Three Essays on the Political Economics of Cultural Diversity

by

Melissa E. Tornari

supervised by Prof. Giovanni Mastrobuoni

Vilfredo Pareto PhD Candidate in Economics

Collegio Carlo Alberto - University of Turin

UNIVERSITÀ DEGLI STUDI DI TORINO

Contents

List of Figures

List of Tables

Chapter 1

Introduction

In the shadow of a new era of mass migration across Europe, reshaping of modern societies' composition led academics, commentators and policy-makers to increasingly debate the consequences of cultural change. Culture - the amalgam of customs, values, beliefs, social organization, etc. - has important implications for a number of political outcomes, such as the success of mediation and the likelihood of war (e.g., Carnevale and Choi, 2000; Bakaki et al., 2016; Bove and Gokmen, 2016).

In this context understanding the kaleidoscopic character of cultural *diversity* and the very directions of its economic implications turns to be of pivotal importance. In particular, a clearer assessment of the extent and the modalities through which the degree of diversity affects socio-economic outcomes plays a major role when it comes to policy related evaluations.

Throughout this thesis we aim to provide novel findings and useful insights for a better understanding of the socio-economic challenges that increasingly diverse societies face. To do so we focus on three economic dimensions on which diversity plays a role: redistributive policies, economic prosperity and bilateral trade.

In Chapter 2 we investigative the impact of birthplace diversity measures on transfers and subsidies. Permanently moving to another country offers valuable opportunities and gains for both migrants and their host societies (see, e.g., Dustmann and Frattini, 2014; Hainmueller et al., 2017), but states can also experience a number of difficulties when trying to integrate large numbers of migrants. Although economic gains are widely accepted, how immigrants and their descendants affect government budgets is a contentious issue. This is a crucial issue as economic hostility toward immigration is driven by concern about their effects on public finances as much as - and probably more than - by the effects on labour market outcomes (Preston, 2014, p.569). There are a number of transmission mechanisms going from immigration inflows to government spending and in Chapter 2 we focus on migration-driven diversity, the degree of birthplace heterogeneity that is caused by immigration. Country-level analyses have made a good deal of progress in exploring how cultural diversity can reduce the willingness to redistribute income and provide public goods; yet, cross-country studies have typically failed to find significant relations between diversity and transfers (e.g., Alesina et al. 2003). Furthermore, previous studies use time-invariant indices based on language and ethnicity (see e.g., Desmet et al., 2009), which do not acknowledge how societal composition has changed following mass migrations. Against this background, first we use a comprehensive dyadic dataset on international migration between 1960 and 2013 for over 230 destination countries and compute indices of birthplace fractionalization and polarization. Second, we explore whether changes in migration-fueled diversity have an effect on the amount of transfers and subsidies, perhaps the most contentious form of public good. As individuals might sort themselves among governments based on local governments' welfare generosity, we use an instrumental variable approach. Following previous studies by e.g., Frankel and Romer (1999), we run a battery of gravity models to predict bilateral migration flows out of a set of exogenous dyadic variables that predate government spending such as geographic and genetic distance. We use these predicted values of bilateral immigration to construct gravity-based predicted indices of fractionalization and polarization and use them as instruments for the growth rates of diversity. Our results suggest that birthplace diversity reduces government redistribution. The coefficient of polarization retains a similar magnitude but decreases in significance. Results are robust across baseline specifications and fairly confirmed by the novel instrumental variable strategy we exploited. These evidences stand in contrast to a number of previous studies on this topic, which have suggested that i) diversity does not actually have any effect on redistribution unless we control for distances between subgroups and that ii) fractionalization and polarization have opposite impact on development indicators. Moreover, we replicate Alesina et al. (2003) and Desmet et al. (2009) analysis with our data, obtaining opposite findings: all coefficients are positive and highly significant across specifications. Measurement errors due to both cross-sectional analysis and time invariant proxies of diversity could explain previous results. In particular, results suggest how it is the time dimension that allows birthplace diversity to capture the degree of social mistrust at play - that time-invariant measures of ethnicity and language fail to depict. We conclude Chapter 2 by investigating the role played by trust in affecting the impact of birthplace diversity on redistribution. Hence we hope that Chapter 2 can shed new light on the economic implications of mass population movements, crucially adding to our understanding of the consequences of immigration for the receiving country's fiscal position.

