasing relevance of language on trade, as assumed by Anderson and Yotov (2016). On the contrary, the impact of language and culture even increased over time.

After the last wave of independence declarations by colonies in the beginning of the 1980s, trade linkages between (former) hegemons and colonies decreased over time, as shown by $COLPOST45$, in line with the observations of Head et al. (2010) on the erosion of colonial linkages. After the 1980s, former colonies within the same empire did not trade more with each other relative to other countries, all else equal. Eastern European countries and the former Soviet Union, which dissolved in 1991, are not included in the sample.

Gravity literature pondered over the seemingly constant, or even rising, impact of geographical distance on trade, despite rising globalization and declining transport costs would suggest a decreasing impact over time (Disdier and Head, 2008). The most recent solution of Bergstrand et al. (2015) to the 'distance puzzle' shows declining distance elasticity if one estimates international trade relative to intra-national trade and controls for unobserved heterogeneity by country-pair fixed effects. I do both in my estimations and find a decreasing distance elasticity relative to the 1980's. Baier et al. (2019, pp. 60), using a one-step PPML estimator, document an increasing distance elasticity after the mid-90s, which is surprisingly largest in 2006. The difference in results might be explained by distinct estimation methods and samples, since a one-step PPML estimator might be biased, as shown in section 4.2.1. I also find that the effect of $LNDIST$ decreases more for lower distance intervals, resulting in a more pronounced non-constant distance elasticity in later years.

The coefficient of the other cultural variable in the sample, $RELIG$, increases from an insignificant 0.15 to a highly significant 0.83. Thus, (ethno-)linguistic, religious and cultural links are more important for trade today than in the past, a result that is not captured by an official language dummy. This again emphasizes the importance for a different measure of language in the gravity literature.

What can I infer from a rise in the impact of cultural determinants? They all represent some form of bilateral trust. In a increasingly globalized world as we experienced in the last decades, especially with enormous technological progress in information technology, one would suspect that language, culture and religion as informal barriers to trade should be easier to overcome. As a result, one would argue that the effect of common language and culture should have decreased, just as Anderson and Yotov (2016) did. However, if common language, religion and culture become more important for international trade, this could represent a more regionalized world. This interpretation is supported by the relatively stronger decrease in the impact of geographical distance on trade for closer countries. At the same time, trade costs, represented by the distance intervals, decreased in general, referring to an overall globalization. In the end, we end up both in a more globalized world, but at the same time, a more regionalized one. This is not a contradiction if worldwide trade increases relative to intra-national trade, but proportionately more with culturally and geographically closer partners. This interpretation is supported by the rising use of regional trade agreements since the beginning of the 1990s, while international trade negotiations at the WTO were less fruitful since the failed Doha Development Round in 2001.

In a robustness test, I perform the same regressions as in table 5.1 for the 78 countries between 1996 and 2016. The new countries added in this sample are mostly developing ones, especially from the Former Eastern Bloc, but also other large emerging economies such as Brazil and South Africa. The results for the 4-year intervals are presented in table E.1 in appendix E. Here, I can only find a small rise in the impact of common native (and spoken) language and an over time decreasing coefficient for $LP0$, which result in a constant $LP1$. All fractional language variables are significant for all years. The dummy variable COL, however, is always insignificant. Distance elasticity even slightly increases until 2016, which could represent withdrawing global value chains and increasing trade restrictions as response to the crisis in 2008. The impact of colonial relations decreases also in this sample.

5.3 Contemporaneous Trade Costs

5.3.1 Methodology

There have been several attempts to measure contemporaneous trade costs by controlling for historical trade costs. Olivero and Yotov (2012) use a dynamic gravity approach and include lagged trade as explanatory variable in a log-linearized model, thus controlling for past trade costs. However, the inclusion of a lagged dependent variable might lead to a correlation in the error terms which again leads to biased results. The usage of year intervals instead of consecutive years may reduces the problem, but does not solve it.

Frensch and Fidrmuc (2020) propose an alternative approach which includes the two step CANOVA approach by Egger and Nigai (2015): They use earlier trade observations to estimate past trade costs. I.e., they split their sample and estimate average trade costs for both sub-samples separately by decomposing trade as in the first step of a CANOVA approach. The estimated trade cost terms of the first period then function as estimates of the historical trade costs, which are introduced as additional explanatory variable in a second step CANOVA regression of the later period. The part of the estimated trade costs not explained by past trade costs can then interpreted as contemporaneous trade costs.

I use the same panel of 78 countries in four year intervals from 1996 to 2016 as in section 4.5 and split it into two panels, one from 1996 to 2000 and the other from 2004 to 2016. Hence, I use the time before the trade boom in the 2000s to estimate historical trade costs.

$$X_{ij,t} = \exp\left(\mu_{i,t} + \pi_{j,t} + \delta_{ij} + \beta_z Z_{ij,t} + \epsilon_{ij,t}\right) \tag{5.1}$$

I use the earlier panel to estimate average past trade costs, with a first stage CANOVA regression as described in equation 5.1 in $t = 1996, 2000$, controlling for time-variant variables RTA, EU, $GATT/WTO$ and $COMCUR$ and lags thereof. I receive estimated average (asymmetric) past trade costs over the first period, $\hat{\delta}_{ij}^{1996-2000}$. I proceed in the same way for the first step CANOVA regression in the later period, $t = 2004, 2008, 2012, 2016$, and receive $\hat{\delta}_{ij}^{2004-2016}$, whereof I use the exponential form as dependent variable in the second step CANOVA regression.

$$\exp(\hat{\delta}_{ij}^{2004-2016}) = \exp\left(\nu_i + \zeta_j + \hat{\delta}_{ij}^{1996-2000} + \beta_{Lang} Lang_{ij} + \beta_k K_{ij} + \epsilon_{ij}\right) \tag{5.2}$$

Equation 5.2 presents the model for the second step. The later trade costs estimates are regressed on the earlier, historical trade costs, $\hat{\delta}_{ij}^{1996-2000}$, a set of explanatory variables, K_{ij}[1], and the language variables COL, CNL and CSL, both together with $LP0$, and $LP1$. Countries that did not trade in the earlier period drop from the sample, because I cannot estimate their past trade costs.

Since $\hat{\delta}_{ij}^{1996-2000}$ is drawn from a first stage regression, it is a generated regressor.

[1] K_{ij} consists of the six distance intervals, $CONTIG$, $COMLEG$, $RELIG$, $COLPOST45$, $SIBPOST45$, and already existing trade agreements (including the European Union), WTO memberships and currency unions. In contrast to the estimations in 4.5, I include $COMCUR$ because in the late sample, it contains the Eurozone.

Standard errors and test statistics obtained from regression 5.2 are generally invalid if I ignore the sampling variation in estimated past trade costs. It is therefore necessary to account for uncertainty of $\hat{\delta}_{ij}^{1996-2000}$ in the estimate of contemporaneous trade costs $\exp(\hat{\delta}_{ij}^{2004-2016})$. Thus, I perform a bootstrap including both the first stage of the earlier sample and the second stage of the later sample for each regression in this section to maintain bootstrapped standard errors in the second step.[2]

5.3.2 Results

	$X_{ij,t}^{Man}$		$X_{ij,t}^{Man,ExtMargin}$		$X_{ij,t}^{Man,IntMargin}$	
	(1)	(2)	(3)	(4)	(5)	(6)
	1996 – 2000	2004 – 2016	1996 – 2000	2004 – 2016	1996 – 2000	2004 – 2016
$GATT_t$	-0.02	0.03	0.12	0.06	-0.45	-0.04
	(0.14)	(0.04)	(0.04)***	(0.03)*	(0.22)**	(0.06)
$GATT_{t-4}$	0.02	-0.11	0.11	0.07	-0.11	-0.18
	(0.07)	(0.03)***	(0.03)***	(0.03)***	(0.12)	(0.04)***
RTA_t	0.38	0.11	0.05	0.00	-0.05	0.08
	(0.07)***	(0.03)***	(0.03)**	(0.01)	(0.09)	(0.05)*
RTA_{t-4}	0.37	-0.01	-0.03	0.02	0.24	-0.00
	(0.07)***	(0.03)	(0.02)	(0.01)*	(0.08)***	(0.04)
EU_t		0.16		0.08		0.16
		(0.07)**		(0.03)**		(0.10)
EU_{t-4}	0.13	0.41	0.03	0.02	0.07	0.30
	(0.05)***	(0.06)***	(0.01)***	(0.01)	(0.05)	(0.06)***
$COMCUR_t$	0.12	-0.12	-0.03	0.02	0.11	0.02
	(0.05)**	(0.04)***	(0.01)***	(0.02)	(0.04)***	(0.09)
$COMCUR_{t-4}$		0.11		0.04		-0.07
		(0.03)***		(0.01)***		(0.10)
Observations	11,380	23,952	11,390	23,948	11,378	23,940
Imputed R^2	0.999	1.000	0.995	0.995	0.999	0.999

Results for importer and exporter fixed effects are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 5.2: First step regressions for early and late period

The results for the first step CANOVA regressions are presented in table 5.2, columns (1) and (2). It is noteworthy that there are no EU accession in the earlier period. I can only measure a lagged effect of the EU enlargement in 1995. The lagged variable for a common currency union is solely used in the later period to capture the effect of the accession of Greece to the Eurozone in 2001. The effect of $COMCUR$ is positive for the original members of the Eurozone, but there is no effect for the later members, i.e. the positive effect of $COMCUR_t$ and the negative effect of $COMCUR_{t-4}$ cancel each other out. Joining or forming a regional trade agreement and the EU accessions have

[2] I use 1000 replications for each regression. For $CSL[0, .25]$ in column (3), table 5.4, I show that the bootstrapped standard errors already converge early to a value between .42 and .45 in figure E.1 in appendix E, which is sufficient for a precise estimate.

positive impacts on trade in both periods. New membership in the WTO has no positive on trade, but rather the opposite.

I proceed with the second step CANOVA approach, regressing the estimated average trade costs from the later period on the estimated trade costs from the earlier period, the language variables and the control variables. Table 5.3 displays the results for each of the language variables, estimated separately to avoid multicollinearity. [3] The effect of past trade costs is positive, significant and explains a large fraction of estimated contemporaneous trade costs, which is reflected in the increase in the Imputed R^2. Compared to the standard gravity regression in E.2, the language variables' coefficients in table 5.3 are all insignificant and smaller in size, yet the coefficients of CNL, CSL and $LP1$ stay positive. Hence, the regularly estimated language effect seems to be mostly a relic of historical trade patterns that still persist until today. Most variables' coefficients diminish in size once I include past trade costs: distance elasticity ranges between 0.19 and 0.24, compared to around 0.8 in table E.2. The effect of RTAs already in place in the first year of the later panel is still highly significant, although it is relatively small. All other variables have no robust significant impact on contemporaneous trade costs. Regional trade agreements and geographical distance are thus the main drivers of contemporaneous trade costs.

In section 4.5.5, I have demonstrated that the magnitude of the effect of fractional language variables also depends on its level, i.e. it is higher for low values. In table 5.4, I estimate each the of three fractional language variables in intervals. CNL in column (1) is now significant, positive and large for the first interval, but not for larger values of common native language. CSL in column (2) is not significant for any interval. In column (3), however, linguistic proximity is now significant in all intervals and the coefficients decrease with the magnitude of $LP1$. I presume that the variable was misspecified in table 5.3, column (4). The large effect for the lowest interval of CNL and $LP1$ could be driven by language minorities. Since CNL and $LP1$ have an impact on contemporaneous trade, but CSL not, it is likely that ethnic and cultural ties had an positive impact on contemporaneous trade, but not so much the ability to communicate in the same language. Presumably, communication within international firms or along global value chains do not need much translation or can be handled effectively by few interpreters. In contrast, knowledge of local norms and habits can hardly be 'translated' and therefore might act as trade barrier, even today.

Figure 4.2 has shown that a substantial part of trade growth between countries that did already trade in 1995 occurred at the extensive product margin. The results in section 4.3.3 indicated that intercommunication distances, i.e. COL, CNL and CSL, mainly work via the extensive product margin. Thus, I estimate the effect of language

[3]For a direct comparison, the regression results without past trade costs as explanatory variables are presented in table E.2 in appendix E.

	(1)	(2)	(3)	(4)
Dependent variable: $\exp(\hat{\delta}_{ij}^{Man,2004-2016})$				
$\hat{\delta}_{ij}^{Man,1996-2000}$	0.60	0.59	0.59	0.60
	(0.09)***	(0.08)***	(0.08)***	(0.09)***
COL	-0.05			
	(0.08)			
CNL		0.12		
		(0.15)		
CSL			0.08	
			(0.11)	
$LP0$		0.17	0.11	
		(0.12)	(0.11)	
$LP1$				0.11
				(0.11)
$LNDIST[0,625]$	-0.20	-0.19	-0.20	-0.19
	(0.08)***	(0.08)**	(0.08)***	(0.08)**
$LNDIST]625,1250]$	-0.21	-0.20	-0.21	-0.20
	(0.07)***	(0.07)***	(0.07)***	(0.07)***
$LNDIST]1250,2500]$	-0.24	-0.23	-0.23	-0.22
	(0.07)***	(0.07)***	(0.06)***	(0.07)***
$LNDIST]2500,5000]$	-0.23	-0.22	-0.22	-0.22
	(0.06)***	(0.06)***	(0.06)***	(0.06)***
$LNDIST]5000,10000]$	-0.24	-0.23	-0.23	-0.23
	(0.06)***	(0.06)***	(0.05)***	(0.06)***
$LNDIST]10000,20000]$	-0.23	-0.22	-0.23	-0.22
	(0.06)***	(0.06)***	(0.05)***	(0.06)***
$CONTIG$	0.10	0.10	0.10	0.09
	(0.06)*	(0.06)	(0.06)	(0.06)
$GATT/WTO$	0.18	0.17	0.15	0.16
	(0.20)	(0.19)	(0.20)	(0.20)
RTA	0.14	0.14	0.14	0.14
	(0.05)***	(0.05)***	(0.05)***	(0.05)***
$COMLEG$	0.05	0.04	0.05	0.04
	(0.04)	(0.04)	(0.04)	(0.04)
$COMCUR$	0.02	0.02	0.02	0.02
	(0.07)	(0.07)	(0.07)	(0.08)
$COLPOST45$	0.02	-0.01	-0.02	-0.01
	(0.09)	(0.09)	(0.10)	(0.09)
$SIBPOST45$	0.06	0.06	0.05	0.07
	(0.10)	(0.11)	(0.10)	(0.11)
$RELIG$	0.17	0.15	0.15	0.16
	(0.09)*	(0.09)	(0.09)	(0.09)*
Observations	5,598	5,598	5,598	5,598
Imputed R^2	0.863	0.862	0.863	0.862

Results for importer and exporter fixed effects are excluded for brevity. Bootstrapped standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 5.3: Contemporaneous trade costs in 2004-2016, second step

	(1)		(2)		(3)	
Dependent variable: $\exp(\hat{\delta}_{ij}^{Man,2004-2016})$						
$\hat{\delta}_{ij}^{Man,1996-2000}$	0.59	(0.08)***	0.59	(0.08)***	0.60	(0.09)***
$CNL]0,.125]$	2.17	(0.90)**				
$CNL].125,.5]$	-0.41	(0.30)				
$CNL].5,1]$	0.20	(0.14)				
$CSL]0,.125]$			0.43	(0.77)		
$CSL].125,.5]$			-0.04	(0.24)		
$CSL].5,1]$			0.07	(0.13)		
$LP1]0,.25]$					1.39	(0.43)***
$LP1].25,.5]$					0.71	(0.22)***
$LP1].5,1]$					0.37	(0.14)***
$LP0$	0.09	(0.12)	0.09	(0.12)		
Observations	5,598		5,598		5,598	
Imputed R^2	0.865		0.864		0.863	

Results for importer and exporter fixed effects, as well as for control variables, are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 5.4: Contemporaneous trade costs in 2004-2016, second step, language intervals

on the contemporaneous extensive product margin of trade, now using the same sample, method and model as described in section 5.3.1.

I split the trade data set for manufacturing trade between 78 countries into intensive and extensive as in section 4.3.3. Furthermore, I construct a proxy for the extensive margin for domestic trade. It is plausible to be at least the sum of all exported product categories by country, since $t_{ii} < t_{ij}$ and therefore, each exported good is most likely sold domestically too. This is though a very crude way to measure the internal extensive margin, since it disregards products that are sold only domestically. However, the results for the second step are robust to the exclusion of internal trade, see tables E.4 and E.5 in appendix E.

The results of the respective first step for international and domestic trade are presented in table 5.2. Columns (3) and (4) report the estimates for the extensive product margin and columns (5) and (6) for the intensive margin. A WTO membership has a positive effect on the extensive margin and a negative one on the intensive margin, confirming the results of Dutt et al. (2013) especially for the earlier period. The effect is reversed for a common currency. EU and RTA membership have only a small impact on the margins, often not even significant. The decomposition again accounts for a large part of unobserved trade costs, with an Imputed R^2 close to one.

Table 5.5 presents the results. All language variables, except for $LP0$, have a significant and positive effect on current cross-country differences in the contemporaneous extensive product margin of trade, $\exp(\hat{\delta}_{ij}^{Man,ExtMargin,2004-2016})$. Geographical distance and preferential trade agreements impact the extensive margin as well. In the appendix E in table E.3, I report the results for the contemporaneous intensive product margin.

Dependent variable: $\exp(\hat{\delta}_{ij}^{Man,ExtMargin,2004-2016})$	(1)	(2)	(3)	(4)
$\hat{\delta}_{ij}^{Man,ExtMargin,1996-2000}$	0.62	0.61	0.61	0.62
	(0.01)***	(0.01)***	(0.01)***	(0.01)***
COL	0.09			
	(0.01)***			
CNL		0.16		
		(0.04)***		
CSL			0.13	
			(0.02)***	
$LP0$		0.04	-0.04	
		(0.03)	(0.03)	
$LP1$				0.11
				(0.03)***
$LNDIST[0,625]$	-0.06	-0.05	-0.05	-0.05
	(0.02)***	(0.02)**	(0.02)**	(0.02)**
$LNDIST]625,1250]$	-0.06	-0.05	-0.06	-0.06
	(0.02)***	(0.02)**	(0.02)***	(0.02)***
$LNDIST]1250,2500]$	-0.07	-0.06	-0.06	-0.06
	(0.02)***	(0.02)***	(0.02)***	(0.02)***
$LNDIST]2500,5000]$	-0.06	-0.06	-0.06	-0.06
	(0.02)***	(0.02)***	(0.02)***	(0.02)***
$LNDIST]5000,10000]$	-0.06	-0.06	-0.06	-0.06
	(0.02)***	(0.02)***	(0.02)***	(0.02)***
$LNDIST]10000,20000]$	-0.07	-0.06	-0.06	-0.06
	(0.02)***	(0.02)***	(0.02)***	(0.02)***
$CONTIG$	-0.00	-0.00	-0.00	0.00
	(0.02)	(0.02)	(0.02)	(0.02)
$GATT/WTO$	0.04	0.07	0.04	0.07
	(0.07)	(0.07)	(0.07)	(0.07)
RTA	0.08	0.08	0.07	0.08
	(0.01)***	(0.01)***	(0.01)***	(0.01)***
$COMLEG$	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
$COMCUR$	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.02)	(0.01)	(0.01)
$COLPOST45$	0.01	0.02	0.01	0.03
	(0.03)	(0.03)	(0.03)	(0.03)
$SIBPOST45$	0.00	0.01	-0.00	0.01
	(0.03)	(0.03)	(0.03)	(0.03)
$RELIG$	0.04	0.03	0.02	0.03
	(0.02)*	(0.02)	(0.02)	(0.02)
Observations	5,603	5,603	5,603	5,603
Imputed R^2	0.965	0.964	0.965	0.964

Results for importer and exporter fixed effects are excluded for brevity. Bootstrapped standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 5.5: Contemporaneous trade costs in 2004-2016, second step, extensive margin

Language variables apart from linguistic proximity have no significant impact on the intensive margin, and the coefficients of COL and CSL are even negative. Past extensive and intensive product margin again explains a large part of the trade margins in the later period, especially for the extensive margin. This is not only reflected by the highly significant and large coefficients of historical margins, but also by the higher Imputed R^2 for both margins, compared to the regressions in section 4.3.3.

A plausible interpretation of these results is similar to the one given in section 4.3.3: Ease in communication, expressed by intercommunication distances COL, CNL and CSL, affect contemporaneous trade mainly through the extensive product margin. Linguistic proximity, representing bilateral trust and common culture, values and norms, seem to affect contemporary trade mainly on the intensive product margin. Since $LP1$ comprise common native language and linguistic proximity, it is significant for both margins and also for total trade. Following the interpretation of the extensive and intensive product margin of Chaney (2008) and Dutt et al. (2013), a common language affects current fixed trade costs.

In conclusion, most of the impact of language on aggregate trade does not represent contemporaneous costs, but historical legacies of trade between countries with a common language. Communication ability however reduces contemporaneous fixed costs of trade. Linguistic distances yet pose costs for contemporaneous trade, presumably representing cultural proximity and informal trust.

Chapter 6

Changing Language Skills and Trade in Europe

6.1 Introduction

Trade economists eagerly tried to explain the causes of the unprecedented trade integration that took place in the two decades before the trade collapse in 2009. The gravity literature has shown positive, significant and plausibly exogenous effects of preferential trade agreements on trade (Baier and Bergstrand 2007; Baier et al. 2019). A decreasing distance elasticity was documented by Yotov (2012) and Bergstrand et al. (2015), hinting to falling costs in international trade relative to domestic trade.