Chapter 3 focuses on the multifaceted impact of alternative proxies for diversity on economic prosperity. Notwithstanding an extensive literature on this nexus, this Chapter may turn to be useful for future research in two ways. On one hand, this Chapter provides the first throughly comparative investigation of the potential effects of diversity on economic prosperity. By exploring each proxy of cultural diversity used in previous literature, we are able to both obtain a novel overall measure of cultural diversity and to disentangle each diversity component independently. In doing so, we also achieve analytical and methodological refinements, avoiding most common measurement errors and endogeneity related biases. We outline a substantial variability in magnitude, significance and sign of the impact of alternative proxies of diversity on long-run growth. We expected these findings as we expect the effect of cultural, ethnic and linguistic diversity to vary over-time (in magnitude and, possibly, in direction). This being proof, previous findings providing average effects may be sensitive to models' specification. On the other hand, we refer to the sensitive issues of the endogenous determination of culture and the arbitrary definition of cultural diversity by providing a synthetic measure of diversity. We obtain preliminary evidences of the impact of our new measure of diversity on economic prosperity at cross-country level for the period 1975-2015, partially overcoming the arbitrary cultural group definition. Remarkably, we are able to isolate the impact that each diversity measure has exerted on economic prosperity. By doing so Chapter 3 provides first evidences on how the speed at which a society became more heterogeneous along alternative cultural dimensions affects the magnitude of the impact of diversity on economic prosperity. At the same time, it attempts to address some drawbacks that prevent the economic literature on cultural diversity from providing convincing analytical tools. Additionally, we explore two main transmission channels through which diversity impacts long-run economic growth. First, following Barro (1991) and Alesina et al. (2016) we investigate the intermediate effect of investments and total factor productivity. Second, we explore whether social cohesion or attitudes towards other individuals can constitute a transmission channel for the impact of diversity on economic growth. In absence of available data on people's sentiments towards diversity, we look at public attitudes towards people outside Europe and trust into social interactions. To do so, we exploit a rich dataset newly assembled by the author. We use the integrated data files of all eight rounds of the ESS covering 2002-2016 (including ESS round 8, edition 2.0) with the usual country-year as unit of analysis. With these specifications, our sample includes 31 European countries. The obtained evidences allow for more nuanced explanations of the impact of diversity on economic prosperity and corroborate Putnam (2007).

In Chapter 4 we assess the influence of cultural distance, vis-a-vis geographic distance, on bilateral trade with a focus on genetic distance. We first introduce genetic distance as the marker of cultural similarity with the largest effect on trade. We find that the impact of genetic distance on trade is always at least as large as that of geographic distance. We also construct a synthetic measure of *cultural distance*, and show that, in the 2000s, the effect of cultural distance on trade is twice as large as that of geographic distance. Therefore, we make a case for the inclusion of cultural distance into the gravity models as a standard determinant, just like geographic distance. We also implement a novel imputational technique for 'zero valued' trade flows, by tackling the issue of 'true zero' in bilateral trade dataset. Finally, we explore the intermediate effect that "anti-immigrants" attitudes exert on trust, determinant of bilateral trade. Our theoretical argument focuses on how attitudes towards foreigners, and therefore towards cultural difference, is associated with trust. Also in this case, we exploit a dataset newly assembled by the author that substantially differs from the one used in Chapter 3 by aggregation level, time window and selected variables. We have used individual-level data from all seven rounds (2002-2014) of the European Social Survey (ESS) and created from these repeated cross-sectional survey data a panel dataset with the units of observation being sub-national regions (rather than individuals). Interesting evidences emerge and corroborate the intuition that whether trust affects trade - as pointed out by Guiso et al. (2006) - a more diverse socio-economic context may hinder trust by triggering negative attitudes towards immigrants, at least in the short-run to medium-run. We think this is a timely and important topic, in particular in light of the profound changes in the racial and ethnic makeup of modern societies in the last few decades and of most recent protectionist treats in terms of international trade.

In the last Chapter of this thesis we briefly provide conclusive remarks. In the appendix to this Chapter the construction of the indices of fractionalization and polarization is outlined[1]. Chapter 2, Chapter 3 and Chapter 4 include discussions over the definition of cultural diversity and provide relevant literature.

[1] We build our own indices in Chapter 2 whereas we use measures taken from previous literature in Chapter 3 and Chapter 4. However the interested reader may want to recall the mathematical form of the mostly used measures throughout this study.

Chapter 2

Which Diversity divides? The impact of Birth-place Diversity on Redistributive Policies. First evidences.

2.1 Introduction

In recent years studies on income, inequalities and public transfers have featured prominently in the economic literature, and some of them such as Piketty (2014) and Stiglitz (2012) have attracted considerable attention. The welfare state plays a key role in tackling inequality, and the strains it has been facing since the global financial crisis pose questions about its sustainability. Indeed, economic forces shape states' capacity to protect and promote the social and economic well-being of their citizens. Yet, among the factors affecting the provision of public goods to the most disadvantaged sectors of a society - altruistic attitudes, feelings of alienation or discrimination (Fehr and Gachter (2000), Croson (2007), Chaudhuri (2011), Rege and Telle (2004)) - cultural homogeneity seems to be a key factor (Desmet et al., 2009). There is ample empirical evidence that cultural diversity, or the variety of cultural, linguistic or ethnic groups within a society, decreases redistribution across groups (inter alia (La Porta et al., 1999), (Alesina et al., 2003)). In theory, diversity can be measured on different dimensions, e.g. by ethnicity, language, religion, place of birth, nationality. It is important to note that these alternative proxies embed different markers of identity, thus may well bring different results. Understanding which feature of diversity divides societies and, more specifically, hinders redistribution, is crucial for economic development and peaceful coexistence in the globalization era. Diversity plays a major role in restraining social capital development, inhibiting individuals' altruistic attitudes across cultural groups and eventually discouraging social trust (Alesina and Ferrara, 2000). Accordingly, several scholars have pointed out how diversity yields coordination problems, which in turn inhibit societal engagement (Letki (2008), Iyer and Do (2007), Banerjee et al. (2005), Alesina and La Ferrara (2000)). This would not only favour suboptimal public goods provision, but may feed irreconcilable social divisions (Esteban and Ray (2011), Reynal-Querol (2002)). As a result, identifying which forms of heterogeneity divide societies is key to implement targeted integration policies. In turn then, how governments manage diversity may promote peace, elicit cooperation and social trust (Smaldino (2015), Santos et al. (2008)).

This Chapter aims to compare the performance of alternative indices of diversity for two main reasons. First, as there cannot be an agreement over the definition of cultural diversity, an agreement cannot be reached on its measurement as well. This implies an increasing number of incomparable evidences over its impact on economic outcomes. To cope with this inevitable multiplicity of diversity concepts and measures, we offer a comprehensive analysis comparing most used proxies with the one we newly introduce in this study. Second, and most importantly, different forms of cultural heterogeneity lead to different - even diverging - outcomes. We specifically look for robust evidences over which form of diversity exerts a negative impact on social transfers.

After providing new evidence on the effects of birthplace diversity on public spending decisions, in particular redistribution policies, we strive to offer a new perspective on the diversity-redistribution nexus. Past work on immigration and the size of public spending has emphasized changes in preferences for labor tax and social capital as the main consequence of increased heterogeneity. We thus explore these two main transmission mechanisms.

We proceed as follows. Section 2.2 discuss and presents the measure of birthplace diversity. In Section 2.3 we overview the most recent literature on diversity, trust and redistribution. Section 2.4 describes the data and defines the variables of interest. Section 2.5 discusses the empirical strategy, including baseline specification and Instrumental Variable strategy. Section 2.6 presents our empirical results. Section 2.7 explores the transmission mechanisms and Section 2.8 provides concluding remarks.

2.2 Birthplace *Diversity*

Even though communities can become more heterogenous regardless of immigration, migration represents a primary source of cultural diversity and generally increases diversity of a recipient society (Collier, 2013). At the same time, whereas it is important to note that migration and ethnicity are different issues, migration processes constitute the primary source of ethnic diversity (Pullock, 2007) and contribute to the melting pot in both origin and destination countries. Whereas every proxy of diversity embeds different dimensions of cultural identity, it could be argued that a trait of diversity that matters particularly for inter-personal trust, social cohesion and welfare redistribution, may well be birthplace. Consistently with anthropological studies on migration, the country of origin represents the leading cultural trait for first generation migrants, while ethnic, linguistic and religious characteristics coalesce together with less observable differences in one's customs, beliefs and preferences (Castles and Miller, 2009, p. 58-59). For this reason, it might be the case for migration to be "the most reliable source of cultural heterogeneity", as observed by the leading political scientist scholar Horowitz (1985, p.451)