Bilateral trade costs, however, also include trade barriers related to different laws, ethnics, religions or languages (Anderson and Van Wincoop, 2004). Usually, these measures are assumed to be either constant or changing only slowly over time. One exception are foreign language skills: A language can be learned within a few years, basics in even shorter time. Decreasing language barriers could have led to falling trade costs, via ease in communication and increased trust between speakers (Melitz, 2008). Thus, they could have contributed to expanding networks in international trade (Chaney, 2014).

I investigate the effect of changing language skills on trade in over thirty, mostly European, countries from the mid-90s to the beginning of the 2010s. In this period, European countries have witnessed an advancing trade integration and large changes in foreign language skills. An increasing number of people learned to communicate in English. At the same time, Russian knowledge declined in many countries of the former Eastern Bloc. I estimate the effect of changing spoken language on trade in a panel data analysis in the gravity model of trade.

To my knowledge, I am the first who uses time-varying data on language in a gravity framework, although Melitz (2008) emphasized non-constant language data as an important next step in the research on language and trade. Language variables have so far been constant in the gravity literature, mainly because of data limitations. I contribute to the literature by (i) using panel data to estimate the effect of a *change* in language skills, (ii) discussing a non-constant effect of changing language skills on trade, (iii) estimating a presumably causal effect, using country-pair fixed effects and trends for general trade integration to control for endogeneity and testing for strict exogeneity of my language variable with a 'feedback test', proposed by Wooldridge (2002) and already used in the gravity literature by Baier and Bergstrand (2007).

However, I am not the first who studies the effect of language on trade in Europe. Fidrmuc and Fidrmuc (2016) investigate trade between Eastern and Western European countries, where the Iron Curtain led to an exogenous divergence in language skills. This 'natural experiment' enabled them to estimate a potentially exogenous effect of language on trade. They find that English and German have a significant and positive impact on trade between East and West, using language data from 2005. I revise their empirical findings, taking into account the change in foreign language skills over 10 years by using language data from the mid-90s. Furthermore, I make use of the most recent methodological developments in gravity literature and estimate the effects by a two step CANOVA approach, following Egger and Nigai (2015).

I introduce the unique panel data set on language in 6.2 and insights drawn from it in section 6.3. In section 6.4, I estimate the impact of a change in common spoken language on trade and also perform an estimation of the trade and welfare effect of the changes in language skills, using the general equilibrium properties of the structural gravity model. Finally, I re-estimate the causal effect of levels of common spoken language using the 'natural-experiment' environment described by Fidrmuc and Fidrmuc (2016) in section 6.5.

6.2 Data

Additional to the data on language described in section 3.2, I use data from earlier surveys and censuses for 32 countries. The main source of data on spoken language are the *Eurobarometer* surveys. For the EU-28 and Turkey, the *Eurobarometer* surveys on Language from 2005, 2010 and 2012 are used. For the EU-15[1], I use three *Eurobarometer* surveys from the mid-90s and four from 1998 to 2001.[2] For the new member states of the European Union and Turkey, I use the *Candidate Countries Eurobarometer* surveys from 2001 and 2002 as well as four of the *Central and Eastern Eurobarometer* surveys

[1]The EU-15 consists of the following member states: Belgium, Germany, France, Italy, Luxembourg, the Netherlands, Denmark, Ireland, Greece, Spain, Portugal, Austria, Finland and Sweden. Belgium and Luxembourg are combined to one country in my data set since for several years, trade data cannot be disentangled for them.

[2]The numbers of the Standard and Special *Eurobarometer* surveys, available at the *GESIS* database (`www.gesis.org`), are 39, 41, 44, 50, 52, 54 und 55.1.

conducted between 1993 to 1997.

The surveys contain about 1000 observations per country, except for Malta and Luxembourg with only 500 observations. For each survey, new, independent and representative samples were drawn. The respondent had to be 15 years or older. In the surveys, the question of interest was: 'Which language do you speak well enough to have a conversation with?'. Fortunately, the phrasing of that question is always similar, so that the results of the different surveys should be comparable.

The *Eurobarometer* surveys are completed by census data, which usually includes questions on mother tongue and spoken language in the former Soviet Republics. For Armenia and Georgia, I use the *Caucasus Barometers* from 2008 to 2013 as well. I also counter check the data with *Ethnologue*, the *CIA Factbook* and language data from Melitz and Toubal (2014), available at *CEPII*. I am able to correct some mistakes in the *Eurobarometer* surveys for the Baltic states[3]. I also include Canada and the United States in the sample because both countries are main trading partners and destination of migrants from Eastern Europe. Canada has detailed data on native and spoken language in their censuses, which take place every five years. For the U.S., I use census data and data from the *American Community Survey Reports*.

Unfortunately, I have to exclude Georgia and Croatia from the econometric analysis because of missing internal trade before 1998. I end up with the following 32 countries for the panel data set in section 6.4: the EU-27 (not including the newest member, Croatia), Turkey, Russia, Kazakhstan, Armenia, the U.S. and Canada. The countries are listed in table F.2 in appendix F.

The cross-sectional data set used in section 6.5 contains 37 countries in the mid-90s. The additional five countries, for which I only got data from the 1990s, are Ukraine, Northern Macedonia, Serbia and Montenegro and Albania form the *Central and Eastern Eurobarometer* surveys and Norway from a *Eurobarometer* survey from 1994.

The construction of the CSL variable is the same as described in section 3.2.2. For the panel data, I construct a time-varying language variable $CSL_{ij,t}$ for the years $t = 1996, 2001, 2006, 2011$. If there is more than one source per period, e.g. the *Eurobarometer* surveys from 1994, 1995 and 1998 for $t = 1996$, I take the average of these observations. This procedure should guard against outliers that might occur because of the small sample size in the surveys.

[3]More precisely, the percentage of Russian speakers is way smaller in the surveys than in the censuses, while the percentage of English speakers and the speakers of the country's official language - Estonian, Latvian and Lithuanian, respectively - is larger. A possible reason might be that the *Eurobarometer* surveys only interviews citizens of the European Union in their surveys from 2005 to 2012. However, a part of the Russian minority in the Baltics does not own a citizenship of the respective country they live in, since speaking some level of the respective official language of the country is mandatory for this. Census data also shows that English is less commonly spoken in the group of Russians in the Baltics. Consequently, I use census data from 2009-10 for the Baltic states and interpolate Russian, English and the respective official language for 2005.

Variable	Mean	Std. Dev.	Min	Max
CSL	.303	.260	.004	1
WTO	.782	.413	0	1
RTA	.651	.477	0	1
EU	.382	.486	0	1
$COMCUR$	.112	.319	0	1
$LNMIGR$	8.589	3.077	0	19.410

Table 6.1: Summary statistics

The dependent variable, exports from country i to country j, is again taken from *CEPII's BACI* trade data set. I use the time-varying covariates RTA, EU, $GATT/WTO$ and $LNMIGR$ in a five-year interval to match the language data. Their sources are the same as described in section 3.

6.3 Changes in Foreign Language Skills

Table 6.1 reports the summary statistics of the explanatory variables. The data set consists of 4096 observations, 1024 in each year. The average CSL is rather high because the sample is linguistically relatively homogeneous, in the sense that it mainly consists of Indo-European languages. Furthermore, international relations between most of the countries lasted for quite some time, which led to a high level of foreign language knowledge. Moreover, in all states of the former Eastern Bloc, learning Russian was compulsory.

A large and over time increasing percentage of countries were members of the World Trade Organization or a Preferential Trade Agreement. The period under observation also includes two EU enlargements, 2004 and 2007, respectively. Since I also use a lagged variable of EU in 6.4, I also capture a potential lagged effect of the EU enlargement in 1995. All EU members formed a RTA with the current EU before joining. However, there was an often considerable lag between the trade agreement and the accession. $COMCUR$ represents the introduction of the Euro and adaption of it by some Eastern and Southern European countries between 2006 and 2011.

I consider 47 different languages that are spoken in at least 2 countries by at least 1 percent of the population. Thus, languages such as Welsh, Basque or Irish are not considered, although they are spoken by a significant part of the population in one country. A full list of all languages are given in table F.1 in the appendix F. The main languages, however, are English, French, German and Russian. Spanish, Italian and Turkish are also of considerable size.

Table 6.2 presents the fraction of native speakers and total speakers in the sample's total population for the main languages in the sample. In 2011, about 30 percent of the 32 countries' population spoke English as mother tongue, and additional 25 percent spoke English as foreign language, which adds up to 55 percent. I.e., more than half of the more

Language		fraction of total population (in percentage points)			
		1996	2001	2006	2011
English	native	29.75	30.12	30.47	30.55
	spoken	47.36	50.55	55.15	55.08
French	native	6.95	6.98	6.89	7.01
	spoken	13.06	12.61	13.92	12.09
German	native	8.31	8.67	8.25	7.82
	spoken	13.45	13.79	14.87	13.10
Italian	native	5.98	5.83	5.56	5.53
	spoken	6.84	6.75	6.89	6.64
Russian	native	14.25	13.06	12.86	12.38
	spoken	19.53	18.50	18.66	17.02
Spanish	native	5.97	6.77	7.19	7.46
	spoken	9.19	10.03	11.39	11.84
Turkish	native	5.27	5.70	6.25	6.47
	spoken	6.24	6.64	6.71	7.02

Table 6.2: Fraction of L1 and L2 speakers by language and year in the panel

than a billion people considered in this sample claim to speak English. Russian is spoken by about 12 percent as mother tongue and by 5 percent as second language. Russian is mainly spoken in the former Eastern Bloc, but seldom in the Western countries. French and German are widespread foreign languages for historical reasons, spoken in almost all countries in the sample by at least a small fraction.

The table also shows the evolution over time. Most remarkably, the percentage of L2-speakers in English increased by around 7 percent within only 15 years, which are about 90 million English L2-speakers more. In the same time, the percentage of Russian speakers declined by 2.5 percent, also due to a smaller number of native speakers. This can partly be attributed to a stagnating or even decreasing population in the Eastern European countries. The increasing fraction of Spanish native speakers can be assigned to the migration from Ibero-America to the United States. Still, the fraction of Spanish L2-speakers increased by 2 percent in the other countries, which hints to a growing interest into Spanish as foreign language. The other languages are quite stable over time, at least when looking at the whole sample's population.

Figures 6.1 and 6.2 display the percentages of English and Russian speakers in Europe by country, respectively. The maps do not show North America, since there were no major changes for these two languages. Furthermore, Croatia, Georgia are covered, and Luxembourg and Belgium have a separate entry. The shading of the countries indicates the fraction of speakers in 2011, while the numbers represent the change in the fraction since the mid-90s.

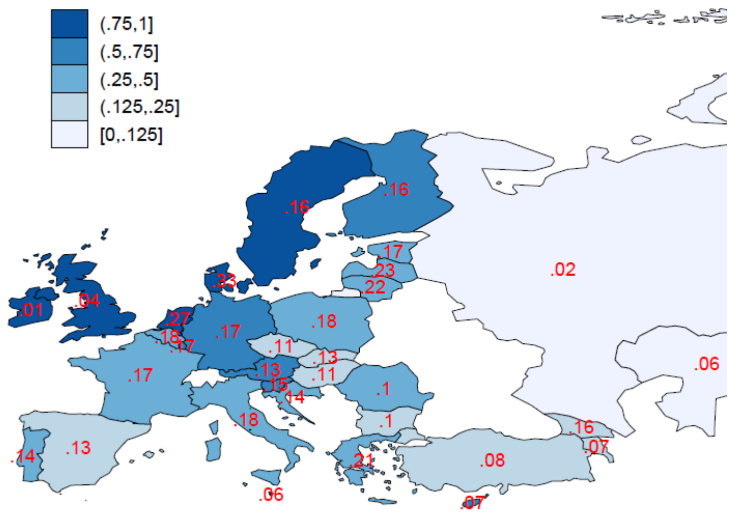

Figure 6.1: Fraction of English speakers in 2011 and change from 1996-2011

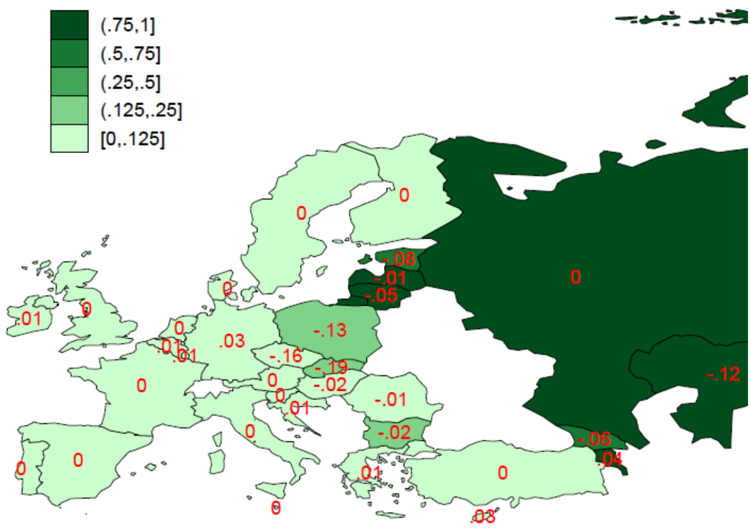

Figure 6.2: Fraction of Russian speakers in 2011 and change from 1996-2011

In figure 6.1, it can be seen that English is wide spread in the Nordic and German countries as well as in the Netherlands and the former British colonies Malta and Cyprus. Interestingly, English is nowadays quite common in many new member states of the European Union. In Russia and Kazakhstan, less than 10 percent of the population speak English. The diverge between East and West, emphasized by Fidrmuc and Fidrmuc (2016), yet still remains. At the beginning of the 2010s, more than two thirds of the population in the West (including North America and Turkey) were able to communicate in English. Only a fraction of 14 percent spoke English in the former Eastern Bloc. Russian still is the *lingua franca* in the East. Two thirds of the population of the countries in the sample speak it there, but only 1-2 percent in the Western countries.

But English was spoken to a lower degree in the mid-1990s in the former Eastern Bloc. Only 7 percent were able to speak it, according to the *Eurobarometer* surveys. As indicated by the numbers in red in figure 6.1, there has been a rise in English skills both in Eastern and Western Europe. Apart from the countries where English is the main language and therefore already at a very high level, the fraction of English speakers has grown by more than 10 percent in any of today's member states of the European Union, in some cases by over 20 percent, e.g. in the Baltic states and Denmark.

Figure 6.2 shows that at the same time, the fraction of Russian speakers declined in the East. Yet, there are differences between the countries. In Central Eastern Europe, the percentage of speakers fell to a large degree. In Hungary and Romania, Russian was not that common, possibly for political reasons and because both countries' native languages are not Slavic ones. In the Baltics, Russian kept being a *lingua franca*, although without official status. In the former Soviet Republics in the sample, Russian is still the most spoken language, despite a decline in the fraction of Russian speakers in the population. In the Western countries, Russian speakers only make up zero to four percent of the population in any country, except for Germany.

It is crucial to reflect on the reasons behind these changes in foreign language skills. First, after the Dissolution of the Soviet Union, today's members of the European Union abandoned Russian as official and as compulsory language in school to further disintegrate from former Soviet Union countries (Pavlenko, 2008). Second, the European Union seek to improve foreign language skills to "opening-up to the wider world" (European Council, 2002, p. 19). In 2002, the European Council emphasized "to improve the mastery of basic skills, in particular by teaching at least two foreign languages from a very early age" (European Council, 2002, p. 20). English was not explicitly stated, but obviously the preferred choice by the member states. Over the last decades, language schooling has expanded in the European Union: language schooling starts now earlier, years of education increased and schooling in a second foreign language was expanded (Eurydice, 2012). Third, the globalization raised the benefits of foreign language skills on the individual level. English as the most widely spoken language worldwide is a reasonable first choice.

I investigate these channels by a closer look into the data from the *Eurobarometer* surveys. Figure 6.3 presents the English and Russian skills in several example countries by age cohorts and over time. For all countries, both in Eastern and Western Europe, the percentage of English speakers is higher for the younger cohorts. Less than 10 percent of the population born before 1960 speak English in the East, but also in Western countries such as Spain. Germany represents the Indo-Germanic countries: English is widespread, also among the elderly.

In Eastern Europe, Russian skills are lower for the very old and the younger age cohorts. This is as expected, since Russian became a mandatory foreign language in school after the World War II in the countries of the Warsaw Pact, except for Romania. It is plausible that many pupils chose English instead of Russian after the Fall of the Iron Curtain, now that Russian was not mandatory anymore. In some countries, the policy

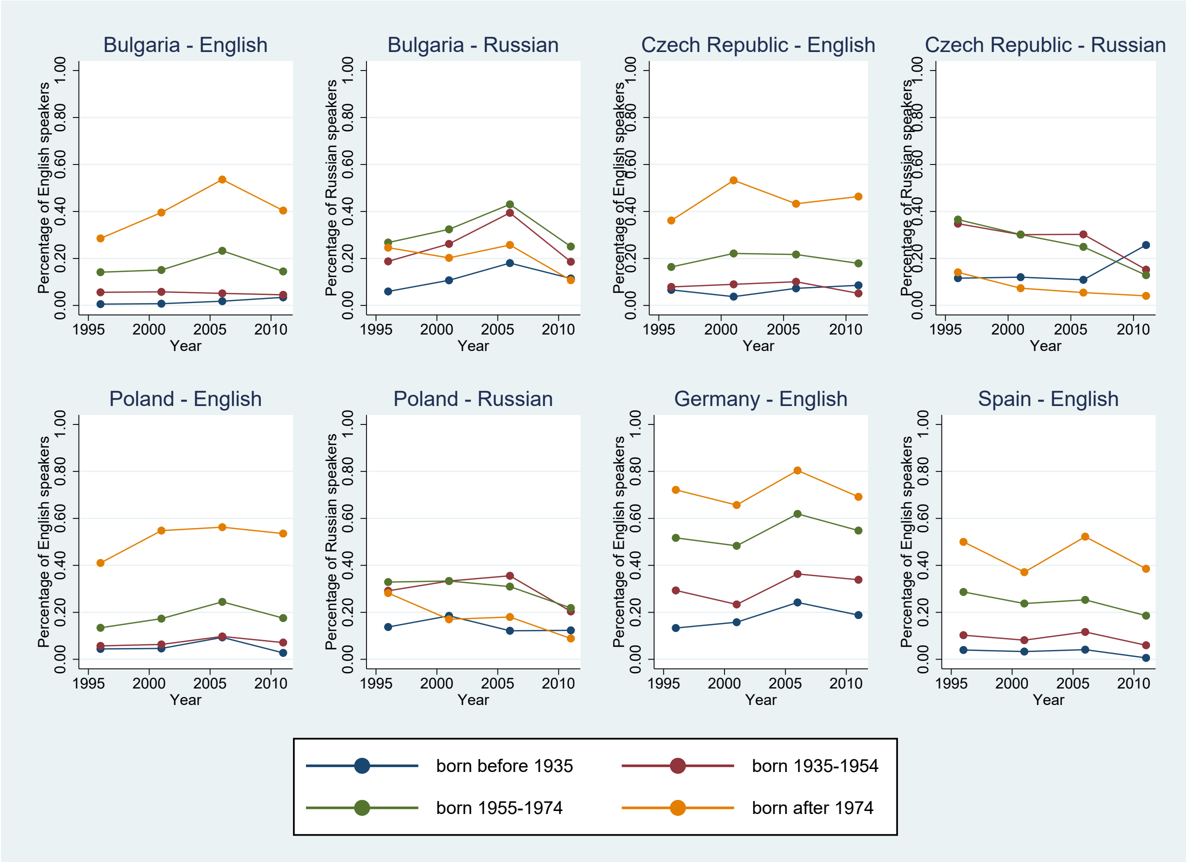

Figure 6.3: Spoken language by age cohorts from 1996-2011 in selected countries

change went even further, with sometimes negative consequences. In Latvia, Russian minority language schools switched the instruction language from Russian to 60 percent Latvian, 40 percent Russian in 2004. Ivlevs and King (2014) show that this language policy resulted in lower exam results in the Russian minority compared to the Latvian majority. In Kazakhstan, the national Kazakh language was promoted by politics. Only in 2011, English was introduced besides Kazakh and Russian (Ginsburgh and Weber, 2020). These examples indicate that the first and foremost interest of former Soviet Republics was to strengthen the respective national language, sometimes to the expense of Russian.

Interestingly, the age cohorts born before 1975 did not increase their English skills significantly over time. The changes in foreign language skills are mainly driven by the younger people with better foreign language knowledge, slowly replacing the older cohorts over time. Adult education did not seem to play a major role, so the changes are most likely driven by language lessons in school.

According to the *Eurobarometer* survey from 2012, language schooling is the most important way to learn a language in Europe. About 70 percent of the European citizens learned a second language at school and 45 percent found language lessons in school to be most effective. Other ways of language learning, such as group or one-to-one lessons, country visits or self-study, are less common and judged less effective. Again, there are differences by age groups. While 87 percent aged between 15 and 24 learned a language in school, only two thirds of those aged between 55 and 64 did so. Consequently, language skills depend on education level. More than 69 percent of the Europeans that finished their education at the age of 16 or older can speak at least one foreign language. Only about 30 percent of those who finished earlier are still able to communicate in a foreign language. Thus, it is credible to attribute part of the general rise in English skills to intensified language schooling.

In conclusion, the EU education policy and the wish of Eastern European countries to partly replace Russian in school curricula led to a language policy that raised English skills and reduced Russian skills in Europe. Increasing economic and cultural integration, both intra-EU and extra-EU, was the goal of the EU politics. The decision of the Eastern countries to abandon Russian was also driven by political and national, not only economic reasons. Part of the changes in common spoken language might therefore be exogenous, although both individual and policy choices are potentially influenced by existing trade relations or the expectation of future trade integration. In the next section, I estimate the correlation between changing common spoken language and bilateral trade in a gravity framework and try to estimate a causal effect of language using several methods to control and test for endogeneity.