We propose a diversity index based on birthplace diversity. More precisely in this Chapter we explore how varying forms of diversity affect the amount of transfers and subsidies, with a focus on migration. Additionally, to date, many contributions use case-studies approach, limiting the external validity of the existent literature. This Chapter primarily contributes to the debate by providing the first panel-data analysis at cross-country level. Most importantly, by including migrants' birthplace in the analysis we explicitly introduce time-variation in the core diversity measure adopted. This is a key advancement with respect to previous contributions. In fact a crucial weakness of the empirical findings so far emerged on the impact of cultural heterogeneity on public goods provision, is that these have considered time-invariant proxies for diversity. This may have a number of unfortunate consequences. To see this clearly it is worthy to recall that cultural diversity is commonly defined as "the cultural variety and cultural differences that exist in a society". Hence diversity is not only a multidimensional concept, as defined along a multiplicity of dimensions, such as language, ethnicity and religion. But as these definitions suggest, diversity is a dynamic concept. The degree of cultural, linguistic or ethnic variety within a society inevitably changes over time, as it becomes more or less diverse along those dimensions. Therefore, time-invariant measures of diversity may fail ex-ante in capturing the actual degree of heterogeneity in destination countries. It is also worth noticing that the systematic exclusion of a time dimension across the proxy for diversity may question some findings at econometric level, especially when considering that the empirical investigation of these phenomena has seen equations with highly volatile dependant variables on the left-hand side and time-invariant diversity on the right-hand side. Introducing a time-varying measure of diversity (i.e. yearly index of birthplace diversity) explicitly addresses this ex-ante limitation. As a consequence measurement errors due to time-invariant explanatory variables do not undermine results' robustness and reliability. In the same fashion, it should be stressed that our variable of interest, redistribution, is slow-moving. In fact, the change in transfers and subsidies at country level is not expected to jump even when data are not yearly interpolated (i.e. with a ten year time window). This turns to be important for the overall robustness of our findings as we aim to compare previously adopted time-invariant measures of ethnic and linguistic diversity with the birth-place diversity index. Hence also the performance of the ethnic and ethnolinguistic indices should not suffer of measurement error biases, thanks to the the slow moving nature of the outcome variable. In the same vein, we also investigate the impact exerted on redistribution - if any -, by time-varying measures of religious diversity. Religion has always played a central role in social and economic issues. Maoz and Henderson (2013) recalls how, even in recent times, and across societies, the prevalence of religious adherence is still substantial. More importantly, religious affiliations have changed in the last few decades, and this has profoundly affected the degree of cohesion within societies.

The unprecedented population movements that still features the so called 'globalization era' have affected the population composition of countries worldwide. Figure 2.1 provides an intuitive representation of increasing migration inflows at cross-country level. The relevance and the extent of the socio - demographic transformation elicited by migration inflows have attracted the interest of a number of scholars and the debate over its characteristics and consequences features prominently in social sciences literature. This worldwide phenomenon ended up in making the bulk of nowadays societies substantially more *diverse* than ever before. This is the case not only in terms of one's birthplace, but along a number of dimensions such as ethnicity, language and religious beliefs. As a consequence, throughout the past decade the social and political implications of social *diversity* (or 'cultural *diversity*') have received widespread attention (e.g., **?**). Economists in particular have explored the impact of cultural diversity on GDP growth, investment, the quality of government and provision of public goods . A discussion of this litera-

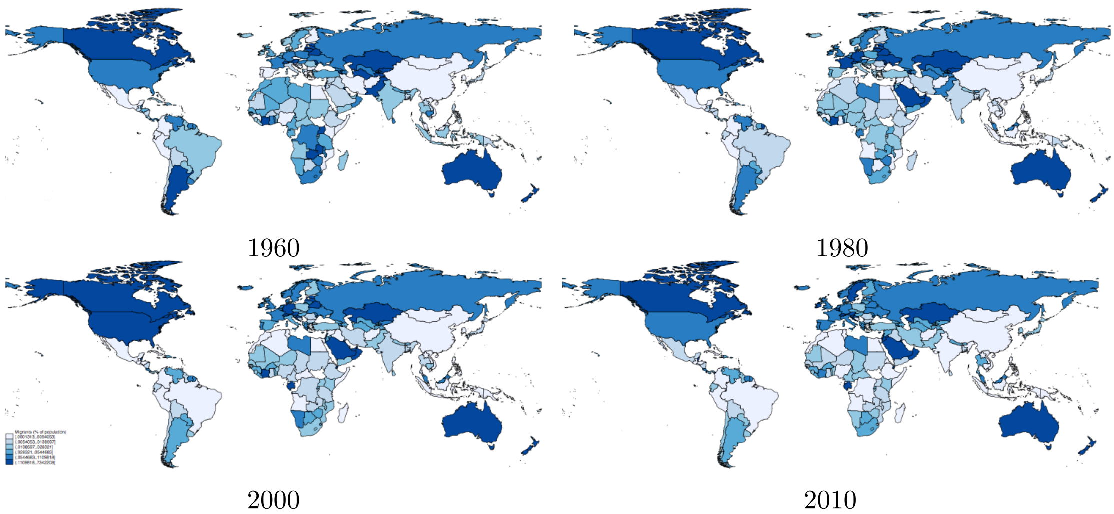


Figure 2.1: World maps of Migration inflows, 1960-2010

Here migrants are defined as people born in a different country from where their live. Author's computation using World Bank data by destination country.

ture is provided by Alesina et al. (2016). As the authors suggest, while the micro evidence clearly points toward a trade-off between costs and benefits of diversity, the macro literature (at least for ethnic diversity) “seems to only uncover costs" (p.6 Alesina et al., 2016).

2.2.1 *Diversity* indices

We borrow from previous studies on diversity two commonly used measures, the fractionalization and polarization indices. These are modified forms of the Herfindal Index and have been used to capture two different dimensions of cultural diversity, being this represented by ethnicity, religion, language or a combination of these. We provide a formal definition of these indices in Appendix A.1. The fractionalization index is meant to return the cultural variety. It measures the probability that two randomly selected individuals in a given area belong to the same group of interest. The polarization index is instead measuring how far the distribution of the cultural groups is from a bipolar distribution. Hence polarization decreases whenever the number of groups is greater than two, whereas having multiple small groups increase fractionalization. In doing so the polarization index is meant to capture a degree of potential cultural conflict citep[see][]reynal2002ethnicity. As a consequence fractionalization and polarization indices, although collinear around low values, describe different shades of population heterogeneity.

The reader should bear this in mind in the review of the reference literature below. Figure 2.2 presents world maps of cultural heterogeneity in the form of (a) Ethnic, (b) Linguistic, (c) Religious and (d) Ethnolinguistic fractionalization as used across previous studies. The measure of diversity that we introduce in the analysis of redistributive outcomes, i.e., birthplace diversity, builds directly on the one used by Ottaviano and Peri (2006) and Alesina et al. (2016). In what follows we explicitly refer to contributions related to impact of diversity on redistributive outcomes and underlying channels.

2.3 Reference literature

One of the most important channels through which population diversity can affect economic redistribution in the host country is social trust. But which are the determinants of social trust itself?[1] A recent strand of studies is pointing at the detrimental effect that population heterogeneity exerts on social trust. Accordingly, the degree of *diversity* or *cultural diversity* of a given society along dimensions such as ethnicity, language and religion negatively affects the level of trust among individuals. This in turns exerts a negative effect on social cohesion and social capital and may weaken welfare redistribution. A few contributions have explored the underlying indirect effect. Yet to our knowledge only Desmet et al. (2009) have addressed the detrimental role of diversity on redistributive outcomes. More precisely the authors point at the negative effect of linguistic diversity on income redistribution by exploiting a cross-section of country-level data. We move from this contribution not only considering alternative measures of diversity but also

[1] For a discussion see: Alesina and Ferrara (2000).