6.4 The Impact of Changing Spoken Language on Trade

6.4.1 Empirical Strategy

The variable of interest in this analysis is $CSL_{ij,t}$, common spoken language. In the same way as Baier and Bergstrand (2007) did it for FTAs, I estimate the average partial effect of CSL on trade with a three-way fixed effects model presented in equation 6.1. As recommended by Santos Silva and Tenreyro (2006), I use the PPML estimator. $\mu_{i,t}$ and $\pi_{j,t}$ capture the outward and inward multilateral resistance terms of the structural gravity equation (Fally, 2015).

$$X_{ij,t} = \exp\left(\mu_{i,t} + \pi_{j,t} + \delta_{ij} + \beta_1 CSL_{ij,t} + \beta_z Z_{ij,t}\right) \times \epsilon_{ij,t} \tag{6.1}$$

I control for reverse causality of CSL, i.e. that individuals have learned the language of the trading partner in the past because of historical economic relations, by directional country-pair fixed effects, δ_{ij}. Unlike a parametric model, the set of country-pair effects explains all constant cross-country variation and thus reduces the potential bias caused by unobserved trade costs (Egger and Nigai, 2015). With δ_{ij} included in the model, the *level* of CSL does not affect the estimation, only the *change over time*. Since CSL is time-varying, I am able to estimate an average treatment effect of the change in common spoken language, $CSL_{ij,t} - CSL_{ij,t-5}$ (Wooldridge, 2002).

I add a set of time-varying control variables, $Z_{ij,t}$, that account for political integration and migration. , $Z_{ij,t}$ includes regional trade agreement (RTA), membership in the WTO (WTO), the European Union (EU) or a currency union ($COMCUR$). Additionally, I include one lag of EU and RTA to account for 'phasing-in' effects (Baier and Bergstrand, 2007), such as the temporarily suspended freedom of movement for workers from New European Union member states in the EU enlargement in 2004. I also include the natural logarithm of the bilateral migrant stock, $LNMIGR$.

Bergstrand et al. (2015) and Baier et al. (2019) control for globalization effects, such as improved communication and transportation technology, that generally increase international trade over time. They argue that otherwise, the estimated coefficients are biased upwards. They propose a dummy variable that takes the value of one for international trade for each year t, and zero otherwise, which I dub $INTERNAT$ in the regression 6.2. Estimating the variable $INTERNAT$ for each year is not possible because of perfect collinearity with the fixed effects, which is why I exclude $INTERNAT \times t$ in the base year. Hence, the coefficients are to be interpreted relative to 1996. Adding the globalization trend is especially important for estimating the effect of common spoken languages, because innovation in communication technology raise benefits from foreign language skills tremendously.

Furthermore, I include a similar variable, $EASTWEST$, that controls for trade growth between the former Eastern Bloc and all other countries in the sample. It equals one if one trading partner is a former Eastern Bloc country and the other not, and zero otherwise. Again, the coefficients are estimated against the base year 1996. After the Fall of the Iron Curtain, East-West trade literally started from zero because of former prohibitive trade restrictions. Trade might have grown faster between Eastern and Western countries than within the West and the East. Trade networks were literally non-existent before 1991, but the costs of establishing them, formerly prohibitively high, now were relatively low compared to already well linked Western Europe. Hence, trade might converged faster to a 'natural' level for East-West trade, i.e. grew faster than other trade.

Disdier and Mayer (2007) and Guiso et al. (2009) use data from *Eurobarometer* surveys to show that bilateral opinions and trust have a positive effect on trade. Besides common spoken language, bilateral trust might have changed over time as well. Since common language is often related to increased bilateral trust (Egger and Lassmann, 2012; Spring and Grossmann, 2016), it would be interesting to include a control variable for bilateral trust. Unfortunately, the surveys stopped asking questions about bilateral trust and opinions by the beginning of the 2000's. However, the trends for $INTERNAT$ and

$EASTWEST$ control for increased trust, both in general and especially between Eastern and Western countries.

$$X_{ij,t} = \exp\left(\mu_{i,t} + \pi_{j,t} + \delta_{ij} + \beta_1 CSL_{ij,t} + \beta_z Z_{ij,t}\right) \times \\ \left(\sum_t \beta_t INTERNAT_{ij} \times t + \sum_t \beta_t EASTWEST_{ij} \times t\right) \times \epsilon_{ij,t} \tag{6.2}$$

Although I control for historical trade costs, it is still possible that trade causes common language and not otherwise, i.e. there is a 'reverse causality' problem. I test this with a so-called 'feedback-test', described in Wooldridge (2002) and already used in a gravity framework by Baier and Bergstrand (2007). I include one lead of the language variable, $CSL_{ij,t+5}$. If the lead variable has a positive and significant coefficient, future increases in language skills can explain contemporaneous trade, which violates the assumption of strict exogeneity of the explanatory variable.

6.4.2 Estimates of the Average Partial Effect

Common Spoken Language

The estimation results are presented in table 6.3. I do not report a pseudo R^2, since it is always close to one due to the high explanation power of country pair fixed effects. I proceed in several steps: First, I estimate regression 6.1 without globalization- and East-West trend in column (1). Remarkably, the coefficient of CSL is about three times higher than usual estimates of the effect of language on trade, although I controlled for reverse causality with pair fixed effects and other time-variant variables, which all have a positive impact on trade integration, except for WTO membership. The change in spoken language yet might capture other channels that influenced trade and therefore be biased, i.e. increased bilateral trust or growing networks of trade.

In columns (2) and (3), I introduce step by step the trends from regression 6.2. International trade increased in all countries, as shown by the highly significant positive coefficient of $INTERNAT$ in each year relative to the base year 1996. The $EASTWEST$ trend is only significant in 2001 and 2011 and its inclusion renders $LNMIGR$ insignificant, but does not change the results for common spoken language. Accounting for a general globalization trend diminishes the coefficient of CSL to a more plausible value. CSL did increase for most countries in the sample and hence captured a large part of the general increase in trade in column (1). The effect is still marginally significant. *Ceteris paribus*, an increase of ten percentage points in CSL is associated with an increase in international trade of $(\exp(0.43) - 1) \times 10 = 5.4$ percent.

RTA's coefficient also decreases from .73 to .54, but stays highly significant. The

	(1)	(2)	(3)	(4)	(5)
Dependent variable: $X_{ij,t}$					
$CSL_{ij,t}$	1.90	0.40	0.43	1.75	0.41
	(0.29)***	(0.23)*	(0.23)*	(0.26)***	(0.27)
$CSL_{ij,t+5}$				1.47	0.01
				(0.43)***	(0.36)
$RTA_{ij,t}$	0.72	0.56	0.59	0.61	0.46
	(0.12)***	(0.10)***	(0.10)***	(0.09)***	(0.09)***
$RTA_{ij,t-5}$	0.46	0.27	0.19	0.39	0.18
	(0.04)***	(0.05)***	(0.06)***	(0.06)***	(0.06)***
$EU_{ij,t}$	0.14	0.25	0.26	0.11	0.15
	(0.05)***	(0.04)***	(0.04)***	(0.05)**	(0.06)**
$EU_{ij,t-5}$	0.15	0.08	0.07	0.07	0.02
	(0.05)***	(0.05)*	(0.05)	(0.14)	(0.11)
$WTO_{ij,t}$	-0.37	-0.28	-0.30	-0.36	-0.27
	(0.14)**	(0.15)*	(0.14)**	(0.17)**	(0.17)
$COMCUR_{ij,t}$	0.20	-0.06	-0.05	0.13	-0.07
	(0.05)***	(0.03)*	(0.03)	(0.05)***	(0.04)*
$LNMIGR_{ij,t}$	0.22	0.06	0.04	0.22	0.07
	(0.04)***	(0.03)**	(0.03)	(0.05)***	(0.03)*
$INTER_{ij,2001}$		0.31	0.30		0.32
		(0.03)***	(0.04)***		(0.05)***
$INTER_{ij,2006}$		0.38	0.37		0.39
		(0.03)***	(0.03)***		(0.03)***
$INTER_{ij,2011}$		0.47	0.46		
		(0.03)***	(0.03)***		
$EASTWEST_{ij,2001}$			0.14		0.12
			(0.06)**		(0.06)**
$EASTWEST_{ij,2006}$			0.11		0.14
			(0.07)		(0.08)*
$EASTWEST_{ij,2011}$			0.14		
			(0.08)*		
Observations	4,096	4,096	4,096	3,069	3,069

Results for importer-time, exporter-time and asymmetric country-pair fixed effects are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses. * $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 6.3: Average partial effect of CSL

significant effect of an EU accession prevails, but there is no significant 'phasing-in' effect any more. The effect of $COMCUR$ switches signs in column (2) and gets insignificant in column (3).

In columns (4) and (5), I apply the 'feedback test' for strict exogeneity on the variable of interest, CSL. I do this by adding one lead of the variable as regressor. This drops the last period of my sample, which explains the lower result in the coefficients of EU, since in 2006, Bulgaria and Romania did not join the European Union yet. In column (4), where the lead is added to the regression from column (1), $CSL_{ij,t+5}$ is positive and highly significant. Future language skills are correlated with contemporaneous trade and the large effect of common spoken language estimated in (1) is therefore not strictly exogenous. I test CSL from the regression from column (3) for strict exogeneity in column (5). Here, the 'feedback test' confirms that the modest and less significant effect of common spoken language is strictly exogenous. However, the effect of CSL is not significant anymore, likely due to the lower number of observations, and only marginally significant in column (3). In conclusion, a change in common spoken language is correlated with changes in bilateral trade, but only has a dubious causal effect.

A robustness check where I exclude North America from the regression, reported in column (1) of table F.3 in appendix F, raises further doubts on an exogenous effect of CSL on trade. I re-estimate column (3) and find no significant effect of common spoken language on trade. In the next section, I do not aggregate all languages into one variable but distinguish between the main languages in the sample, which all show different trends, as demonstrated in section 6.3.

Separate Languages

Dependent variable: $X_{ij,t}$	(1)	(2)	(3)	(4)
$CSL\_ENGLISH_{ij,t}$	2.45	0.88	0.94	0.95
	(0.69)***	(0.39)**	(0.39)**	(0.43)**
$CSL\_GERMAN_{ij,t}$	-1.86	-0.41		
	(0.70)***	(0.43)		
$CSL\_FRENCH_{ij,t}$	0.21	0.27		
	(0.63)	(0.35)		
$CSL\_RUSSIAN_{ij,t}$	-1.88	-0.36		
	(1.07)*	(0.75)		
$CSL\_OTHER_{ij,t}$	1.39	0.39		
	(0.58)**	(0.45)		
$CSL\_NO\_ENGLISH_{ij,t}$			0.37	0.35
			(0.23)	(0.28)
$CSL\_ENGLISH_{ij,t+5}$				1.24
				(0.51)**
$RTA_{ij,t}$	0.72	0.60	0.60	0.46
	(0.11)***	(0.10)***	(0.10)***	(0.09)***
$RTA_{ij,t-5}$	0.49	0.18	0.19	0.18
	(0.04)***	(0.06)***	(0.06)***	(0.06)***
$EU_{ij,t}$	0.22	0.26	0.26	0.15
	(0.05)***	(0.04)***	(0.04)***	(0.06)**
$EU_{ij,t-5}$	0.13	0.08	0.08	0.05
	(0.05)***	(0.04)*	(0.04)*	(0.09)
$WTO_{ij,t}$	-0.30	-0.29	-0.31	-0.30
	(0.15)**	(0.14)**	(0.14)**	(0.17)*
$COMCUR_{ij,t}$	0.25	-0.04	-0.03	-0.04
	(0.05)***	(0.03)	(0.03)	(0.04)
$LNMIGR_{ij,t}$	0.24	0.04	0.04	0.06
	(0.05)***	(0.03)	(0.03)	(0.03)*
$INTER$- and $EASTWEST$-trend	No	Yes	Yes	Yes
Observations	4,096	4,096	4,096	3,069

Results for importer-time, exporter-time and asymmetric country-pair fixed effects, as well as globalization and East-West trend, are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses. * $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 6.4: Average partial effect by language, particularly English

A change in overall CSL in table 6.3 might not be detailed enough. The changes in each language sometimes offset each other. E.g., the increase in English speakers in the Czech Republic increased CSL for the country pair Czechia-Germany, but the simultaneous decrease in German skills reduces CSL for the same country pair. Overall, the variable neither measure the increase in common spoken English nor the decrease in common spoken German correctly. Therefore, I estimate the impact of a change in the four most widely spoken languages, English, German, French and Russian, separately.

I split up CSL by language into $CSL\_ENGLISH$, $CSL\_RUSSIAN$, CSL_GERMAN and CSL_FRENCH in column (1) and (2) in table 6.4. The remaining languages are subsumed in CSL_OTHER. In column (1), I do not include the $INTER$- or $EASTWEST$-trend. Out of the four main languages, only English has an positive and significant effect. An increase in German and Russian is even associated with less trade. In column (2), I control for a general globalization trend and an East-West trend, but omit the output in the table. The language variables' coefficients have the same sign as in column (1), however, only the effect of English is still significantly different from zero.

What is there to learn from this results? Knowledge of Russian and German decreased in Eastern Europe, when at the same time international trade rose within the region and with Central European, German speaking countries. This results in a negative correlation between the change in both languages and trade, which turns insignificant once I control for a general rise in trade integration. The decrease in Russian and German skills also did not lead to reduced trade flows, which would have been indicated by positive coefficients.[4] Partly, Russian and German was replaced as international language by English, especially in the New Member States of the European Union in Eastern and Southeastern Europe. This explains why the impact of $CSL\_ENGLISH$ is larger than that of aggregate CSL in table 6.3.

Since the impact of CSL on trade seems to be driven by English skills and the reduction in common German and Russian knowledge did not lead to a significant reduction in trade, I focus on English in the further analysis. In column (3), I distinguish between English and non-English languages, i.e. all other languages, including German, Russian and French. The impact of $CSL\_ENGLISH$ is again significant at the 5 percent level. An increase of ten percentage points in $CSL\_ENGLISH$ is correlated with an increase in international trade of $(\exp(0.94) - 1) \times 10 = 15.6$ percent.

In column (4), however, $CSL\_ENGLISH$ fails the feedback test. The effect of English is not strictly exogenous, even though I control for a globalization trend. In a robustness test I exclude North America. Table F.3 in appendix F displays the results. There, the feedback test confirms strict exogeneity since the effect of $CSL\_ENGLISH_{t+5}$ is

[4]Importantly, this does not mean that, e.g., the common Russian language does not coincide with more trade within the former Eastern Bloc. This on average stronger trade is accounted for by the constant country-pair effects.

insignificant, but the coefficient is still positive and large. In conclusion, the results on an exogenous effect of changing language skills on trade are still ambiguous.

Non-constant Effect of Language on Trade

As described in section 2.2, translation complicates the impact of a common spoken language for two trading partners. Already a small number of bilinguals could be sufficient to distribute information between both countries (Melitz, 2008). Additionally, low values of common spoken language could indicate that countries are still in the contact phase of trade and common language is a more important trade restriction. This might be particularly relevant for English in the Former Eastern Bloc, since it is a relatively new foreign language in these countries that enables trade with new trading partners in the West.

As demonstrated in section 4.5.5, the same increase in common spoken language has a larger impact for a lower level of percentage of speakers than for a higher one, i.e. a decreasing marginal effect of language on trade can be observed. E.g., an increase of $CSL\_ENGLISH$ from 15 percent to 25 percent should have a larger effect on bilateral trade than a change from 55 percent to 65 percent.

To test this hypothesis, I split $CSL\_ENGLISH$ in the following five intervals that represents the distribution of the non-negative observations of the variable: [1,.5], [.5,.25], [.25,.125], [.125,.0625] and [.0625,0]. The results in column (1) in table 6.5 confirm the hypothesis and are re-assuring for the results in section 4.5.5. For the lowest interval, the trade volume effect of an increase in common spoken English, $\exp(3.1) - 1 = 21.2$, is a multiple of the highest interval, $\exp(1.5) - 1 = 3.5$. The coefficients of all intervals are highly significant and in general larger than the estimate of a constant language semi-elasticity. In conclusion, countries with a low percentage of English speakers, such as Central Eastern and Eastern European countries, profited most from an increase in English. All intervals pass the feedback test in column (2). The interval specification therefore describes a strictly exogenous effect. Thus, the reason for the endogeneity in 6.4 might be a model mis-specification, assuming a constant effect of $CSL\_ENGLISH$.

To make the coefficients more readily interpretable, they can be translated to tariff equivalent effects, using the properties of the structural gravity equation. All that is needed is an reliable estimate of the trade elasticity of substitution, dubbed σ in section 2.3. The estimates range between 3 and 7, where I take the the preferred value of Head and Mayer (2014), $\sigma = 5$. Then, an increase in common spoken English from 15 percent to 25 percent is equivalent to a fall in *ad valorem* tariffs of $(\exp(2.09/5) - 1) \times 10 = 5.2$ percent.

In table 6.5, column (3), I include an interaction between $EASTWEST$ and the English language intervals. For trade between East and West, there is no country pair

Dependent variable: $X_{ij,t}$	(1)		(2)		(3)	
$CSL\_ENGLISH_{ij,t}$						
]0,0.0625]	3.10	(0.79)***	2.02	(0.83)**	3.04	(0.88)***
]0.0625,0.125]	2.55	(0.59)***	2.02	(0.57)***	2.58	(0.62)***
]0.125,0.25]	2.09	(0.53)***	1.69	(0.52)***	2.04	(0.55)***
]0.25,0.5]	1.69	(0.48)***	1.39	(0.48)***	1.59	(0.51)***
]0.5,1]	1.50	(0.45)***	1.29	(0.45)***	1.41	(0.47)***
$CSL\_NO\_ENGLISH_{ij,t}$	0.22	(0.22)	0.30	(0.28)	0.22	(0.25)
$CSL\_ENGLISH_{ij,t+5}$						
]0,0.0625]			-1.26	(0.96)		
]0.0625,0.125]			-0.18	(0.69)		
]0.125,0.25]			0.25	(0.65)		
]0.25,0.5]			0.20	(0.64)		
]0.5,1]			0.31	(0.59)		
$EASTWEST \times CSL\_ENGLISH_{ij,t}$						
]0,0.0625]					-0.33	(1.83)
]0.0625,0.125]					-0.75	(1.28)
]0.125,0.25]					-0.32	(0.91)
]0.25,0.5]					0.30	(0.76)
$EASTWEST \times CSL\_NO\_ENGLISH_{ij,t}$					-0.10	(0.46)
$RTA_{ij,t}$	0.60	(0.10)***	0.49	(0.09)***	0.59	(0.11)***
$RTA_{ij,t-5}$	0.19	(0.06)***	0.16	(0.06)**	0.20	(0.06)***
$EU_{ij,t}$	0.25	(0.04)***	0.16	(0.06)**	0.26	(0.04)***
$EU_{ij,t-5}$	0.08	(0.04)*	0.04	(0.09)	0.08	(0.04)*
$WTO_{ij,t}$	-0.30	(0.14)**	-0.26	(0.17)	-0.35	(0.14)**
$COMCUR_{ij,t}$	-0.04	(0.03)	-0.04	(0.04)	-0.04	(0.03)
$LNMIGR_{ij,t}$	0.05	(0.03)*	0.08	(0.03)**	0.05	(0.03)
Observations	4,096		3,069		4,096	

Results for importer-time, exporter-time and asymmetric country-pair fixed effects, as well as globalization and East-West trend, are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 6.5: Average partial effect of English intervals

with $CSL\_ENGLISH$ in the last interval, which is why no effect can be estimated. The impact of $CSL\_ENGLISH$ is lower than for other trade, except for the third interval, but not significantly so. This reassures that the country pair fixed effects reliably control for any constant trade costs and the East-West-trend sufficiently controls for the trade integration of the former Eastern Bloc.

The results presented in this section might be driven by the largest country in the sample that is moreover an English speaking country, i.e. the United States. In a robustness check, I re-estimate the regressions from table 6.5 in table F.4 in appendix F without the North American countries U.S. and Canada. The robustness test confirms the results for a non-constant effect of language. Therefore, I choose the robust specification in column (1) in table 6.5 to estimate general equilibrium effects in the next section.

6.4.3 General Equilibrium Trade and Welfare Effects

In this section, I compute the trade and welfare effects of the increase in English speakers in the sample. The counterfactual is that English skills did not change in any of the countries. I use the estimated partial effects for the $CSL\_ENGLISH$ intervals from table 6.5, column (1). The effects therefore rely on the respective starting point in terms of English knowledge in the country. I put the results in comparison to the Enlargement of the European Union in 2004 and 2007.

I use a simple general equilibrium model from Baier et al. (2019), described in section 2.3. As in the previous section, I assume that $\sigma = 5$. The base year for the counterfactual is 1996, before the observed changes in language skills took place.

The change in $CSL\_ENGLISH$ between the base year 1996 and 2011 depends on the respective changes in exporter and importer country, reported in figure 6.1, and thus varies by country pair. The largest change in the probability that two randomly chosen people from two countries speak English is 23.6 for the pair Netherlands-Sweden, while the lowest changes, which are less than one percent, take place for trade with the Russian Federation.

Additionally, the partial effect of $CSL\_ENGLISH$ in my specification depends on the respective level of $CSL\_ENGLISH$ for each country pair. Since the effect diminishes with the level of $CSL\_ENGLISH$, country pairs with already large percentage of English speakers are relatively less affected. As a result, the lowest change in trade barriers is assigned to the pair UK-Ireland, where English as a native language was already spoken by more than 90 percent of the population. The effect is a bit larger for the pairs including Russia, since less than 6 percent of the Russians spoke English, according to my data. With a value of more than .43, the highest changes in trade barriers took place for both Lithuania and Latvia with the Netherlands and Sweden, due to the low level of English speakers in the former countries in 1996 and the large increase in speakers in all four states.

Table 6.6 reports the estimated general equilibrium effects by country of the increase in English skills for total exports, total imports and welfare and compares them to the respective predictions for the effects of the EU Enlargement to the East in the 2000's. For the estimates for $CSL\_ENGLISH$, I also report the bootstrapped standard errors im parenthesis.

It can be seen that all countries profit from the increase in English skills, except for Russia, where there is no significant impact on trade and welfare. The region that profited the most are the Baltic states, which started from a low level of English knowledge which increased strongly, as shown in figure 6.1, and the Netherlands. The latter did not only see a relatively strong rise in English speakers, the also had high initial trade shares with countries that increased English knowledge in the population. States with relatively low

	change in CSL English			EU enlargement		
Country	Δ% Exports	Δ% Imports	Δ% Welfare	Δ% Ex.	Δ% Im.	Δ% W.
ARM	7.04 (6.37, 7.71)	1.37 (1.03, 1.70)	0.64 (0.30, 0.99)	-0.96	-0.19	-0.05
AUT	15.99 (11.78, 20.20)	13.40 (7.21, 19.58)	2.67 (0.91, 4.44)	7.12	5.97	1.12
BGR	7.68 (5.70, 9.67)	8.88 (7.31, 10.46)	1.36 (0.60, 2.12)	13.57	15.69	2.39
BLX	7.33 (4.80, 9.85)	8.02 (4.34, 11.69)	3.32 (1.20, 5.44)	0.26	0.29	0.13
CAN	4.26 (2.35, 6.17)	5.26 (1.70, 8.81)	0.59 (0.17, 1.01)	-0.11	-0.13	-0.01
CYP	12.37 (9.09, 15.65)	3.28 (1.73, 4.83)	2.02 (0.73, 3.31)	24.67	6.55	3.42
CZE	11.86 (10.25, 13.47)	10.00 (7.69, 12.31)	1.64 (0.75, 2.54)	24.80	20.92	3.50
DEU	16.02 (10.43, 21.61)	19.09 (10.90, 27.28)	1.38 (0.48, 2.29)	2.32	2.77	0.20
DNK	16.43 (8.53, 24.33)	15.32 (6.59, 24.06)	2.93 (0.81, 5.04)	1.73	1.61	0.29
ESP	6.57 (4.43, 8.71)	5.51 (3.88, 7.14)	0.43 (0.20, 0.65)	0.48	0.40	0.03
EST	14.64 (11.91, 17.37)	9.08 (7.74, 10.42)	4.06 (1.62, 6.49)	17.44	10.81	4.85
FIN	15.83 (7.76, 23.90)	21.67 (12.76, 30.58)	2.49 (0.75, 4.24)	4.88	6.68	0.74
FRA	6.48 (3.75, 9.21)	6.14 (4.15, 8.13)	0.46 (0.19, 0.73)	0.64	0.61	0.05
GBR	10.20 (4.10, 16.30)	8.83 (4.71, 12.95)	0.76 (0.22, 1.30)	0.80	0.69	0.06
GRC	24.60 (14.85, 34.36)	9.38 (5.51, 13.25)	2.00 (0.76, 3.23)	2.41	0.92	0.17
HUN	9.35 (8.24, 10.46)	7.61 (6.29, 8.94)	2.44 (1.05, 3.84)	19.58	15.94	5.28
IRL	3.11 (1.47, 4.76)	4.30 (2.45, 6.15)	0.99 (0.28, 1.70)	0.18	0.25	0.06
ITA	6.43 (3.25, 9.61)	8.31 (5.93, 10.69)	0.41 (0.19, 0.63)	1.36	1.76	0.09
KAZ	1.95 (1.09, 2.81)	1.33 (0.15, 2.51)	0.46 (0.16, 0.76)	-0.41	-0.28	-0.03
LTU	10.95 (8.90, 13.00)	8.32 (6.56, 10.09)	5.52 (2.38, 8.65)	11.43	8.69	5.69
LVA	15.66 (13.40, 17.91)	8.77 (6.86, 10.69)	4.70 (1.87, 7.52)	14.80	8.29	4.28
MLT	8.56 (5.22, 11.91)	4.46 (2.83, 6.09)	2.58 (0.81, 4.36)	19.37	10.09	6.16
NLD	10.98 (5.11, 16.84)	11.12 (5.99, 16.25)	4.64 (1.31, 7.97)	0.41	0.41	0.18
POL	24.65 (21.46, 27.84)	16.95 (13.30, 20.60)	1.65 (0.72, 2.58)	32.37	22.26	2.16
PRT	8.08 (5.15, 11.00)	6.17 (4.22, 8.12)	0.67 (0.31, 1.03)	0.20	0.16	0.02
ROU	12.44 (10.44, 14.45)	10.16 (8.50, 11.81)	0.68 (0.31, 1.05)	22.43	18.31	1.20
RUS	-0.41 (-1.44, 0.62)	-0.29 (-1.24, 0.67)	0.03 (-0.06, 0.12)	-2.14	-1.49	-0.07
SVK	8.83 (7.55, 10.11)	7.67 (5.71, 9.63)	2.61 (1.16, 4.06)	17.54	15.24	5.34
SVN	16.51 (8.31, 24.71)	14.42 (7.84, 21.00)	2.06 (0.75, 3.37)	26.43	23.09	3.40
SWE	17.88 (10.28, 25.49)	21.19 (9.75, 32.64)	2.90 (0.77, 5.04)	5.29	6.27	0.82
TUR	12.68 (10.68, 14.68)	6.92 (5.19, 8.64)	0.62 (0.29, 0.96)	-0.97	-0.53	-0.02
USA	9.50 (4.90, 14.11)	8.25 (4.87, 11.62)	0.15 (0.04, 0.25)	-0.41	-0.35	0.00
EU-15	10.95 (6.44, 15.46)	11.18 (6.65, 15.71)	1.22 (0.41, 2.03)	1.59	1.66	0.16
EU-NMS	14.57 (12.46, 16.68)	11.41 (9.10, 13.72)	1.85 (0.79, 2.91)	23.80	18.27	3.08
non-EU	7.24 (4.37, 10.11)	6.67 (3.94, 9.40)	0.19 (0.05, 0.32)	-0.44	-0.40	-0.01
all countries	10.35 (6.44, 14.26)	10.35 (6.44, 14.26)	0.77 (0.26, 1.28)	2.12	2.12	0.17

The table reports the results from a general equilibrium simulation of the effects of the increase in English skills and compares them to the results of the effect of the EU enlargements in 2004 and 2007. For the former set of results, I include bootstrapped 95% confidence intervals (10000 replications) in parentheses.

Table 6.6: General equilibrium trade and welfare effects

initial trade shares with these countries, such as the Romance countries Italy, France and Spain, were less affected although the increase in percentage of English speakers was similar to Germany, where welfare effects were more than three times larger.

The right panel of table 6.6 presents the welfare and trade effects from the EU Enlargement 2004 and 2007. For the Baltics, the effects of the increase of English skills in the sample are comparable to that of the EU accession. Exports increased by 10-17 percent, imports by 8-11 percent and welfare by 4-5.7 percent, assuming again a trade elasticity of 5. For the other New Member States, however, the impact of a change in

English skills on trade and welfare was clearly lower than the effect of the EU accession.

At the bottom of table 6.6, I present results for aggregates over countries. The trade and welfare effects are largest for the ten new member states of the European Union, and lowest for the non-EU countries. Overall, welfare increased by 0.77 percent for the whole sample. The welfare effect of the EU accession in the right panel is larger for the new member states, positive, but lower, for the old members and almost zero for non-EU countries. Changes in trade for non-EU countries are negative due to trade diversion. The welfare and trade effects for the whole sample are smaller, which can be attributed to the fact that English skills increased in almost all countries, but only ten out of 32 countries joined the EU between 1996 and 2011. The only country not gaining from the overall increase in English skills is Russia, where the percentage of English speakers was already low and did not increase over time. The impacts of rising language knowledge are therefore not only of significant magnitude, they can be more evenly distributed and less exclusive as preferential trade agreements too.

6.5 Re-Estimating Fidrmuc and Fidrmuc (2016) 'Natural Experiment'

So far, I have investigated the effect of a change in common spoken language on trade in Europe and found that the magnitude of this impact depends on the initial level of common spoken language. However, it is not clear if the differences in levels themselves influence trade in this sample, since their effect was captured by country-pair fixed effects.

East-West trade is especially interesting in this respect, since different language policies were in place for more than five decades in Western and Eastern countries and at the same time, there was almost no trade across the Iron Curtain. It is therefore a suitable environment to estimate the causal effect of common spoken language on trade. Hence, I recapitulate the investigation of the effect of language on trade in the 'quasi-natural experiment' of the East-West divide carried out by Fidrmuc and Fidrmuc (2016). However, there are two main differences to their approach. First, while they use language and trade data from 2005, which is enough time after the Fall of the Iron Curtain to learn a foreign language for a larger part of the population, I use data from the mid and late 1990s. As seen in section 6.3, language skills changed noticeably between these two points in time. Second, I use the most recent estimation methods for the gravity model, the two-step CANOVA approach by Egger and Nigai (2015), described in section 4.2. The thus obtained results most likely differ from the OLS results estimated by Fidrmuc and Fidrmuc.

I use consecutive trade data from 1995 to 1999 and language data from the mid-1990s for 37 countries. As mentioned in section 6.2, the *Central and Eastern Eurobarometer* surveys conducted in the 1990s also contain language data for some additional countries that could not be used in section 6.4. The wider sample now includes Albania, North Macedonia, Norway, Serbia and Montenegro and Ukraine. Former Yugoslavia left the Warsaw Pact already in 1948 and Albania later in 1968, but both countries remained communist dictatorships. In the following, I count Albania and the successors of Yugoslavia as Eastern countries.

$$\hat{\delta}_{ij} = \exp\left(\nu_i + \zeta_j + \beta_{CSL1} CSL_{ij,EASTWEST=1} + \beta_{CSL2} CSL_{ij,EASTWEST=0}\right) \times \\ \left(\beta_{EW} EASTWEST_{ij} + \beta_k K_{ij} + \epsilon_{ij}\right) \tag{6.3}$$

In the first step, I decompose trade by exporter-time, importer-time and constant, asymmetric country-pair fixed effects. The model for the second step is described in equation 6.3. I regress the country-pair fixed effects from the first step, $\hat{\delta}_{ij}$, on CSL_{ij} and a set of covariates, K_{ij}, and a set of importer and exporter fixed effects, just as in chapter 4. The explanatory variables however differ: I estimate the effect of common spoken language separately for East-West-trade and other trade. I include a dummy variable for East-West-trade too, to control for any special feature of trade between East and West, e.g. relatively under-developed trade networks. As in the previous chapters, I control for linguistic proximity, $LP0$, for geography using distance intervals and a contiguity dummy, GATT/WTO membership, regional trade agreements, EU membership (for the West), a common legal origin, common religion and colonial past. Additionally, I include a dummy that equals one if a country-pair belonged to the same (colonial) empire between 1815 (after the Congress of Vienna) and 1945, $EMPIREBEFORE45$, to capture historical and cultural similarities between these countries that might induce higher levels of trade. This could be relevant for trade between the former hegemons Germany, Austria and Turkey and their former dependencies in Eastern and South Eastern Europe. Since migration partly explained the relationship between language and trade in section 4.5.4 and in the first half of the 1990s, massive emigration from Eastern Europe to the West took place, I control for the stock of migrants in 1995 in one of the specifications.

Table 6.7 reports the estimation results. In column (1), a common spoken language has a significant impact on trade only for East-West-trade, and the coefficient is remarkably large. It suggests that a ten percentage points larger probability that an individual from a Western country meets someone in the Eastern partner country who speaks the same language is associated with $(\exp(1.91) - 1) \times 10 = 57.5$ percent more trade between those countries relative to other East-West-country pairs. Trade between East and West, however, is generally lower, as indicated by the negative coefficient of $EASTWEST$. My other cultural variables, $LP0$ and $RELIG$, as well as $COMLEG$, all have a positive effect. Distance elasticity almost equals one, a surprisingly standard result. In the previous

	(1)		(2)		(3)		(4)	
Dependent variable: $\exp(\hat{\delta}_{ij})$								
CSL if $EASTWEST = 1$	1.91	(0.46)***	0.90	(0.50)*	2.28	(0.43)***	1.31	(0.45)***
CSL if $EASTWEST = 0$	0.30	(0.20)	0.05	(0.23)	0.52	(0.15)***	0.29	(0.17)*
$EASTWEST$	-0.23	(0.10)**	-0.17	(0.10)*	-0.19	(0.09)**	-0.14	(0.09)
$LP0$	0.54	(0.18)***	0.54	(0.18)***	0.39	(0.18)**	0.42	(0.17)**
$LNDIST[0, 625]$	-0.96	(0.12)***	-0.85	(0.12)***	-0.92	(0.10)***	-0.80	(0.10)***
$LNDIST]625, 1250]$	-0.99	(0.11)***	-0.88	(0.11)***	-0.94	(0.09)***	-0.81	(0.09)***
$LNDIST]1250, 2500]$	-1.01	(0.10)***	-0.90	(0.10)***	-0.95	(0.08)***	-0.83	(0.09)***
$LNDIST]2500, 5000]$	-1.02	(0.10)***	-0.90	(0.10)***	-0.97	(0.08)***	-0.84	(0.08)***
$LNDIST]5000, 10000]$	-1.06	(0.09)***	-0.98	(0.09)***	-0.99	(0.07)***	-0.89	(0.08)***
$LNDIST]10000, 20000]$	-1.09	(0.09)***	-0.99	(0.09)***	-1.01	(0.08)***	-0.91	(0.08)***
$CONTIG$	-0.03	(0.08)	-0.07	(0.08)	0.02	(0.08)	-0.03	(0.07)
$GATT/WTO$	0.03	(0.20)	0.20	(0.19)	0.25	(0.21)	0.44	(0.19)**
RTA	0.15	(0.09)*	0.11	(0.09)	0.25	(0.09)***	0.21	(0.09)**
EU	0.00	(0.11)	-0.02	(0.11)	0.07	(0.11)	0.03	(0.11)
$COMLEG$	0.25	(0.06)***	0.19	(0.06)***	0.35	(0.06)***	0.29	(0.06)***
$RELIG$	0.40	(0.11)***	0.31	(0.12)***	0.16	(0.13)	0.05	(0.14)
$COLPOST45$	1.43	(0.24)***	1.04	(0.24)***				
$SIBPOST45$	1.44	(0.23)***	1.00	(0.22)***				
$EMPIREBEFORE45$	0.14	(0.06)**	0.09	(0.06)				
$LNMIGR$			0.12	(0.02)***			0.12	(0.02)***
$COLPOST45\_SU$					0.32	(0.33)	-0.12	(0.30)
$COLPOST45\_OTHER$					1.77	(0.20)***	1.38	(0.22)***
$SIBPOST45\_SU$					0.83	(0.31)***	0.37	(0.28)
$SIBPOST45\_OTHER$					2.38	(0.63)***	1.92	(0.47)***
$EMPIRE\_AUSTRIA$					0.40	(0.10)***	0.33	(0.10)***
$EMPIRE\_RUSSIA$					0.40	(0.14)***	0.31	(0.14)**
$EMPIRE\_TURKEY$					0.83	(0.23)***	0.85	(0.21)***
$EMPIRE\_OTHER$					-0.18	(0.08)**	-0.18	(0.08)**
Observations	1,326		1,326		1,326		1,326	
Imputed R^2	0.904		0.909		0.925		0.929	

Results for importer and exporter fixed effects are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 6.7: Effect of language on trade in the late 1990s

chapters, distance elasticity was generally lower. A common border has no significant impact on trade, as well as the membership in the European Union. The positive effect of $GATT/WTO$ and RTA is significant only in some regressions. The colonial variables are all significant and positive.

In column (2), I include migration as additional explanatory variable. The coefficients of most other variables decrease, while the stock of migrants has a highly significant impact on trade. The effect of a ten percentage point change in CSL for East-West trade now diminishes to 14.6 percent. Linguistic proximity, however, still has the same effect on trade as in column (1). The impact of empires before 1945 turns insignificant.

It might be the case that historical and cultural effects of former empires differ by empire. Therefore, I estimate separate effects for the three largest of them in Mainland Europe: the Austrian-Hungarian Empire, the Ottoman Empire, and the Russian Empire.

	(1)		(2)		(3)		(4)	
Dependent variable: $\exp(\hat{\delta}_{ij})$								
for $EASTWEST = 1$								
$CSL\_ENGLISH$	0.26	(0.90)	-0.90	(0.93)	0.31	(0.89)	-0.67	(0.90)
CSL_GERMAN	1.39	$(0.63)^{**}$	1.15	$(0.62)^{*}$	0.74	(0.60)	0.54	(0.58)
CSL_FRENCH	0.86	(1.91)	0.04	(1.97)	1.67	(1.62)	1.03	(1.59)
$CSL\_RUSSIAN$	-1.12	(3.91)	-5.61	(3.68)	1.76	(4.32)	-2.60	(4.04)
CSL_OTHER	5.08	$(1.96)^{***}$	3.35	$(1.91)^{*}$	5.07	$(1.61)^{***}$	3.57	$(1.53)^{**}$
for $EASTWEST = 0$								
$CSL\_ENGLISH$	0.18	(0.29)	0.00	(0.31)	0.11	(0.25)	-0.03	(0.27)
CSL_GERMAN	-0.34	(0.51)	-0.32	(0.50)	-0.43	(0.42)	-0.42	(0.42)
CSL_FRENCH	0.41	(0.33)	0.33	(0.32)	0.31	(0.30)	0.26	(0.30)
$CSL\_RUSSIAN$	-0.96	$(0.38)^{**}$	-1.41	$(0.37)^{***}$	1.43	$(0.68)^{**}$	0.80	(0.66)
CSL_OTHER	0.33	(0.24)	0.11	(0.25)	0.43	$(0.18)^{**}$	0.23	(0.20)
Migration	no		yes		no		yes	
Separate empires	no		no		yes		yes	
Observations	1326		1326		1326		1326	
Imputed R^2	0.912		0.918		0.931		0.934	

Results for importer and exporter fixed effects, as well as for control variables, are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 6.8: Effect of language on trade in the late 1990s, separate main languages

Furthermore, I distinguish between the Soviet Union and other colonial empires, such as the British Empire, after 1945. Head et al. (2010) show that colonial trade links weakened faster after a separation that was accompanied by conflicts, as it was the case for the Soviet Union.

Results are presented in column (3) and (4), where I control for total migration stock in the latter column. It can be seen that historical effects differ between empires. Because of a certain degree of multicollinearity, the interpretation of the effects is sometimes difficult. E.g., former Soviet states do not seem to trade more with its former hegemon Russia, but with each other. However, parts of the Russian Empire, which also includes the later Soviet Union, trade more with each other. For the former parts of the Austrian and Turkish Empire, however, the effects are more readily to interpret, since both dissolved in 1918 and there is no multicollinearity with $COLPOST45$. For both regressions, the impact of CSL on trade increases, both for East-West trade and other trade. The impact of $COLPOST45\_OTHER$ reflects colonial relations between the United Kingdom and Malta and Cyprus that seem to persist until today.

The impact of CSL probably differs by language, since each language has spread at different times and for different reasons. French was the world language in the 19th century, German spread over centuries through the German and Austrian expansions and migration movements to the East, and Russian via the expansion of the Russian Empire and, more recently, through the mandatory Russian language schooling in the Eastern Bloc. The rise of English in Western Europe took place in the 20th century.

Fidrmuc and Fidrmuc (2016) find significant effects for English and German in the

2000s. Both results are suspicious: German spread to the East for historical reasons and therefore, the correlation with trade might be a relic of these historical relations. Foreign English skills were lower in the 1990s than in the mid-2000s, as shown in section 6.3. Thus, the effect for both results might not be exogenous. To investigate effects of separate languages, I split up CSL into the four main European languages already used in 6.4 and a fifth category for all other languages. I re-estimate the four regressions from table 6.7, but only report the results for the CSL variables in table 6.8. In columns (1), all languages but Russian have a positive coefficient on East-West-trade, but only German and the cumulative other languages are significant. The impact of English turns negative if I control for a migration-trade-link in column (2) and the effects of CSL_GERMAN and CSL_OTHER are only marginally significant. CSL_OTHER subsumes many relevant language relations between East and West, such as foreign Finnish knowledge in Estonia, proficiency in Italian and Greek in Albania, or the native language of the Turkish minority in Bulgaria.[5]

If I use the more nuanced measures of historical relations in column (3), all coefficients for trade between East and West are positive, but only CSL_OTHER is significant. With Migration in column (4), the impact of English and Russian switch sign, but stay insignificant. In a robustness check in table F.5 in appendix F, I estimate the last regression for each of the four main languages separately, but for East-West-trade only the respective cumulative language variable has a significant impact. I conclude that no single language has a significant effect of its own, but the general knowledge of foreign languages increased trade between East and West, in line with the results from section 4.5.3.

I controlled for geographic, cultural and linguistic distance, historical relations and migration networks in a 'quasi-natural experiment' environment and therefore I am confident that the result from table 6.7, column (4), can be interpreted as causal. Since the marginal effect of common spoken language is decreasing, as demonstrated in section 4.5.5, the relatively large effect of $\exp(1.31) - 1 = 2.7$ percent for a one percentage point higher CSL can be attributed to the low levels of CSL between Western and Eastern countries in the sample. CSL is smaller than 0.5 for all East-West country pairs in the 1990s.