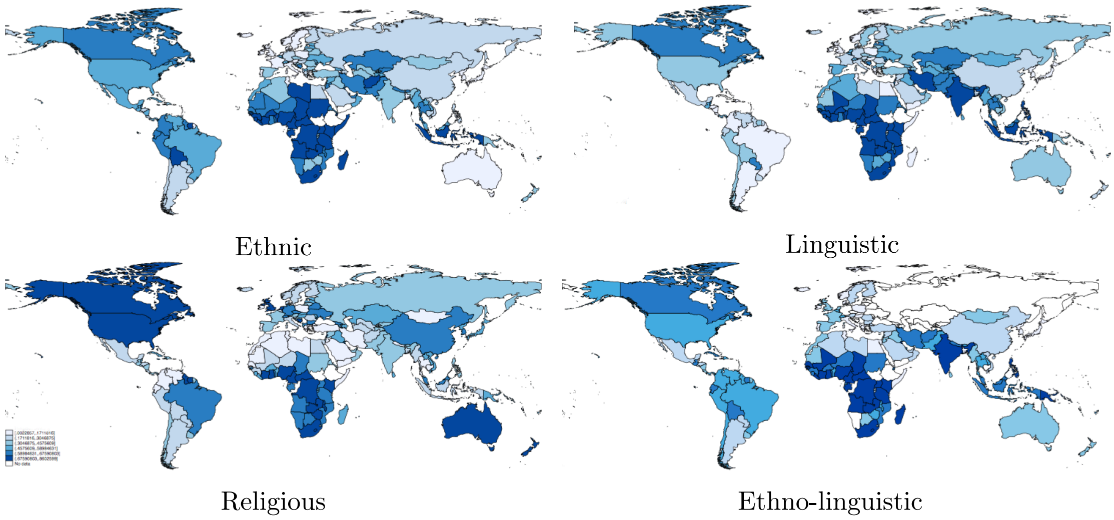


Figure 2.2: World maps of kinds of *Diversity*

Author's computation of Diversity proxies (fractionalization indices) used in previous contributions: (a) Reynal-Querol (2002), (b) citetdesmet2009linguistic, (c) Maoz and Henderson (2013), (d) Alesina et al. (2003). Measures (a) to (c) are time-invariant, (d) is an average over the period 1945-2010.

introducing time variation through the use of birthplace diversity. An overview of previous studies presented in this Section, including indices for diversity can be found in Table 2.1. To date the paper by Desmet et al. (2009), constitutes the only contribution on the impact of cultural diversity on redistributive outcomes. Alesina et al. (1997), Miguel and Gugerty (2005), Habyarimana et al. (2007), Baldwin and Huber (2010) and Gisselquist et al. (2016) have been looking at the impact that different forms of cultural diversity have on the provision of public goods. It is useful to briefly recall the core distinction between the concepts of redistribution in the form of income transfers and subsidies, as considered in this Chapter, vis-a-vis public goods. Remarkably, subsidies and transfers involve targeted welfare policies whereas public goods concern everyone in the society. In fact, as opposed to welfare transfer policies, a public goods is simply defined as a good consumed by everyone and from which no one can be excluded (e.g. roads, public education, national defence, street lights). As a consequence the effect that social trust exerts on public goods and on targeted redistributive policies may well diverge. If anything, also cultural diversity could exhibit a different impact on the provision of public goods and on welfare policies *tout court*, both in sign and magnitude. Although this distinction matters, its extent is usually mitigated in practice. In fact, the impoverished social groups targeted by subsidies and transfers tend to be primary recipients of the public goods provided (see Desmet et al., 2012). Not surprisingly, Desmet 's (2009) work leads to results generally supported across the literature focusing on the implications of diversity for the provision of public goods.

The economic literature generally supports the view that identifies social trust as leading determinant for public goods provision. The starting point of this empirical strand of studies is the seminal work by Alesina et al. (1997). The paper documents how public goods supplied in US cities inversely relate to the level of ethnic diversity, in a cross-section of US counties in 1994. The authors find that the share of public spending devoted to public goods is particularly low in two cases. The first arises in presence of two major ethnic groups of comparable size, i.e. when the residential community features a high degree of ethnic polarization. The second context featuring a particularly low investment in public goods materializes where politicians have ethnic constituencies. Ethnic-based interest groups are likely to value public goods that benefit their group, compared to the benefits of others. This may occur because different ethnic groups hold different preferences in regard to their tax contribution to the availability of a public goods. Additionally, an ethnic group has lower utility from a public goods if other ethnic groups also utilise it. Hence, political actors may choose to divert more public resources to private patronage toward a specific ethnic group.

Miguel and Gugerty (2005) provide the first empirical study on this topic looking at a Sub-Saharan Africa case, namely rural western Kenya. The authors develop a case study focusing on the interplay of ethnic heterogeneity with social sanctions in sustaining local public goods provision in the form of primary schools. Across rural Sub-Saharan Africa, primary education institutions generally rely on local voluntary fundraising as main source of funding, which is likely to be strongly incentivised by social sanctions within each community. The identification strategy exploits this social mechanism to reveal whether it results in higher funding in more homogenous rural communities compared with those more ethnically fractionalised. The key finding of this contribution is that ethnic diversity is associated with sharply lower primary school funding through voluntary fundraising events and to lower quality school infrastructure. Pupils questionnaires records indicate that ethnically diverse schools use fewer community social sanctions than in more homogenous areas, providing support for the claim that free-riding may be more prevalent in diverse communities because of the inability to create effective community sanctions. This contribution constitutes also a first empirical exploration of how diversity may both reduce trust across groups and increase within-group trust. Diversity ultimately undermines trust across the whole population.

The work by Habyarimana et al. (2007) looks instead at the empirical relationship between ethnic heterogeneity and underprovision of public goods as the social outcome of a game-theoretic model of social interaction. The empirical study involves 300 randomly selected subjects in Kawempe, the poorest region in Kampala, Uganda, an area characterised by high level of ethnic diversity and low levels of public goods provision. The evidences the authors supply suggest that successful public goods provision in homogenous ethnic communities can be attributed to a strategy selection mechanism, in which co-ethnics players behave cooperatively. In particular, the threat of social sanction fosters cooperation, as it works more effectively on co-ethnics because they tend to be more closely linked on social network. As a consequence Habyarimana et al. (2007) suggest that individuals' reputation influences opportunities for cooperation, ultimately favouring higher levels of public goods provision.

Baldwin and Huber (2010) add to the debate the role played by economic inequality in affecting the supply of public goods in the context of ethnolinguistic diversity. In particular Baldwin and Huber aim to identify the varying effects of three diversity indices/dimensions: ethnolinguistic fractionalization (ELF), cultural fractionalization (GF) and between group inequality (BGI). The authors take advantage of a number of different sources in order to compare the extent of the effect as captured by each index, considering a cross-section of 46 countries (democracies only)[2]. Their OLS model identifies a strong negative relation between differences in inequality across groups (BGI index) and the level of public goods provision. Interestingly, the overall level of inequality itself shows no impact. Their results are robust and the extent of the BGI effect is greater in developing democracies. However ELF and GF indices neither have similar strength nor perform significantly. As overviewed so far in this Section, the negative impact that ethnic diversity has on the provision of public goods is widely accepted by economic scholars. Moreover, the underlying evidences add to a larger wave of contributions, highlighting negative effects played by varying forms of diversity on social, economic as well as political outcomes. All these findings together support the so called 'diversity debit hypothesis', which was developed by Easterly and Levine in 1997 to describe the negative impact of ethnic diversity on social, economic, and political outcomes.

Yet, positive effects that diversity exerts on political economic dimensions may be pointed out. For example, the demand for public services may well be greater due to inter-group competition in labour market and education system (Bates, 1974). Considering ethnic diversity, modernization and development may have weakened traditional ethnic affiliations, thus buffering the implications of ethnic divisions. Moreover, political institutions can incentivise politicians to work across ethnic lines (Gibson and Hoffman, 2013). In sum, there might be room for positive association between diversity and key welfare outcomes.

[2] The vast majority of research on regime type and public goods allocation supports the idea that public goods are better provided under democratic regimes (see **?**). While there are differences between explanations for higher levels of public goods provision under democratic regimes, most explanations highlight the incentives that government officials have to promote good/bad public policy.

Consistently with these positive diversity drivers, Gisselquist et al. (2016) display empirically that ethnic fractionalization is not associated with the under provision of public goods and, in some cases, has a positive relationship with some key outcomes. The authors identify a lack of distinction made between analyses at national versus sub-national level across previous contributions. They compile a disaggregated dataset on a number of budgetary and welfare outcomes in Zambia, at district level. In doing so they draw from a few sources, including administrative, broader budget and survey data[3]. According to the study, ethnic diversity does not necessarily undermine public goods provision when diversity is not equivalent to division. They argue that division, rather than diversity *per se*, is what drives the diversity debit hypothesis. Where ethnic identity is comparatively stronger than national identity, we can clearly see remarkable inequalities in public goods provisions. In sharp contrast with the majority of studies, Gisselquist et al. (2016) provide strong evidence for the existence of a diversity dividend.

Overall most of contributions supports a detrimental role of diversity on public goods provisions. Table 2.1 summarises the state of art of the literature on the impact of *diversity* on redistributive dimensions. However, there are few evidences of opposite signs. Key findings by Desmet et al. (2009) confirm this view in the only study explicitly looking at redistribution as dependant variable. Although the theoretical distinction between redistribution (subsidies and income transfers) and public goods is implicitly considered as negligible in the debate, it may still play a role. This further complicates the possibility of making strong claims on the impact of diversity on welfare outcomes at large. Moreover, all the studies discussed provide cross-sectional evidences only. As discussed in Section 2.3 this may be unfortunate as measurement errors could lead to biased conclusions. The prevalence of case-studies approach also introduces the issue of external validity. Controversial definitions of the concept of diversity further limit cross comparison

[3]Primarily government sources, collected during the fieldwork (2010-2011); Census of Population and Housing (2000 and 2010); Living Conditions Monitoring survey (2006); Annual Government Financial Report (2004-09); Ministry of Health and Ministry of Education (2009-11).

of findings. These may even turn to be questionable due to the econometric implications that the adoption of time-invariant measures may imply. Finally, there are no studies focusing on the range of cultural differences brought by immigrants as a form of diversity. An investigation focusing on redistribution at cross-country level and comparing alternative forms of diversity seems necessary.