For trade between Western countries, CSL has only a small effect on trade, and for the estimations in table 6.8, no single Western language impacts trade. Supposedly, communication barriers have been overcome in the West. However, cultural differences, reflected by $RELIG$ and $LP0$, are still an obstacle to trade. For the Russian language, only spoken by larger fractions of the population in Eastern countries, the impact is ambiguous. In columns (1) and (2) of table 6.8, the negative effect of Russian most likely compensates for the too large estimate of the colonial relations in the former Soviet

[5]Western populations, apart from groups of native speakers, have only low skills in languages from the Eastern Bloc, such as Russian or BCMS ('Serbo-Croatian').

Union. Correcting for this with separate colonial variables in column (3), the coefficient turns positive, suggesting that Russian skills enhance trade in the former Eastern Bloc.

In a robustness test, I exclude North America, as in the robustness checks in section 6.4, and the West Balkan states. I exclude Former Yugoslavia and Albania since they left the Eastern Bloc and established trade relations with Western countries early, casting doubt on the exogeneity of language skills in these countries. Table F.6 in appendix F reports the estimation results for this smaller sample. Surprisingly, the impact of common spoken language even increases. Interestingly, French has now a positive and significant impact on East-West-trade. The main driver of this result has to be Romania, the only country with considerable French language skills in the East. German is still only significant for the less detailed historical controls and English stays insignificant in all estimations.

Chapter 7

Conclusion

In my dissertation, I re-evaluated the impact of common language on trade. The motivation behind it were the recent methodological developments in gravity literature (Egger and Nigai, 2015) and the still frequent use of simple common language dummies in gravity literature, although Melitz (2008) and Melitz and Toubal (2014) introduced more detailed measures. Additionally, I wanted to shed more light on the contemporaneous effect of language and the impact of changing language skills on trade.

First, I created an updated version of *CEPII*'s language measures in chapter 3 and constructed five different language variables, in line with Melitz and Toubal (2014): The three intercommunication distances are the previously mentioned common official language dummy, common native language, which measures the probability that two randomly chosen individuals from two different countries speak the same mother tongue, and common spoken language, which also considers foreign language skills. Furthermore, I constructed two measures of linguistic proximity, using the *Levenshtein distance* between native languages.

In chapter 4, I (i) re-estimated the effect of language variables on trade, using the most recent methodology in gravity literature and (ii) compared the four fractional language measures, first introduced by Melitz and Toubal (2014), with the common language dummy. I demonstrated the vulnerability of the empirical results for the dummy variable with respect to the estimation method in section 4.2.

In section 4.3, I directly compared my results to those of Melitz and Toubal. I regressed international trade in goods on the language variables in a sample of 207 countries and 'entities' between 1996 and 2016. I was able to confirm the OLS results of Melitz and Toubal with a two stage CANOVA approach. However, for this sample, trade costs were not measured relative to domestic trade.

Rauch (1999) assumes that a common language is especially important for the early contact phase of trade, when traders search for buyers and sellers on the international market. Hence, common language should impact the fixed costs of trade. Following Dutt et al. (2013), I distinguished between the extensive and intensive product margin of trade in section 4.3.3 and found that intercommunication distances mainly affect the fixed costs of trade, following the interpretation of Chaney (2008). For future research, it would be interesting to extend the network theory of trade by Chaney (2014) by common language to confirm the hypothesis of Rauch (1999).

For international trade in services, I also estimated a significant impact of language in section 4.4, which varies by sector and is especially large for common spoken language. However, the caveat of missing domestic trade still cast doubt on the result, a problem I tackled in section 4.5 for a smaller sample of inter- and intra-national trade in manufactured goods between 78 countries that account for over 80 percent of worldwide trade. It turned out that the theory-consistent inclusion of internal trade rendered the common official language dummy insignificant. The other language variables though stayed significant. An increase in common spoken language by ten percentage points is correlated with an increase in trade of 6.3 percent, all else equal. I also confirm the results of Anderson and Yotov (2016) that the impact of language varies largely by industry sector and that for most sectors, the common official language dummy is insignificant. However, the other language measures again perform better on sector level. In conclusion, the fractional language variables are better suited to capture the effect of language on trade than a simple common language dummy.

I further investigated other hypotheses regarding the impact of language and trade in chapter 4.5. Large world languages, such as English, French or Spanish, are naturally important for trade, but according to my results, they are not more efficient than other languages. Language might also affect trade via migrant networks. I showed that the results for language are robust to the inclusion of migration as explanatory variable. A new contribution is the test for a non-constant semi-elasticity of common spoken language, which can be interpreted as a decreasing marginal effect. While the increase of common spoken language from 5 to 15 percent might gives a huge boost to the communication and translation ability between two countries, an increase from 55 to 65 percent does less so, since already a large part of the populations can talk to each other without an interpreter. My empirical results hinted to such a decreasing effect for common spoken language. An immense effect for the lowest interval of common native language could be explained by migrant minorities, i.e. the migration-trade-link.

In chapter 5, I focused on the historical perspective of trade. Anderson and Yotov (2016) assumed that the impact of language and culture on trade subsided over time, given the trade integration of the 'Global South' and the technological improvements, especially in communication technologies. However, I found that the relevance of language, religion and (ethno-)linguistic proximity, i.e. culture in general, increased since the 1980s. A possible explanation could be that the globalization of the last decades, captured by a decreasing distance elasticity of trade, was accompanied by rising regionalism, due to the increased use of regional trade agreements instead of trade solutions on the global scale.

So far, most of the gravity literature did not take into account that an estimated correlation between language and trade might only reflect past trade relations. I estimated contemporaneous trade costs in section 5.3, using a new method by Frensch and Fidrmuc (2020) to control for historical trade costs. I split my sample into two periods, a later one from 2004-2016 and an earlier one from 1996-2000, where the latter was used to estimate past trade costs. I found that common native language affected current trade only for low values, i.e. language minorities. Common spoken language has no significant influence on contemporaneous trade costs. Linguistic proximity, once estimated in intervals, had a significant and positive impact which was largest for (ethno-)linguistically distant countries. In conclusion, pure communication ability did not affect current trade, but common culture and ethnicity did. As in chapter 4, I distinguished between extensive and intensive product margin and found a significant impact of intercommunication distances, i.e. common official, native and spoken language, on the contemporaneous fixed costs of trade.

In chapter 6, I used a unique data set on time-varying language skills in 32, mostly European countries, to investigate the impact of changing common spoken language on trade. The main source of the data are the *Eurobarometer* surveys from 1994 to 2012, complemented by other surveys and census data. The data documents a large increase in English skills in most countries in the sample, and also a decline in Russian knowledge in the former Eastern Bloc. The changes were driven by younger cohorts with different foreign language skills than the older ones. The plausible explanation are changes in language policy, which are exogenous to the individual and were often caused by political rather than economical decisions.

I estimated the impact of these changes in language skills on trade. I controlled for endogeneity by country-pair fixed effects, for a general increase in international trade relative to domestic trade, and for a convergence between East and West. A rise in common spoken language is correlated with an increase in bilateral trade, which is mostly driven by the rise in English knowledge. On average, an increase of ten percentage points in the probability that two randomly chosen people from two countries speak English is correlated with an increase in trade of 15.6 percent. A robust causal effect cannot be found for a constant semi-elasticity of common spoken language on trade. However, I show the effect of a *change* in English diminishes with its *level*. E.g., the same increase in common spoken English is correlated with a larger increase in trade for the country pair Latvia-Sweden than for the pair Netherlands-Sweden, since the initial percentage of English speakers is lower in Latvia than in the Netherlands. This is in line with the decreasing marginal effect of language on trade in section 4.5.5. The thus found effect is robust and presumably exogenous, since I controlled for various sources of endogeneity and it passes the feedback effect for strict exogeneity.

I used the general equilibrium properties of the structural gravity analysis and a simple model by Baier et al. (2019) to project the general equilibrium trade and welfare effects of the increase in English skills in the sample, using the previously estimated non-constant language semi-elasticity. According to the results, all countries except for Russia profited from the rise in the percentage of English speakers. For the Baltics, the welfare gains were comparable to those of the EU accession. Overall, welfare in the whole sample increased by 0.77 percent.

Additionally, I revisited the 'natural experiment' of the East-West divide in language schooling by Fidrmuc and Fidrmuc (2016). I found a large, positive and significant effect for trade between Western and Eastern countries for overall common spoken language, but not for any separate language. The difference to Fidrmuc and Fidrmuc's results can be explained by the different estimation method and the earlier time period. In particular English skills were lower in the 1990s than in 2005.

Increasing the population's foreign language skills thus seems to be a successful strategy for internationalization. Because of data limitations, the evidence presented here is restricted to changes in Europe, where one foreign language, English, is clearly dominating. For future research, it would be interesting to look at other regions and other rising world languages, such as Spanish, Arabic and Chinese. The example of Russian illustrated the decline of colonial languages. There are already studies on the effect of changing language policies in former colonies on school test scores and labor market outcomes (see Ginsburgh and Weber (2020, pp. 385) for an overview). The impact of language policy on trade in former colonies would be a promising topic for future research.

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Appendices

Appendix A

Data Appendix

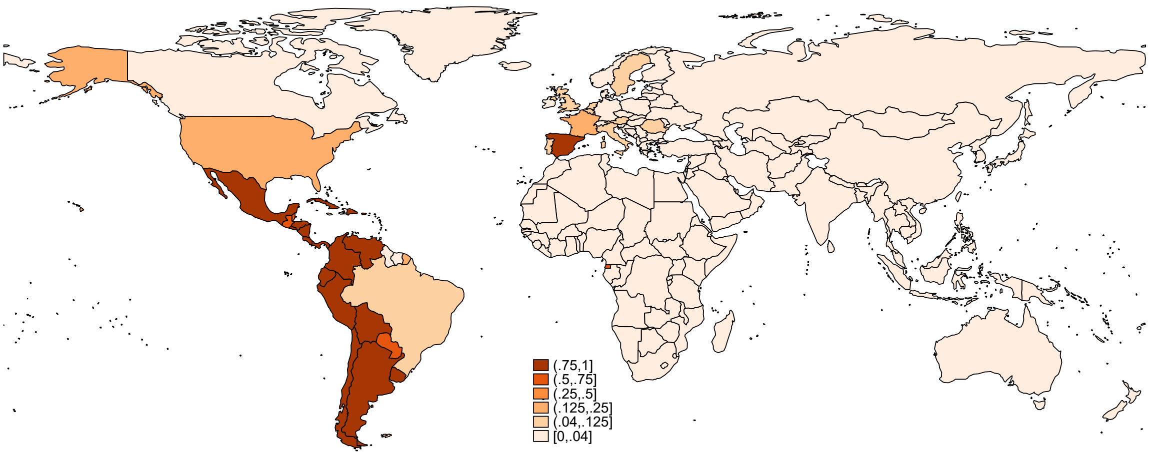

Figure A.1: Fraction of Spanish speakers worldwide

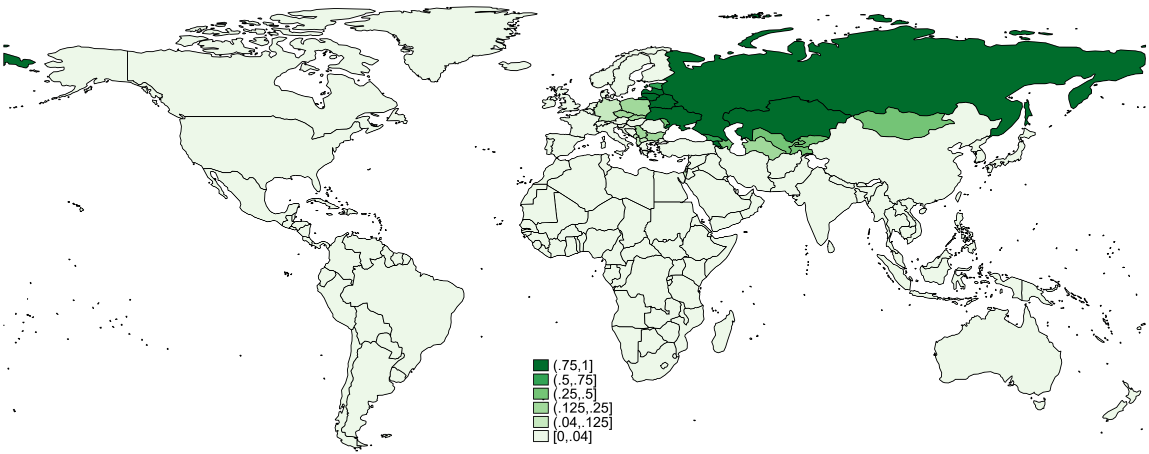

Figure A.2: Fraction of Russian speakers worldwide

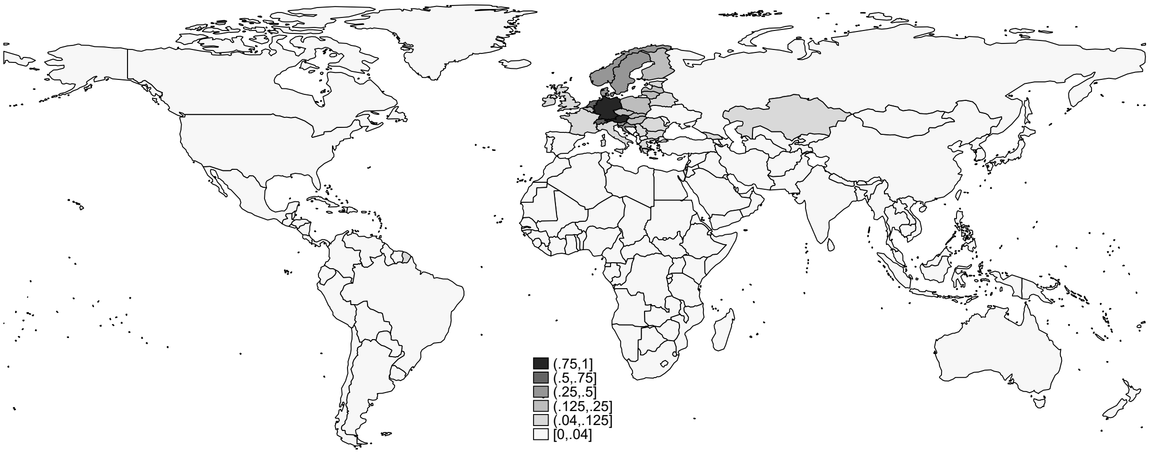

Figure A.3: Fraction of German speakers worldwide

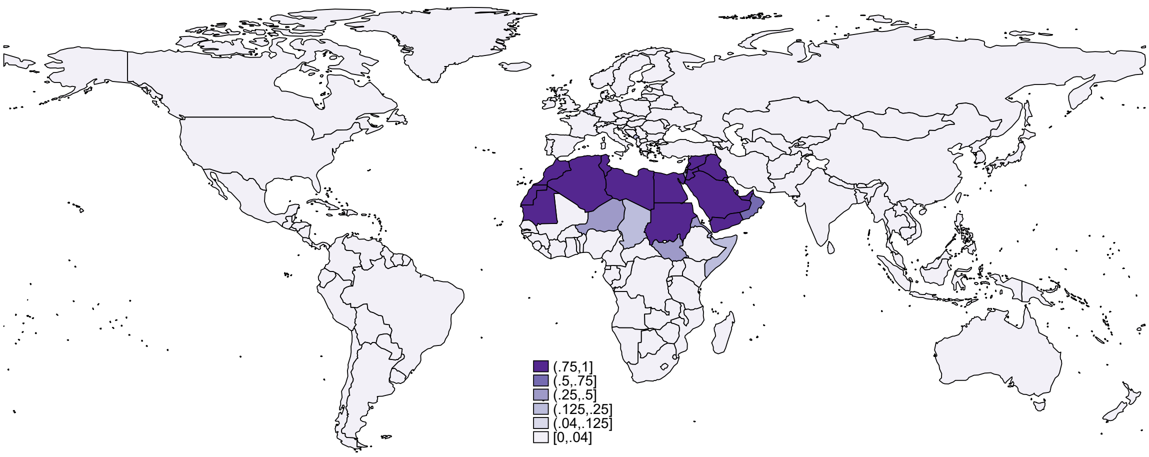

Figure A.4: Fraction of Arabic speakers worldwide

Indo-European	**Turkic**	**Niger-Congo**	Senoufo	**Nilo-Saharan**
Albanian	Azerbaijani	Aja	Serer-Sine	Bari
Armenian	Kazakh	Akan	Shona	Dinka
Irish	Kyrgyz	Baoulé	Soga	Fur
Greek	Tatar	Bassa	Soninke	Kalenjin
Balto-Slavic	Turkish	Bemba	Sotho	Kanuri
BCMS	Turkmen	Beti	Sukuma	Lugbara
Bulgarian	Uyghur	Chichewa	Susu	Maasai
Czech	Uzbek	Chokwe	Suundi	Masalit
Latvian	**Austronesian**	Comorian	Swahili	Ngambay
Lithuanian	Ambae	Dagare	Swati	Nobiin
Polish	Are'are	Dagbani	Teke	Nuer
Russian	Balanta	Dan	Themne	Otuho
Slovak	Banda	Éwé	Tonga	Shilluk
Slovenian	Bisaya	Fon	Tsonga	Southern Luo
Ukrainian	Cebuano	Fulfulde	Tswana	Teso-Turkana
Germanic	Chamorro	Gen	Tumbuka	Zaghawa
Afrikaans	Chuukese	Gikuyu	Tupuri	Zarma
Danish	Cook Islands Maori	Gourmanchémá	Umbundu	**Austro-Asiatic**
Dutch	Drehu	Grebo	Venda	Khmer
English	East Fijian	Herero	Wolof	Khmu
German	Efate	Igbo	Xhosa	Vietnamese
Norwegian	Enga	Jola	Yao	**Indigenous American**
Swedish	Hiligayon	Kabiyé	Yom	Aymara
Indo-Iranian	Ilocano	Kimbundu	Yoruba	Greenlandic
Balochi	Javanese	Kissi	Zande	Garifuna
Bengali	Kiribati	Kongo	Zulu	Kekchí
Hindi	Kwara'ae	Konkomba	**Afro-Asiatic**	Mayathan
Kurdish	Malagasy	Kpelle	Amharic	Quechua
Maithili	Malay	Kuranko	Arabic	Guaraní
Maldivian	Mambae	Kuria	Bedawiyet	**Creole**
Marathi	Maori	Lingala	Hausa	Eastern Atlantic English Creole
Nepali	Marshallese	Lobi	Hebrew	Pacific English Pidgin
Pashto	Nauruan	Luba	Maay	Suriname English Creole
Persian	Niue	Luvale	Maltese	West African English Pidgin
Punjabi	Palauan	Makhuwa	Oromo	Western Atlantic English Creole
Romani	Pohnpeian	Mandingo	Saho-Afar	Antillean French Creole
Sindhi	Samoan	Mende	Somali	Bourbonnais French Creole
Sinhala	Sunda	Mòoré	Tamashek	Guianese French Creole
Takestani	Tagalog	Ndebele	Tamazight	Haitian French Creole
Romance	Tahitian	Ngangela	Tigré	Papiamento
Catalan	Tanna	Ngbaka	Tigrigna	Sango
French	Tetun	Nsenga	**Kra-Dai**	Lower Guinea Portuguese Creole
Italian	Tongan	Nyakyusa-Ngonde	Lao	Upper Guinea Portuguese Creole
Occitan	Tuvaluan	Nyankore	Thai	**Others**
Portuguese	Wallisian	Nyiha	**Sino-Tibetan**	Hmong
Romanian	West Fijian	Oluluyia	Bantawa	Japanese
Spanish	**Dravidian**	Oshiwambo	Bumthang	Georgian
Uralic	Brahui	Papel	Burmese	Khoekhoe
Estonian	Malayalam	Punu	Chinese	Korean
Finnish	Tamil	Rundi	Dzongkha	Makasae
Hungarian	Telugu	Sena	Tshangla	Mongolian

Languages spoken in only one country or by less than one percent of the population in more than one country are excluded. See text for further details.

Table A.1: Languages used for CSL, sorted by language family

	LNDIST	*CONTIG*	*COMLEG*	*COLPOST45*	*SIBPOST45*	*GATT/WTO*	*RTA*	*COMCUR*	*EU*	*RELIG*
CONTIG	-0.31	1								
COMLEG	-0.13	0.08	1							
COLPOST45	-0.03	0.06	0.07	1						
SIBPOST45	-0.06	0.05	0.20	-0.03	1					
GATT/WTO	-0.11	0.04	0.05	0.02	0.00	1				
RTA	-0.35	0.19	0.05	0.05	0.02	0.15	1			
COMCUR	-0.22	0.12	0.07	0.03	0.08	0.05	0.17	1		
EU	-0.24	0.09	-0.01	0.00	-0.04	0.12	0.26	0.29	1	
RELIG	-0.17	0.11	0.13	0.02	0.01	0.03	0.13	0.07	0.04	1
COL	-0.07	0.09	0.27	0.12	0.40	-0.05	0.07	0.10	-0.04	0.21
CNL	-0.23	0.14	0.13	0.08	0.09	0.00	0.16	0.06	-0.01	0.25
CSL	-0.19	0.12	0.10	0.12	0.12	-0.01	0.22	0.10	0.13	0.25
LP0	-0.17	0.05	0.04	0.02	0.06	0.00	0.15	0.03	0.10	0.19
LP1	-0.31	0.18	0.14	0.09	0.10	0.01	0.25	0.08	0.05	0.34

Table A.2: Correlations between exogenous variables

Appendix B

Appendix to Method Comparison

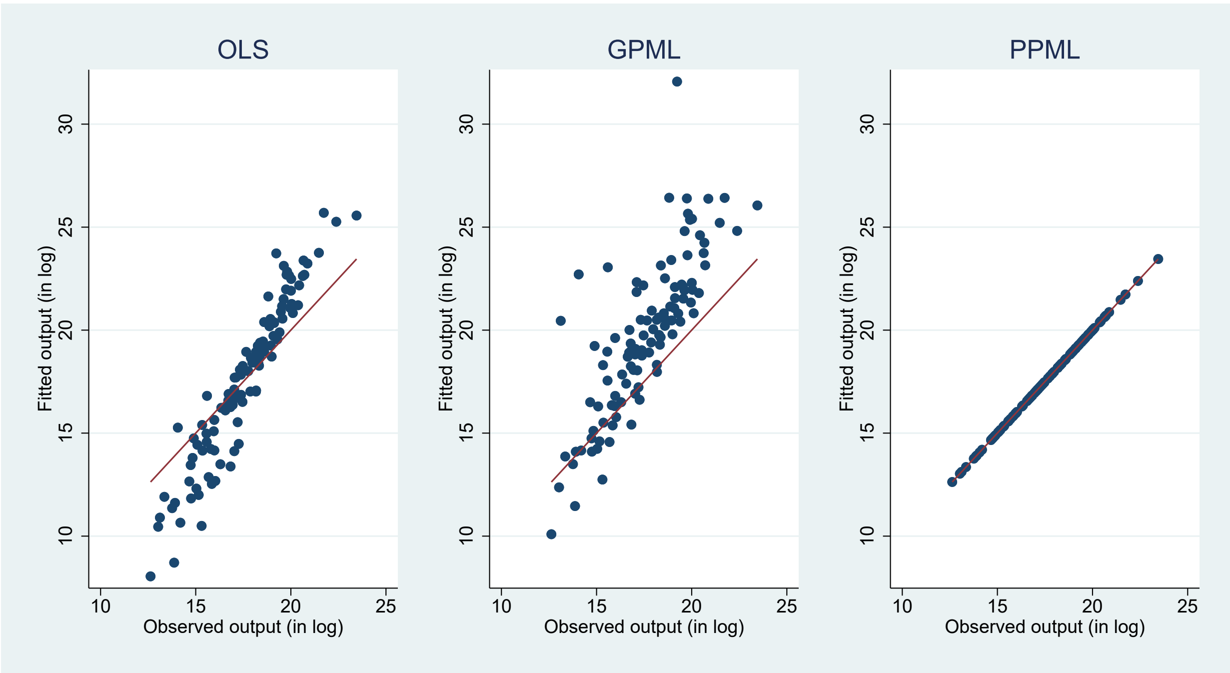

Figure B.1: Comparing fitted and observed output for OLS, GPML and PPML

According to Fally (2015), both OLS and GPML fail to estimate the correct size of total output, the sum of international and internal trade. Figure B.1 compares the (log) fitted output with the (log) observed output for one-step OLS, GPML and PPML. While PPML matches observed output perfectly by construction, OLS underestimates total exports for small countries and both OLS and GPML overestimate it for large countries in my sample, in line with Fally (2015, Fig. 1).

	One-step procedures			Two-step procedures		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	PPML	GPML	OLS	PPML	GPML
	$\ln(X_{ij})$	X_{ij}	X_{ij}	$\hat{\delta}_{ij}$	$\exp\hat{\delta}_{ij}$	$\exp\hat{\delta}_{ij}$
COL	0.56	-0.09	0.58	0.56	0.40	0.53
	(0.07)***	(0.07)	(0.08)***	(0.06)***	(0.11)***	(0.07)***
$LNDIST[0,625]$	-1.08	-0.67	-0.98	-1.00	-0.91	-0.80
	(0.11)***	(0.10)***	(0.12)***	(0.09)***	(0.10)***	(0.09)***
$LNDIST]625,1250]$	-1.08	-0.65	-1.06	-1.01	-0.92	-0.88
	(0.10)***	(0.09)***	(0.10)***	(0.08)***	(0.09)***	(0.08)***
$LNDIST]1250,2500]$	-1.11	-0.67	-1.10	-1.04	-0.94	-0.93
	(0.09)***	(0.08)***	(0.10)***	(0.08)***	(0.08)***	(0.08)***
$LNDIST]2500,5000]$	-1.11	-0.65	-1.11	-1.03	-0.96	-0.96
	(0.08)***	(0.08)***	(0.09)***	(0.07)***	(0.08)***	(0.07)***
$LNDIST]5000,10000]$	-1.12	-0.68	-1.12	-1.05	-0.97	-0.98
	(0.08)***	(0.07)***	(0.08)***	(0.06)***	(0.07)***	(0.06)***
$LNDIST]10000,20000]$	-1.11	-0.66	-1.11	-1.04	-0.96	-0.96
	(0.07)***	(0.07)***	(0.08)***	(0.06)***	(0.07)***	(0.06)***
$CONTIG$	0.65	0.44	0.72	0.66	0.36	0.76
	(0.12)***	(0.07)***	(0.14)***	(0.11)***	(0.08)***	(0.11)***
$GATT/WTO$	0.43	1.05	0.18	-0.04	0.19	-0.27
	(0.22)*	(0.40)***	(0.25)	(0.19)	(0.19)	(0.16)*
RTA	0.53	0.32	0.50	0.56	0.46	0.46
	(0.04)***	(0.06)***	(0.05)***	(0.04)***	(0.06)***	(0.04)***
$COMCUR$	-0.48	-0.08	-0.39	-0.49	-0.07	-0.27
	(0.08)***	(0.08)	(0.10)***	(0.07)***	(0.18)	(0.07)***
$COMLEG$	0.21	0.18	0.22	0.23	0.25	0.23
	(0.04)***	(0.04)***	(0.04)***	(0.03)***	(0.05)***	(0.03)***
$COLPOST45$	0.96	0.36	0.75	0.99	0.57	0.82
	(0.14)***	(0.16)**	(0.15)***	(0.12)***	(0.13)***	(0.12)***
$SIBPOST45$	1.22	0.58	0.87	1.09	0.53	0.80
	(0.09)***	(0.13)***	(0.09)***	(0.08)***	(0.08)***	(0.07)***
$RELIG$	0.55	0.51	0.54	0.48	0.58	0.69
	(0.09)***	(0.11)***	(0.10)***	(0.08)***	(0.10)***	(0.08)***
Observations	10,105	11,130	11,130	10,582	10,582	10,582
Imputed R^2	0.850	0.927	0.816	0.664	0.608	0.573
CNL	1.12	-0.01	1.03	1.09	0.71	0.99
	(0.13)***	(0.14)	(0.16)***	(0.11)***	(0.22)***	(0.13)***
CSL	1.06	-0.19	0.87	0.94	0.82	0.89
	(0.09)***	(0.12)	(0.11)***	(0.08)***	(0.17)***	(0.09)***
$LP1$	1.21	-0.06	1.18	1.12	0.97	1.08
	(0.12)***	(0.13)	(0.15)***	(0.10)***	(0.20)***	(0.12)***

Results for importer and exporter fixed effects are excluded for brevity. The lower panel reports the results for other language variables, excluding results for covariates for brevity.
Robust standard errors, clustered by country pair, are in parentheses. * $p < 0.10$, ** $p < .05$, *** $p < .01$

Table B.1: Method comparison, without domestic trade

Appendix C

Additional Results to Sectoral Estimates

	(1) TRANSP	(2) TRAVEL	(3) COMMUN	(4) CONSTR	(5) INSUR	(6) FINANCE	(7) IT	(8) RYLTIES	(9) OTHBUS	(10) CULTURE	(11) GMNT
Dependent variable: $\exp(\hat{\delta}_{ij}^{Srv})$											
$GATT/WTO_t$	0.07	0.24	0.21	0.05	0.07	0.34	0.15	0.19	0.09	-0.14	0.06
	(0.07)	(0.10)**	(0.09)**	(0.12)	(0.24)	(0.16)**	(0.17)	(0.37)	(0.10)	(0.20)	(0.10)
$COMCUR_t$	-0.05	0.11	-0.04	0.27	0.18	0.30	0.04	0.47	-0.01	-0.46	0.13
	(0.05)	(0.06)*	(0.11)	(0.15)*	(0.16)	(0.16)*	(0.09)	(0.16)***	(0.06)	(0.13)***	(0.11)
RTA_t	-0.06	-0.02	-0.00	-0.15	-0.03	0.04	-0.02	0.27	-0.01	0.29	0.00
	(0.03)**	(0.03)	(0.04)	(0.07)**	(0.08)	(0.07)	(0.07)	(0.11)**	(0.04)	(0.20)	(0.07)
RTA_{t-4}	0.03	-0.06	0.05	0.06	0.08	0.04	-0.04	-0.14	0.02	0.10	0.10
	(0.04)	(0.03)**	(0.05)	(0.07)	(0.11)	(0.07)	(0.06)	(0.14)	(0.05)	(0.12)	(0.05)*
EU_t	0.41	0.32	0.16	0.37	0.70	0.42	0.08	0.24	0.24	-0.02	0.12
	(0.06)***	(0.06)***	(0.11)	(0.21)*	(0.14)***	(0.12)***	(0.09)	(0.13)*	(0.07)***	(0.16)	(0.09)
EU_{t-4}	0.20	0.04	0.01	-0.02	-0.12	-0.09	0.21	0.15	0.04	0.21	0.05
	(0.05)***	(0.04)	(0.08)	(0.18)	(0.13)	(0.13)	(0.08)**	(0.11)	(0.06)	(0.11)*	(0.09)
Observations	163,440	163,910	159,095	123,043	139,430	147,260	134,005	101,663	163,525	118,078	163,320
Imputed R^2	0.983	0.990	0.961	0.917	0.990	0.982	0.984	0.984	0.986	0.965	0.988

Results for importer-time-product, exporter-time-product and asymmetric country-pair-product fixed effects are excluded for brevity.
Robust standard errors, clustered by country pair, are in parentheses. * $p < 0.10$, ** $p < .05$, *** $p < .01$

Table C.1: Trade in services, first step, sectoral results

	(1) TRANSP	(2) TRAVEL	(3) COMMUN	(4) CONSTR	(5) INSUR	(6) FINANCE	(7) IT	(8) RYLTIES	(9) OTHBUS	(10) CULTURE	(11) GMNT
Dependent variable: $\exp(\hat{\delta}_{ij}^{Srv})$											
CSL	0.48	0.74	0.44	0.52	0.56	0.69	0.52	0.59	0.49	0.40	0.41
	(0.16)***	(0.10)***	(0.09)***	(0.11)***	(0.08)***	(0.11)***	(0.11)***	(0.15)***	(0.11)***	(0.11)***	(0.08)***
$LP0$	0.51	-0.08	-0.02	0.28	0.41	-0.02	0.72	0.08	-0.01	0.36	0.35
	(0.20)**	(0.23)	(0.20)	(0.23)	(0.22)*	(0.23)	(0.27)***	(0.34)	(0.25)	(0.18)**	(0.15)**
$LNDIST[0,625]$	-0.76	-0.67	-0.42	-0.71	-0.16	-0.27	-0.40	-0.45	-0.52	-0.42	-0.31
	(0.16)***	(0.12)***	(0.09)***	(0.11)***	(0.12)	(0.10)***	(0.17)**	(0.16)***	(0.12)***	(0.10)***	(0.07)***
$LNDIST]625,1250]$	-0.79	-0.67	-0.45	-0.68	-0.17	-0.31	-0.44	-0.43	-0.53	-0.40	-0.31
	(0.16)***	(0.10)***	(0.08)***	(0.09)***	(0.10)*	(0.08)***	(0.14)***	(0.14)***	(0.10)***	(0.08)***	(0.06)***
$LNDIST]1250,2500]$	-0.79	-0.70	-0.51	-0.71	-0.19	-0.32	-0.46	-0.39	-0.56	-0.42	-0.35
	(0.15)***	(0.09)***	(0.07)***	(0.08)***	(0.09)**	(0.08)***	(0.13)***	(0.12)***	(0.09)***	(0.08)***	(0.06)***
$LNDIST]2500,5000]$	-0.78	-0.72	-0.54	-0.70	-0.18	-0.31	-0.44	-0.32	-0.58	-0.40	-0.37
	(0.14)***	(0.09)***	(0.07)***	(0.08)***	(0.08)**	(0.07)***	(0.12)***	(0.11)***	(0.09)***	(0.07)***	(0.05)***
$LNDIST]5000,10000]$	-0.77	-0.71	-0.54	-0.69	-0.19	-0.30	-0.45	-0.32	-0.57	-0.41	-0.37
	(0.13)***	(0.08)***	(0.06)***	(0.07)***	(0.08)**	(0.07)***	(0.11)***	(0.10)***	(0.08)***	(0.07)***	(0.05)***
$LNDIST]10000,20000]$	-0.75	-0.71	-0.55	-0.69	-0.22	-0.32	-0.47	-0.35	-0.58	-0.42	-0.38
	(0.12)***	(0.08)***	(0.06)***	(0.07)***	(0.07)***	(0.06)***	(0.10)***	(0.10)***	(0.08)***	(0.06)***	(0.04)***
$CONTIG$	0.43	0.76	0.32	0.62	0.70	0.49	0.30	0.46	0.41	0.62	0.05
	(0.15)***	(0.07)***	(0.08)***	(0.11)***	(0.10)***	(0.09)***	(0.15)**	(0.17)***	(0.09)***	(0.09)***	(0.08)
$GATT/WTO$	0.23	0.38	0.16	0.22	0.11	0.28	0.29	0.36	0.10	0.10	0.11
	(0.10)**	(0.11)***	(0.09)*	(0.08)***	(0.09)	(0.09)***	(0.11)***	(0.18)**	(0.08)	(0.11)	(0.05)**
RTA	0.21	0.17	0.31	0.16	-0.11	-0.05	0.22	0.07	0.24	0.05	0.17
	(0.06)***	(0.06)***	(0.04)***	(0.06)***	(0.06)**	(0.05)	(0.06)***	(0.12)	(0.05)***	(0.05)	(0.04)***
$COMCUR$	0.06	0.08	0.35	0.63	0.44	0.36	0.34	0.61	0.42	0.13	0.15
	(0.13)	(0.14)	(0.11)***	(0.14)***	(0.15)***	(0.12)***	(0.19)*	(0.28)**	(0.12)***	(0.21)	(0.11)
$COMLEG$	-0.02	0.15	0.08	0.07	0.06	0.04	0.16	-0.02	0.16	0.08	0.09
	(0.06)	(0.03)***	(0.03)**	(0.04)	(0.03)*	(0.04)	(0.06)***	(0.08)	(0.03)***	(0.04)**	(0.03)***
$COLPOST45$	1.15	1.21	1.02	0.88	0.78	0.99	0.89	0.89	0.93	0.97	0.97
	(0.12)***	(0.13)***	(0.12)***	(0.14)***	(0.14)***	(0.15)***	(0.13)***	(0.20)***	(0.13)***	(0.13)***	(0.13)***
$SIBPOST45$	0.23	0.17	0.25	0.14	0.21	0.13	0.08	0.40	0.31	0.18	0.26
	(0.09)***	(0.06)***	(0.06)***	(0.08)*	(0.08)***	(0.07)*	(0.11)	(0.18)**	(0.06)***	(0.09)**	(0.05)***
$RELIG$	0.10	0.07	0.18	0.02	0.20	-0.04	-0.05	-0.08	0.03	-0.05	0.07
	(0.12)	(0.09)	(0.08)**	(0.14)	(0.09)**	(0.10)	(0.13)	(0.17)	(0.10)	(0.12)	(0.07)
Observations	32,688	32,782	31,819	24,636	27,874	29,452	26,801	20,319	32,705	23,606	32,664
Imputed R^2	0.806	0.732	0.525	0.548	0.208	0.177	0.691	0.236	0.577	0.184	0.393

Results for importer-product and exporter-product fixed effects are excluded for brevity.
Robust standard errors, clustered by country pair, are in parentheses. * $p < 0.10$, ** $p < .05$, *** $p < .01$

Table C.2: Trade in services, second step, detailed sectoral results for CSL

	(1) FOOD	(2) TEXTILE	(3) WOOD	(4) PAPER	(5) CHEMICALS	(6) MINERALS	(7) METALS	(8) MACHINERY
Dependent variable: $\exp(\hat{\delta}_{ij}^{Man})$								
$GATT/WTO_t$	0.04	-0.23	0.23	0.33	0.17	0.22	0.04	0.25
	(0.07)	(0.10)**	(0.11)**	(0.13)**	(0.05)***	(0.06)***	(0.06)	(0.11)**
$COMCUR_t$	0.36	0.30	0.61	0.36	0.40	0.06	0.29	0.11
	(0.05)***	(0.20)	(0.10)***	(0.07)***	(0.12)***	(0.05)	(0.07)***	(0.08)
RTA_t	0.15	0.03	0.13	0.09	0.20	0.10	0.35	0.09
	(0.05)***	(0.08)	(0.09)	(0.07)	(0.04)***	(0.06)*	(0.14)**	(0.04)**
RTA_{t-4}	0.11	-0.00	0.27	0.17	0.10	0.08	0.03	0.01
	(0.09)	(0.12)	(0.08)***	(0.08)**	(0.05)**	(0.05)	(0.10)	(0.04)
EU_t	0.50	0.13	0.48	0.58	0.38	0.24	0.60	0.47
	(0.05)***	(0.12)	(0.08)***	(0.07)***	(0.07)***	(0.06)***	(0.08)***	(0.11)***
EU_{t-4}	0.84	-0.19	0.14	0.55	0.55	0.29	0.41	0.13
	(0.05)***	(0.12)	(0.06)***	(0.09)***	(0.07)***	(0.04)***	(0.11)***	(0.06)**
Observations	33,492	34,410	31,278	30,576	34,122	30,450	30,720	35,226

Results for importer-time-product, exporter-time-product and asymmetric country-pair-product fixed effects are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses. * $p < 0.10$, ** $p < .05$, *** $p < .01$

Table C.3: Trade in manufactured goods, first step, sectoral results

	(1) FOOD	(2) TEXTILE	(3) WOOD	(4) PAPER	(5) CHEMICALS	(6) MINERALS	(7) METALS	(8) MACHINERY
Dependent variable: $\exp(\hat{\delta}_{ij}^{Man})$								
CSL	0.59	0.32	0.58	1.04	0.23	-0.27	-0.05	0.85
	(0.23)***	(0.19)	(0.24)**	(0.27)***	(0.31)	(0.41)	(0.25)	(0.16)***
LP0	-0.23	-0.02	0.28	0.77	0.71	0.77	0.45	0.26
	(0.37)	(0.26)	(0.40)	(0.36)**	(0.33)**	(0.38)**	(0.32)	(0.22)
LNDIST [0,625]	-1.03	-0.62	-1.07	-0.44	-0.58	-1.45	-0.88	-0.48
	(0.25)***	(0.13)***	(0.25)***	(0.24)*	(0.28)**	(0.31)***	(0.28)***	(0.13)***
LNDIST]625,1250]	-1.00	-0.66	-0.98	-0.45	-0.61	-1.42	-0.89	-0.47
	(0.23)***	(0.12)***	(0.23)***	(0.22)**	(0.26)**	(0.29)***	(0.25)***	(0.11)***
LNDIST]1250,2500]	-1.03	-0.71	-1.02	-0.48	-0.68	-1.42	-0.90	-0.51
	(0.21)***	(0.11)***	(0.21)***	(0.21)**	(0.24)***	(0.26)***	(0.23)***	(0.11)***
LNDIST]2500,5000]	-0.97	-0.72	-0.96	-0.49	-0.70	-1.36	-0.83	-0.48
	(0.19)***	(0.10)***	(0.20)***	(0.19)**	(0.22)***	(0.25)***	(0.21)***	(0.10)***
LNDIST]5000,10000]	-0.94	-0.75	-1.01	-0.56	-0.76	-1.35	-0.88	-0.53
	(0.18)***	(0.10)***	(0.19)***	(0.17)***	(0.19)***	(0.22)***	(0.20)***	(0.09)***
LNDIST]10000,20000]	-0.93	-0.71	-1.00	-0.52	-0.75	-1.47	-0.86	-0.52
	(0.17)***	(0.09)***	(0.17)***	(0.17)***	(0.20)***	(0.21)***	(0.19)***	(0.09)***
CONTIG	0.47	0.41	0.75	0.65	0.52	0.44	0.32	0.45
	(0.17)***	(0.12)***	(0.18)***	(0.17)***	(0.16)***	(0.16)***	(0.16)**	(0.11)***
GATT/WTO	1.23	-0.05	-0.29	0.67	0.18	0.32	0.45	0.71
	(0.23)***	(0.20)	(0.27)	(0.34)**	(0.29)	(0.38)	(0.35)	(0.17)***
RTA	0.11	0.49	0.37	0.49	0.11	0.34	0.01	0.41
	(0.13)	(0.09)***	(0.16)**	(0.17)***	(0.17)	(0.18)*	(0.14)	(0.08)***
COMLEG	0.04	0.24	0.21	0.39	0.44	0.59	0.42	0.17
	(0.10)	(0.06)***	(0.10)**	(0.13)***	(0.11)***	(0.13)***	(0.10)***	(0.05)***
COLPOST45	1.24	1.01	1.04	1.10	0.78	1.17	0.83	0.53
	(0.32)***	(0.15)***	(0.27)***	(0.38)***	(0.32)**	(0.17)***	(0.42)*	(0.15)***
SIBPOST45	0.43	0.26	0.89	0.40	0.66	0.99	0.72	0.92
	(0.23)*	(0.16)	(0.18)***	(0.32)	(0.22)***	(0.29)***	(0.25)***	(0.21)***
RELIG	1.11	-0.11	0.53	0.49	0.32	0.27	0.37	-0.12
	(0.24)***	(0.16)	(0.27)**	(0.27)*	(0.26)	(0.40)	(0.28)	(0.15)
Observations	5,504	5,657	5,136	5,020	5,610	4,999	5,043	5,793
Imputed R^2	0.845	0.705	0.661	0.880	0.531	0.911	0.506	0.589

Results for importer-product and exporter-product fixed effects are excluded for brevity.
Robust standard errors, clustered by country pair, are in parentheses. * $p < 0.10$, ** $p < .05$, *** $p < .01$

Table C.4: Trade in manufactured goods, second step, detailed sectoral results for CSL

Appendix D

Results of Chapter 4.5 without Domestic Trade

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: $\exp(\hat{\delta}_{ij}^{All,Inter})$						
COL	0.28					
	(0.12)**					
CNL		0.68		0.94		
		(0.23)***		(0.25)***		
CSL			0.76		0.85	
			(0.17)***		(0.17)***	
$LP0$				0.84	0.56	
				(0.23)***	(0.19)***	
$LP1$						0.83
						(0.21)***
$LNDIST[0,625]$	-0.69	-0.69	-0.69	-0.64	-0.67	-0.64
	(0.17)***	(0.16)***	(0.16)***	(0.16)***	(0.15)***	(0.16)***
$LNDIST]625,1250]$	-0.73	-0.73	-0.73	-0.69	-0.70	-0.68
	(0.15)***	(0.14)***	(0.14)***	(0.14)***	(0.14)***	(0.14)***
$LNDIST]1250,2500]$	-0.76	-0.75	-0.75	-0.71	-0.73	-0.70
	(0.14)***	(0.13)***	(0.13)***	(0.13)***	(0.13)***	(0.13)***
$LNDIST]2500,5000]$	-0.76	-0.76	-0.75	-0.71	-0.73	-0.71
	(0.13)***	(0.12)***	(0.12)***	(0.12)***	(0.12)***	(0.12)***
$LNDIST]5000,10000]$	-0.77	-0.77	-0.77	-0.73	-0.74	-0.73
	(0.12)***	(0.11)***	(0.11)***	(0.11)***	(0.11)***	(0.11)***
$LNDIST]10000,20000]$	-0.78	-0.77	-0.76	-0.73	-0.74	-0.73
	(0.11)***	(0.11)***	(0.10)***	(0.10)***	(0.10)***	(0.11)***
$CONTIG$	0.29	0.32	0.31	0.33	0.31	0.32
	(0.09)***	(0.09)***	(0.09)***	(0.09)***	(0.09)***	(0.09)***
$GATT/WTO$	0.11	0.10	-0.02	0.11	-0.02	0.12
	(0.14)	(0.14)	(0.15)	(0.14)	(0.15)	(0.14)
RTA	0.36	0.34	0.30	0.33	0.29	0.33
	(0.08)***	(0.08)***	(0.08)***	(0.08)***	(0.08)***	(0.07)***
$COMLEG$	0.14	0.13	0.12	0.11	0.11	0.11
	(0.05)***	(0.05)**	(0.05)**	(0.05)**	(0.05)**	(0.05)**
$COLPOST45$	0.53	0.54	0.40	0.51	0.38	0.52
	(0.17)***	(0.17)***	(0.17)**	(0.17)***	(0.17)**	(0.17)***
$SIBPOST45$	0.69	0.76	0.67	0.75	0.65	0.75
	(0.12)***	(0.11)***	(0.12)***	(0.11)***	(0.12)***	(0.11)***
$RELIG$	0.64	0.59	0.50	0.52	0.46	0.54
	(0.11)***	(0.10)***	(0.11)***	(0.10)***	(0.11)***	(0.10)***
Observations	5,933	5,933	5,933	5,933	5,933	5,933
Imputed R^2	0.619	0.632	0.640	0.640	0.644	0.639

Results for importer and exporter fixed effects are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table D.1: Trade in all goods, international trade only, second step

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: $\exp(\hat{\delta}_{ij}^{Man,Inter})$						
COL	0.22					
	(0.11)*					
CNL		0.71		0.97		
		(0.21)***		(0.24)***		
CSL			0.67		0.75	
			(0.17)***		(0.18)***	
$LP0$				0.87	0.50	
				(0.23)***	(0.20)**	
$LP1$						0.85
						(0.19)***
$LNDIST[0, 625]$	-0.78	-0.77	-0.77	-0.73	-0.75	-0.72
	(0.16)***	(0.15)***	(0.15)***	(0.15)***	(0.15)***	(0.15)***
$LNDIST]625, 1250]$	-0.80	-0.79	-0.79	-0.74	-0.76	-0.74
	(0.14)***	(0.14)***	(0.13)***	(0.13)***	(0.13)***	(0.13)***
L$NDIST]1250, 2500]$	-0.82	-0.81	-0.81	-0.77	-0.79	-0.77
	(0.13)***	(0.13)***	(0.12)***	(0.12)***	(0.12)***	(0.12)***
$LNDIST]2500, 5000]$	-0.84	-0.82	-0.82	-0.78	-0.80	-0.78
	(0.12)***	(0.12)***	(0.11)***	(0.11)***	(0.11)***	(0.11)***
$LNDIST]5000, 10000]$	-0.84	-0.83	-0.83	-0.79	-0.81	-0.79
	(0.11)***	(0.11)***	(0.11)***	(0.10)***	(0.10)***	(0.11)***
$LNDIST]10000, 20000]$	-0.84	-0.83	-0.83	-0.79	-0.81	-0.79
	(0.11)***	(0.10)***	(0.10)***	(0.10)***	(0.10)***	(0.10)***
$CONTIG$	0.36	0.39	0.38	0.39	0.38	0.39
	(0.10)***	(0.10)***	(0.10)***	(0.09)***	(0.09)***	(0.09)***
$GATT/WTO$	0.11	0.11	0.00	0.13	-0.00	0.13
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
RTA	0.48	0.45	0.42	0.44	0.42	0.44
	(0.08)***	(0.08)***	(0.08)***	(0.08)***	(0.08)***	(0.08)***
$COMLEG$	0.16	0.14	0.13	0.12	0.13	0.11
	(0.06)***	(0.05)**	(0.05)**	(0.06)**	(0.05)**	(0.06)**
$COLPOST45$	0.63	0.63	0.51	0.60	0.48	0.61
	(0.14)***	(0.14)***	(0.15)***	(0.14)***	(0.15)***	(0.14)***
$SIBPOST45$	0.71	0.77	0.69	0.76	0.67	0.75
	(0.13)***	(0.12)***	(0.12)***	(0.12)***	(0.12)***	(0.12)***
$RELIG$	0.70	0.62	0.56	0.54	0.52	0.56
	(0.13)***	(0.11)***	(0.12)***	(0.11)***	(0.12)***	(0.11)***
Observations	5,924	5,924	5,924	5,924	5,924	5,924
Imputed R^2	0.630	0.643	0.653	0.644	0.649	0.651

Results for importer and exporter fixed effects are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table D.2: Trade in manufactured goods, international trade only, second step

	(1)	(2)	(3)	(4)
Dependent variable: $\exp(\hat{\delta}_{ij}^{All,Inter})$				
CNL_WORLD	0.37			
	(0.24)			
CNL_OTHER	0.28			
	(0.26)			
CSL_WORLD		0.30		
		(0.30)		
CSL_OTHER		0.42		
		(0.24)*		
$CNL\_ENGLISH$			-0.22	
			(0.39)	
$CNL\_NO\_ENGLISH$			0.45	
			(0.19)**	
$CSL\_ENGLISH$				-0.03
				(0.42)
$CSL\_NO\_ENGLISH$				0.53
				(0.18)***
$LP0$	0.23	0.27	0.26	0.31
	(0.70)	(0.72)	(0.69)	(0.71)
$LNDIST[0, 625]$	-0.58	-0.57	-0.55	-0.55
	(0.14)***	(0.14)***	(0.14)***	(0.14)***
$LNDIST]625, 1250]$	-0.62	-0.61	-0.60	-0.59
	(0.12)***	(0.13)***	(0.13)***	(0.12)***
$LNDIST]1250, 2500]$	-0.66	-0.65	-0.64	-0.64
	(0.12)***	(0.12)***	(0.12)***	(0.11)***
$LNDIST]2500, 5000]$	-0.72	-0.71	-0.70	-0.70
	(0.11)***	(0.11)***	(0.11)***	(0.11)***
$LNDIST]5000, 10000]$	-0.70	-0.69	-0.68	-0.68
	(0.10)***	(0.10)***	(0.10)***	(0.10)***
$LNDIST]10000, 20000]$	-0.75	-0.74	-0.73	-0.73
	(0.09)***	(0.09)***	(0.09)***	(0.09)***
$CONTIG$	0.48	0.46	0.48	0.45
	(0.12)***	(0.12)***	(0.13)***	(0.12)***
$GATT/WTO$	0.72	0.73	0.72	0.71
	(0.31)**	(0.31)**	(0.31)**	(0.30)**
RTA	0.64	0.64	0.65	0.64
	(0.13)***	(0.13)***	(0.13)***	(0.13)***
$COMCUR$	0.51	0.51	0.54	0.54
	(0.26)**	(0.26)*	(0.26)**	(0.26)**
$COMLEG$	-0.05	-0.07	-0.05	-0.07
	(0.10)	(0.10)	(0.10)	(0.10)
$COLPOST45$	0.82	0.79	0.83	0.77
	(0.17)***	(0.17)***	(0.17)***	(0.17)***
$SIBPOST45$	0.58	0.54	0.57	0.53
	(0.15)***	(0.15)***	(0.15)***	(0.15)***
$RELIG$	0.76	0.72	0.72	0.66
	(0.22)***	(0.22)***	(0.23)***	(0.23)***
Observations	32,290	32,290	32,290	32,290
Imputed R^2	0.775	0.766	0.773	0.774

Results for importer and exporter fixed effects are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table D.3: International trade in all goods, second step, world languages

Appendix E

Additional Tables to Chapter 5

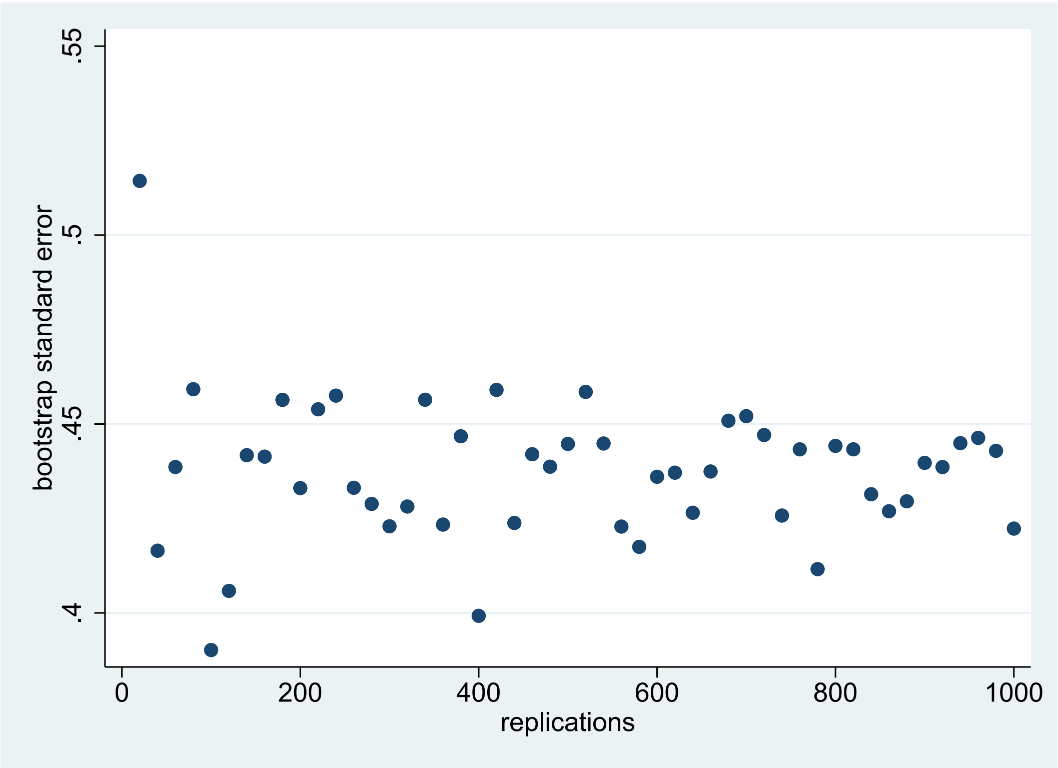

Figure E.1: Convergence of the bootstrapped standard errors for $LP1[0, 0.25]$ in column (1) of table 5.4

Dependent variable:	(1) $\exp(\hat{\delta}_{ij}^{Man,1996})$	(2) $\exp(\hat{\delta}_{ij}^{Man,2000})$	(3) $\exp(\hat{\delta}_{ij}^{Man,2004})$	(4) $\exp(\hat{\delta}_{ij}^{Man,2008})$	(5) $\exp(\hat{\delta}_{ij}^{Man,2012})$	(6) $\exp(\hat{\delta}_{ij}^{Man,2016})$
$LP1$	0.47	0.52	0.49	0.48	0.51	0.46
	(0.12)***	(0.14)***	(0.12)***	(0.12)***	(0.14)***	(0.15)***
$LNDIST[0,625]$	-0.68	-0.74	-0.75	-0.82	-0.84	-0.79
	(0.09)***	(0.11)***	(0.10)***	(0.11)***	(0.11)***	(0.12)***
$LNDIST]625,1250]$	-0.71	-0.73	-0.74	-0.81	-0.84	-0.78
	(0.08)***	(0.10)***	(0.09)***	(0.10)***	(0.10)***	(0.11)***
$LNDIST]1250,2500]$	-0.74	-0.76	-0.77	-0.85	-0.87	-0.83
	(0.08)***	(0.09)***	(0.08)***	(0.09)***	(0.09)***	(0.10)***
$LNDIST]2500,5000]$	-0.72	-0.73	-0.75	-0.81	-0.84	-0.80
	(0.07)***	(0.09)***	(0.08)***	(0.09)***	(0.09)***	(0.09)***
$LNDIST]5000,10000]$	-0.74	-0.76	-0.78	-0.83	-0.85	-0.82
	(0.06)***	(0.08)***	(0.07)***	(0.08)***	(0.08)***	(0.09)***
$LNDIST]10000,20000]$	-0.72	-0.75	-0.76	-0.81	-0.83	-0.79
	(0.06)***	(0.08)***	(0.07)***	(0.07)***	(0.08)***	(0.08)***
$CONTIG$	0.41	0.53	0.44	0.44	0.35	0.35
	(0.08)***	(0.10)***	(0.08)***	(0.07)***	(0.08)***	(0.07)***
RTA	0.44	0.39	0.37	0.41	0.47	0.45
	(0.05)***	(0.05)***	(0.05)***	(0.05)***	(0.07)***	(0.06)***
$COMLEG$	0.23	0.15	0.14	0.15	0.14	0.15
	(0.04)***	(0.05)***	(0.04)***	(0.04)***	(0.04)***	(0.04)***
$COMCUR$	-1.90	-0.53	-0.47	-0.36	-0.40	-0.30
	(0.15)***	(0.09)***	(0.10)***	(0.09)***	(0.09)***	(0.08)***
$COLPOST45$	1.27	1.02	0.88	0.75	0.78	0.75
	(0.13)***	(0.14)***	(0.15)***	(0.12)***	(0.12)***	(0.10)***
$SIBPOST45$	1.23	0.91	0.95	0.94	0.92	0.93
	(0.10)***	(0.20)***	(0.15)***	(0.13)***	(0.12)***	(0.13)***
$RELIG$	0.40	0.47	0.51	0.40	0.49	0.52
	(0.08)***	(0.09)***	(0.10)***	(0.10)***	(0.10)***	(0.11)***
Observations	5,484	5,726	5,836	5,854	5,858	5,872
Imputed R^2	0.887	0.897	0.868	0.857	0.856	0.852
CNL	0.44	0.48	0.46	0.52	0.56	0.52
	(0.14)***	(0.18)***	(0.17)***	(0.18)***	(0.21)***	(0.23)**
$LP0$	0.78	0.93	0.83	0.64	0.65	0.57
	(0.20)***	(0.20)***	(0.17)***	(0.15)***	(0.16)***	(0.16)***
Imputed R^2	0.890	0.903	0.875	0.861	0.859	0.855
CSL	0.46	0.44	0.45	0.53	0.53	0.62
	(0.10)***	(0.12)***	(0.11)***	(0.11)***	(0.12)***	(0.12)***
$LP0$	0.56	0.67	0.59	0.37	0.37	0.31
	(0.18)***	(0.18)***	(0.16)***	(0.15)**	(0.15)**	(0.15)**
Imputed R^2	0.888	0.903	0.877	0.867	0.866	0.865
COL	-0.03	0.00	0.02	0.02	-0.04	-0.13
	(0.07)	(0.09)	(0.08)	(0.08)	(0.08)	(0.09)
Imputed R^2	0.886	0.894	0.863	0.853	0.854	0.856

Results for importer- and exporter-fixed effects, as well as for control variables in the lower panels, are excluded for brevity. Robust standard errors, clustered by country pair, in parentheses. * $p < 0.10$, ** $p < .05$, *** $p < .01$

Table E.1: Change in bilateral trade costs in 20 years, 1996-2016

	(1)	(2)	(3)	(4)
Dependent variable: $\exp(\hat{\delta}_{ij}^{Man,2004-2016})$				
COL	-0.03			
	(0.11)			
CNL		0.52		
		(0.23)**		
CSL			0.53	
			(0.14)***	
$LP0$		0.83	0.56	
		(0.19)***	(0.18)***	
$LP1$				0.50
				(0.17)***
$LNDIST[0,625]$	-0.77	-0.75	-0.75	-0.73
	(0.13)***	(0.12)***	(0.11)***	(0.13)***
$LNDIST]625,1250]$	-0.77	-0.74	-0.74	-0.72
	(0.11)***	(0.11)***	(0.10)***	(0.11)***
$LNDIST]1250,2500]$	-0.81	-0.77	-0.77	-0.76
	(0.10)***	(0.10)***	(0.09)***	(0.10)***
$LNDIST]2500,5000]$	-0.79	-0.75	-0.74	-0.74
	(0.09)***	(0.09)***	(0.08)***	(0.09)***
$LNDIST]5000,10000]$	-0.81	-0.78	-0.77	-0.77
	(0.09)***	(0.08)***	(0.08)***	(0.09)***
$LNDIST]10000,20000]$	-0.78	-0.74	-0.74	-0.73
	(0.08)***	(0.08)***	(0.08)***	(0.08)***
$CONTIG$	0.45	0.45	0.44	0.43
	(0.10)***	(0.10)***	(0.10)***	(0.10)***
$GATT/WTO$	0.51	0.50	0.40	0.48
	(0.26)*	(0.26)*	(0.25)	(0.26)*
RTA	0.33	0.35	0.33	0.35
	(0.08)***	(0.08)***	(0.07)***	(0.08)***
$COMLEG$	0.21	0.20	0.21	0.17
	(0.05)***	(0.05)***	(0.05)***	(0.05)***
$COMCUR$	-0.29	-0.31	-0.30	-0.30
	(0.13)**	(0.12)***	(0.12)**	(0.12)**
$COLPOST45$	0.71	0.59	0.48	0.62
	(0.17)***	(0.16)***	(0.16)***	(0.17)***
$SIBPOST45$	0.79	0.79	0.70	0.81
	(0.15)***	(0.14)***	(0.13)***	(0.14)***
$RELIG$	0.47	0.37	0.30	0.41
	(0.14)***	(0.14)***	(0.13)**	(0.14)***
Observations	5,598	5,598	5,598	5,598
Imputed R^2	0.738	0.747	0.754	0.740

Results for importer and exporter fixed effects are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table E.2: Trade costs in 2004-2016, second step

	(1)	(2)	(3)	(4)
Dependent variable: $\exp(\hat{\delta}_{ij}^{Man,IntMargin,2004-2016})$				
$\hat{\delta}_{ij}^{Man,IntMargin,1996-2000}$	0.54	0.54	0.54	0.54
	(0.07)***	(0.08)***	(0.08)***	(0.08)***
COL	-0.07			
	(0.13)			
CNL		0.18		
		(0.20)		
CSL			-0.06	
			(0.15)	
$LP0$		0.97	0.89	
		(0.33)***	(0.30)***	
$LP1$				0.44
				(0.19)**
$LNDIST[0, 625]$	-0.36	-0.36	-0.37	-0.32
	(0.17)**	(0.17)**	(0.16)**	(0.17)*
$LNDIST]625, 1250]$	-0.35	-0.34	-0.36	-0.31
	(0.15)**	(0.15)**	(0.14)**	(0.14)**
$LNDIST]1250, 2500]$	-0.38	-0.37	-0.38	-0.34
	(0.14)***	(0.14)**	(0.14)***	(0.14)**
$LNDIST]2500, 5000]$	-0.36	-0.35	-0.36	-0.33
	(0.13)***	(0.13)***	(0.13)***	(0.13)**
$LNDIST]5000, 10000]$	-0.35	-0.33	-0.35	-0.31
	(0.12)***	(0.12)***	(0.12)***	(0.12)**
$LNDIST]10000, 20000]$	-0.34	-0.33	-0.35	-0.30
	(0.12)***	(0.12)***	(0.11)***	(0.12)***
$CONTIG$	0.06	0.04	0.05	0.02
	(0.10)	(0.11)	(0.11)	(0.11)
$GATT/WTO$	-0.29	-0.29	-0.28	-0.30
	(0.26)	(0.26)	(0.26)	(0.26)
RTA	-0.16	-0.16	-0.16	-0.14
	(0.08)**	(0.08)*	(0.08)**	(0.08)*
$COMCUR$	0.34	0.31	0.31	0.34
	(0.14)**	(0.13)**	(0.13)**	(0.14)**
$COMLEG$	0.07	0.05	0.06	0.05
	(0.07)	(0.06)	(0.07)	(0.07)
$COLPOST45$	0.19	0.13	0.16	0.12
	(0.14)	(0.13)	(0.13)	(0.13)
$SIBPOST45$	0.28	0.22	0.23	0.25
	(0.14)**	(0.14)	(0.13)*	(0.14)*
$RELIG$	-0.38	-0.41	-0.38	-0.43
	(0.16)**	(0.16)***	(0.16)**	(0.17)**
Observations	5,596	5,596	5,596	5,596
Imputed R^2	0.856	0.862	0.860	0.859

Results for importer and exporter fixed effects are excluded for brevity. Bootstrapped standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table E.3: Contemporaneous trade costs in 2004-2016, second step, intensive margin

	(1)	(2)	(3)	(4)
Dependent variable: $\exp(\hat{\delta}_{ij}^{Man,Inter,ExtMargin,2004-2016})$				
$\hat{\delta}_{ij}^{Man,Inter,ExtMargin,1996-2000}$	0.62	0.62	0.62	0.63
	(0.01)***	(0.01)***	(0.01)***	(0.01)***
COL	0.17			
	(0.02)***			
CNL		0.27		
		(0.05)***		
CSL			0.17	
			(0.03)***	
$LP0$		0.04	-0.09	
		(0.05)	(0.05)*	
$LP1$				0.19
				(0.04)***
$LNDIST[0,625]$	-0.09	-0.08	-0.09	-0.08
	(0.03)***	(0.03)***	(0.03)***	(0.03)***
$LNDIST]625,1250]$	-0.08	-0.08	-0.08	-0.08
	(0.03)***	(0.03)***	(0.03)***	(0.03)***
$LNDIST]1250,2500]$	-0.09	-0.09	-0.10	-0.09
	(0.03)***	(0.03)***	(0.03)***	(0.03)***
$LNDIST]2500,5000]$	-0.09	-0.09	-0.10	-0.09
	(0.02)***	(0.02)***	(0.02)***	(0.02)***
$LNDIST]5000,10000]$	-0.09	-0.09	-0.09	-0.09
	(0.02)***	(0.02)***	(0.02)***	(0.02)***
$LNDIST]10000,20000]$ -0.09	-0.09	-0.10	-0.09	
	(0.02)***	(0.02)***	(0.02)***	(0.02)***
$CONTIG$	0.02	0.03	0.03	0.03
	(0.03)	(0.03)	(0.03)	(0.03)
$GATT/WTO$	0.00	0.03	0.01	0.04
	(0.08)	(0.08)	(0.08)	(0.08)
RTA	0.09	0.09	0.09	0.09
	(0.02)***	(0.02)***	(0.02)***	(0.02)***
$COMLEG$	-0.02	-0.02	-0.01	-0.02
	(0.01)*	(0.01)	(0.01)	(0.01)
$COMCUR$	-0.07	-0.07	-0.08	-0.08
	(0.02)***	(0.02)***	(0.02)***	(0.02)***
$COLPOST45$	-0.01	0.03	0.01	0.04
	(0.04)	(0.04)	(0.04)	(0.04)
$SIBPOST45$	0.04	0.06	0.04	0.05
	(0.04)	(0.04)	(0.04)	(0.04)
$RELIG$	0.04	0.03	0.03	0.03
	(0.03)	(0.03)	(0.03)	(0.03)
Observations	5,603	5,603	5,603	5,603
Imputed R^2	0.891	0.890	0.889	0.890

Results for importer and exporter fixed effects are excluded for brevity. Bootstrapped standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table E.4: Contemporaneous trade costs in 2004-2016, second step, extensive margin, international trade only

	(1)	(2)	(3)	(4)
Dependent variable: $\exp(\hat{\delta}_{ij}^{Man,Inter,IntMargin,2004-2016})$				
$\hat{\delta}_{ij}^{Man,Inter,IntMargin,1996-2000}$	0.40	0.40	0.40	0.40
	(0.07)***	(0.07)***	(0.07)***	(0.07)***
COL	-0.06			
	(0.05)			
CNL		-0.07		
		(0.10)		
CSL			-0.13	
			(0.08)*	
$LP0$		0.23	0.24	
		(0.13)*	(0.12)**	
$LP1$				0.05
				(0.09)
$LNDIST[0, 625]$	-0.29	-0.29	-0.29	-0.28
	(0.08)***	(0.09)***	(0.09)***	(0.08)***
$LNDIST]625, 1250]$	-0.31	-0.31	-0.31	-0.30
	(0.08)***	(0.08)***	(0.08)***	(0.08)***
$LNDIST]1250, 2500]$	-0.32	-0.32	-0.32	-0.31
	(0.07)***	(0.07)***	(0.07)***	(0.07)***
$LNDIST]2500, 5000]$	-0.31	-0.30	-0.31	-0.30
	(0.07)***	(0.07)***	(0.07)***	(0.07)***
$LNDIST]5000, 10000]$	-0.30	-0.30	-0.30	-0.29
	(0.06)***	(0.06)***	(0.06)***	(0.06)***
$LNDIST]10000, 20000]$	-0.29	-0.29	-0.29	-0.28
	(0.06)***	(0.06)***	(0.06)***	(0.06)***
$CONTIG$	0.17	0.17	0.18	0.16
	(0.06)***	(0.06)***	(0.06)***	(0.06)***
$GATT/WTO$	-0.30	-0.32	-0.30	-0.32
	(0.17)*	(0.17)*	(0.17)*	(0.17)*
RTA	0.05	0.05	0.06	0.05
	(0.04)	(0.05)	(0.05)	(0.04)
$COMLEG$	0.06	0.06	0.06	0.06
	(0.04)*	(0.04)	(0.04)*	(0.04)
$COMCUR$	0.23	0.22	0.22	0.23
	(0.06)***	(0.06)***	(0.06)***	(0.06)***
$COLPOST45$	0.05	0.03	0.06	0.02
	(0.09)	(0.09)	(0.09)	(0.09)
$SIBPOST45$	0.04	0.02	0.04	0.03
	(0.08)	(0.08)	(0.08)	(0.08)
$RELIG$	0.02	0.01	0.02	0.00
	(0.08)	(0.09)	(0.09)	(0.09)
Observations	5,596	5,596	5,596	5,596
Imputed R^2	0.397	0.397	0.398	0.397

Results for importer and exporter fixed effects are excluded for brevity. Bootstrapped standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table E.5: Contemporaneous trade costs in 2004-2016, second step, intensive margin, international trade only

Appendix F

Appendix to Chapter 6

Albanian	Greek	Romani
Arabic	Hebrew	Romanian
Armenian	Hindi	Russian
Azerbaijani	Hungarian	Slovak
Bulgarian	Italian	Slovenian
Catalan	Japanese	Spanish
Chinese	Kazakh	Swedish
Czech	Korean	Tagalog
Danish	Latvian	Tamil
Dutch	Lithuanian	Tatar
English	Maltese	Turkish
Estonian	Norwegian	Ukrainian
Finnish	Polish	Uyghur
French	Portuguese	Uzbek
Georgian	Punjabi	Vietnamese
German	BCMS (Bosnian-Croatian-Montenegrin-Serbian)	

Languages spoken in only one country (e.g. Irish, Welsh) or by less than one percent of the population in more than one country (e.g. Afrikaans, Malay) are excluded. See text for further details.

Table F.1: Considered languages for CSL

(ALB*)	Albania	KAZ*	Kazakhstan
ARM*	Armenia	LTU*	Lithuania
AUT	Austria	LVA*	Latvia
BGR*	Bulgaria	(MKD*)	North Macedonia
BLX	Belgium-Luxembourg	MLT	Malta
CAN	Canada	NLD	The Netherlands
CYP	Republic of Cyprus	(NOR)	Norway
CZE*	Czech Republic	POL*	Poland
DEU	Germany	PRT	Portugal
DNK	Denmark	ROU*	Romania
ESP	Spain	RUS*	Russian Federation
EST*	Estonia	(SCG*)	Serbia and Montenegro
FIN	Finland	SVK*	Slovak Republic
FRA	France	SVN*	Slovenia
GBR	United Kingdom	SWE	Sweden
GRC	Greece	TUR	Turkey
HUN*	Hungary	(UKR*)	Ukraine
IRL	Ireland	USA	United States of America
ITA	Italy		

Countries that are specified as 'East' are indicated by an asterisk. Countries in parenthesis are used only in section 6.5. Figures 6.1 and 6.2 include Georgia and Croatia as well, which are excluded from the econometric analysis because of missing data on internal trade in the 1990s. See text for further details.

Table F.2: Country coverage and abbreviations

I included Canada and the United States in the sample since both countries are important Western economies, trading partners, and destination countries of many emigrants from Eastern Europe. Yet there are reasons to exclude both countries. First, the U.S. are by far the largest single economy in the sample, thus representing a huge outlier. Second, both U.S.' and Canada's main language is English, which I focus on in the main part. Therefore it would be crucial to test if the results from chapter 6.4.2 also hold if I exclude the two North American states.

Column (1) in table F.3 reports the estimation with CSL, finding no significant impact for a change in overall common spoken language on trade. The results for separate languages in columns (2)-(4) confirm the corresponding estimates in table 6.4. Contrary to the results in the main text, $CSL\_ENGLISH$ passes the feedback test, although the coefficient of the lead variable is relatively large.

In table F.4, I re-estimate the regressions from table 6.5 without U.S. and Canada. All results are robust and the coefficients are almost the same. Again, the interactions between the $CSL\_ENGLISH$ intervals and $EASTWEST$ are not significantly different from zero, but negative.

Dependent variable: $X_{ij,t}$	(1)	(2)	(3)	(4)
$CSL_{ij,t}$	0.32			
	(0.23)			
$CSL\_ENGLISH_{ij,t}$		1.22	1.16	1.28
		(0.45)***	(0.46)**	(0.52)**
$CSL\_GERMAN_{ij,t}$		-0.27		
		(0.40)		
$CSL\_FRENCH_{ij,t}$		0.44		
		(0.35)		
$CSL\_RUSSIAN_{ij,t}$		-0.41		
		(0.79)		
$CSL\_OTHER_{ij,t}$		0.13		
		(0.42)		
$CSL\_NO\_ENGLISH_{ij,t}$			0.35	0.15
			(0.21)*	(0.26)
$CSL\_ENGLISH_{ij,t+5}$				1.00
				(0.62)
$RTA_{ij,t}$	0.60	0.61	0.61	0.48
	(0.10)***	(0.11)***	(0.11)***	(0.09)***
$RTA_{ij,t-5}$	0.20	0.19	0.19	0.20
	(0.06)***	(0.06)***	(0.06)***	(0.07)***
$EU_{ij,t}$	0.24	0.24	0.24	0.13
	(0.04)***	(0.04)***	(0.04)***	(0.06)**
$EU_{ij,t-5}$	0.08	0.09	0.09	0.08
	(0.05)*	(0.04)**	(0.04)**	(0.08)
$WTO_{ij,t}$	-0.36	-0.37	-0.37	-0.35
	(0.14)**	(0.14)***	(0.14)***	(0.17)**
$COMCUR_{ij,t}$	-0.01	0.01	0.01	0.04
	(0.04)	(0.03)	(0.03)	(0.04)
$LNMIGR_{ij,t}$	0.03	0.02	0.03	0.06
	(0.03)	(0.03)	(0.03)	(0.03)*
$INTER_{ij,2001}$	0.22	0.20	0.22	0.20
	(0.04)***	(0.04)***	(0.04)***	(0.04)***
$INTER_{ij,2006}$	0.33	0.34	0.34	0.33
	(0.04)***	(0.03)***	(0.03)***	(0.03)***
$INTER_{ij,2011}$	0.45	0.45	0.46	
	(0.04)***	(0.04)***	(0.04)***	
$EASTWEST_{ij,2001}$	0.21	0.24	0.24	0.25
	(0.06)***	(0.06)***	(0.06)***	(0.06)***
$EASTWEST_{ij,2006}$	0.17	0.23	0.21	0.27
	(0.07)**	(0.07)***	(0.07)***	(0.07)***
$EASTWEST_{ij,2011}$	0.17	0.21	0.20	
	(0.08)**	(0.08)***	(0.08)***	
Observations	3,600	3,600	3,600	2,697

Results for importer-time, exporter-time and asymmetric country-pair fixed effects are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table F.3: Average partial effect of language, without U.S. and Canada

	(1)		(2)		(3)	
Dependent variable: $X_{ij,t}$						
$CSL\_ENGLISH_{ij,t}$						
]0,0.0625]	3.00	(0.81)***	2.67	(0.85)***	2.88	(0.90)***
]0.0625,0.125]	2.55	(0.63)***	2.69	(0.61)***	2.65	(0.66)***
]0.125,0.25]	2.23	(0.58)***	2.37	(0.57)***	2.34	(0.60)***
]0.25,0.5]	1.91	(0.55)***	2.14	(0.53)***	1.99	(0.57)***
]0.5,1]	1.71	(0.51)***	1.94	(0.51)***	1.79	(0.53)***
$CSL\_NO\_ENGLISH_{ij,t}$	0.21	(0.20)	-0.02	(0.26)	0.26	(0.24)
$CSL\_ENGLISH_{ij,t+5}$						
]0,0.0625]			-1.16	(0.93)		
]0.0625,0.125]			-0.39	(0.71)		
]0.125,0.25]			-0.14	(0.71)		
]0.25,0.5]			-0.25	(0.71)		
]0.5,1]			-0.10	(0.66)		
$EASTWEST \times CSL\_ENGLISH_{ij,t}$						
]0,0.0625]					-0.16	(1.92)
]0.0625,0.125]					-1.05	(1.32)
]0.125,0.25]					-0.76	(0.92)
]0.25,0.5]					-0.41	(0.76)
$EASTWEST \times CSL\_NO\_ENGLISH_{ij,t}$					-0.13	(0.48)
$RTA_{ij,t}$	0.61	(0.11)***	0.50	(0.09)***	0.58	(0.11)***
$RTA_{ij,t-5}$	0.19	(0.06)***	0.19	(0.07)***	0.21	(0.06)***
$EU_{ij,t}$	0.23	(0.04)***	0.14	(0.06)**	0.24	(0.04)***
$EU_{ij,t-5}$	0.09	(0.04)**	0.09	(0.08)	0.09	(0.04)**
$WTO_{ij,t}$	-0.38	(0.14)***	-0.32	(0.17)*	-0.38	(0.14)***
$COMCUR_{ij,t}$	0.00	(0.03)	0.04	(0.04)	0.00	(0.03)
$LNMIGR_{ij,t}$	0.04	(0.03)	0.08	(0.03)**	0.03	(0.03)
Observations	3,600		2,697		3,600	

Results for importer-time, exporter-time and asymmetric country-pair fixed effects, as well as globalization and East-West trend, are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table F.4: Average partial effect of English intervals, without U.S. and Canada

	(1)	(2)	(3)	(4)	(5)
Dependent variable: $\exp(\hat{\delta}_{ij})$					
for $EASTWEST = 1$					
$CSL\_ENGLISH$	-0.69				
	(0.88)				
$CSL\_NO\_ENGLISH$	1.73				
	(0.49)***				
CSL_GERMAN		0.22			
		(0.57)			
CSL_NO_GERMAN		1.56			
		(0.64)**			
CSL_FRENCH			1.20		
			(1.68)		
CSL_NO_FRENCH			1.27		
			(0.45)***		
$CSL\_RUSSIAN$				-0.88	
				(4.09)	
$CSL\_NO\_RUSSIAN$				1.25	
				(0.48)***	
CSL_MAIN					0.62
					(0.49)
CSL_NO_MAIN					3.61
					(1.49)**
for $EASTWEST = 0$					
$CSL\_ENGLISH$	0.02				
	(0.27)				
$CSL\_NO\_ENGLISH$	0.16				
	(0.17)				
CSL_GERMAN		-0.37			
		(0.42)			
CSL_NO_GERMAN		0.36			
		(0.16)**			
CSL_FRENCH			0.31		
			(0.29)		
CSL_NO_FRENCH			0.26		
			(0.18)		
$CSL\_RUSSIAN$				0.96	
				(0.66)	
$CSL\_NO\_RUSSIAN$				0.26	
				(0.18)	
CSL_MAIN					0.05
					(0.21)
CSL_NO_MAIN					0.21
					(0.19)
$LP0$	0.40	0.44	0.43	0.39	0.35
	(0.18)**	(0.19)**	(0.18)**	(0.17)**	(0.17)**
Observations	1,326	1,326	1,326	1,326	1,326
Imputed R^2	0.929	0.932	0.929	0.929	0.931

Results for importer and exporter fixed effects, as well as for control variables, are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table F.5: Effect of language on trade in the late 1990s, separate main languages

Dependent variable: $\exp(\hat{\delta}_{ij})$	(1)		(2)		(3)		(4)	
CSL if $EASTWEST = 1$	2.89	(0.74)***	1.66	(0.77)**	3.38	(0.69)***	2.24	(0.71)***
CSL if $EASTWEST = 0$	0.46	(0.31)	0.18	(0.32)	0.67	(0.25)***	0.42	(0.25)*
$EASTWEST$	-0.24	(0.11)**	-0.14	(0.11)	-0.19	(0.10)*	-0.10	(0.11)
$LP0$	0.52	(0.18)***	0.56	(0.18)***	0.28	(0.18)	0.34	(0.19)*
$LNDIST[0, 625]$	-0.83	(0.11)***	-0.76	(0.10)***	-0.83	(0.10)***	-0.77	(0.10)***
$LNDIST]625, 1250]$	-0.86	(0.10)***	-0.78	(0.09)***	-0.84	(0.09)***	-0.77	(0.09)***
$LNDIST]1250, 2500]$	-0.89	(0.09)***	-0.81	(0.09)***	-0.87	(0.08)***	-0.80	(0.08)***
$LNDIST]2500, 5000]$	-0.90	(0.09)***	-0.81	(0.09)***	-0.89	(0.08)***	-0.81	(0.08)***
$LNDIST]5000, 10000]$	-0.97	(0.09)***	-0.86	(0.09)***	-0.95	(0.09)***	-0.85	(0.09)***
$CONTIG$	0.00	(0.08)	-0.02	(0.08)	0.03	(0.08)	0.00	(0.07)
$GATT/WTO$	-0.53	(0.36)	-0.34	(0.35)	0.43	(0.32)	0.57	(0.32)*
RTA	0.26	(0.10)***	0.24	(0.10)**	0.35	(0.10)***	0.33	(0.10)***
EU	0.29	(0.16)*	0.28	(0.15)*	0.40	(0.15)***	0.38	(0.15)**
$COMLEG$	0.24	(0.08)***	0.18	(0.07)**	0.28	(0.07)***	0.22	(0.07)***
$COLPOST45$	1.44	(0.32)***	0.97	(0.31)***				
$SIBPOST45$	1.68	(0.34)***	1.20	(0.34)***				
$RELIG$	0.35	(0.12)***	0.20	(0.13)	0.29	(0.12)**	0.15	(0.13)
$EMPIREBEFORE45$	0.12	(0.06)*	0.05	(0.07)				
$LNMIGR$			0.13	(0.02)***			0.11	(0.02)***
$COLPOST45\_OTHER$					1.75	(0.28)***	1.32	(0.28)***
$COLPOST45\_SU$					-0.22	(0.42)	-0.55	(0.43)
$SIBPOST45\_SU$					0.50	(0.39)	0.12	(0.40)
$SIBPOST45\_OTHER$					-0.05	(0.35)	-0.12	(0.35)
$EMPIRE\_AUSTRIA$					0.50	(0.12)***	0.40	(0.12)***
$EMPIRE\_RUSSIA$					0.36	(0.14)**	0.26	(0.14)*
$EMPIRE\_TURKEY$					0.34	(0.21)	0.33	(0.21)
$EMPIRE\_OTHER$					-0.13	(0.09)	-0.17	(0.10)*
Observations	929		929		929		929	
Imputed R^2	0.928		0.929		0.940		0.939	

Dependent variable: $\exp(\hat{\delta}_{ij})$	(1)		(2)		(3)		(4)	
for $EASTWEST = 1$								
$CSL\_ENGLISH$	1.02	(1.48)	-1.16	(1.53)	2.28	(1.46)	0.36	(1.53)
CSL_GERMAN	1.71	(0.76)**	1.60	(0.80)**	1.42	(0.74)*	1.29	(0.79)
CSL_FRENCH	2.64	(1.39)*	2.44	(1.36)*	2.76	(1.31)**	2.57	(1.27)**
$CSL\_RUSSIAN$	-2.65	(4.22)	-7.21	(3.94)*	0.60	(4.63)	-3.29	(4.45)
CSL_OTHER	8.43	(1.76)***	6.00	(1.99)***	8.16	(1.81)***	6.19	(2.04)***
for $EASTWEST = 0$								
$CSL\_ENGLISH$	-0.05	(0.32)	-0.33	(0.33)	0.16	(0.30)	-0.10	(0.32)
CSL_GERMAN	-0.27	(0.46)	-0.26	(0.48)	-0.21	(0.39)	-0.22	(0.42)
CSL_FRENCH	0.55	(0.29)*	0.50	(0.31)*	0.39	(0.28)	0.38	(0.29)
$CSL\_RUSSIAN$	-0.84	(0.42)**	-1.15	(0.41)***	1.20	(0.65)*	0.81	(0.66)
CSL_OTHER	0.56	(0.34)*	0.28	(0.32)	0.62	(0.30)**	0.38	(0.30)
Migration	no		yes		no		yes	
Separate empires	no		no		yes		yes	
Observations	929		929		929		929	
Imputed R^2	0.937		0.937		0.945		0.945	

Results for importer and exporter fixed effects, as well as for control variables in the lower panel, are excluded for brevity. Robust standard errors, clustered by country pair, are in parentheses.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table F.6: Effect of language on trade in the late 1990s, without West Balkans and North America