Authors	Model	Main Dataset	Diversity Dataset	Effects
Alesina, A., Baqir, R.& Easterly, W. (1997)	Cross Section Pooled OLS	US Census (level: MSA, County, City)	Ethnic Self-Ass.ent, US Census (1990)	FRA(-)
Gissequist, R. M., Leiderer, S., & Nio-Zaraza, M. (2016)	OLS, 2SLS, GMM, SGMM and LIML	Zambia Census, Living Conditions Monitoring Survey, Government Financial Reports	Population & Housing	FRA (+)
Desmet et al. (2009)	Cross Section	Economic Freedom Data Network	Ethnologue, Fifteenth Edition	FRA(-) POL (-)
Baldwin, K., & Huber, J. D. (2010)	Cross Section	Afrobarometer, WVS, Comparative Study of Electoral Systems	Fearon (2003)	Inequality [Betw. group] (-)
Miguel, E., & Gugerty, M. K. (2005)	Cross Section	ICS Africa (SAP), 1996 Pupil Questionnaire data		FRA(-)

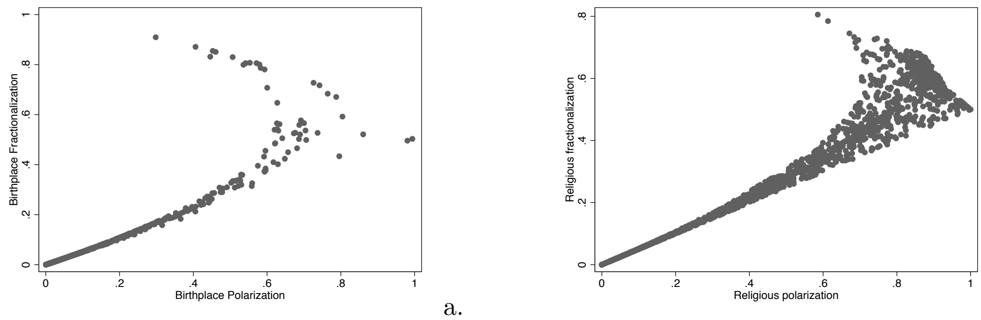
Table 2.1: The impact of *Diversity* on public goods provision and Redistribution. Previous findings.

2.3.1 Constructed measures of *Diversity*

We have briefly discussed how polarization and fractionalization indeces are built in the Appendix of the Introduction to this thesis (A.1). We report below graphical inspections of how the measures we have built to the end of this Chapter correlate. Figure 2.3 presents the scatterplots of birthplace and religious fractionalization versus polarization using respectively World Bank and Maoz et al. (2013) data. For low levels of fractionalization the correlation with polarization is positive, while for intermediate levels of fractionalization, the correlation is zero. For high levels of fractionalization the correlation with polarization becomes negative. Therefore, the correlation is low when there is a high degree of heterogeneity. Generally speaking, if the number of groups is larger than two, the existence of many small groups increases fractionalization but reduced polarization.

2.4 Data

In our study we compute indices of population diversity (i.e., π_i includes the natives) as well as the degree of diversity within the immigrant group only. As pointed out in the Section 2.1, we seek to offer a through out comparison of the performance of diversity indices already used in the literature, including ethnic diversity, ethno-linguistic diversity, linguistic diversity, religious diversity. In doing so, we also introduce to the literature two measures of birthplace diversity. This study covers the time period between 1970 and 2010 and all the data we use are available online. Our dependent variable is measured with yearly data on transfers and subsidies at country level, supplied by the World Bank. A world map of our dependant variable overtime is provided in Figure 2.4. As defined by the World Bank, this data informs on the level of redistribution within a country as share of total spending. Subsidies, grants, and other social benefits include all unrequited, nonrepayable transfers on current account to private and public enterprises; grants to foreign governments, international organizations, and other government units; and social security, social assistance benefits, and employer social benefits in cash and in kind. For most countries, central government finance data has been consolidated into one account, but for others only budgetary central government accounts



a. Birthplace Fractionalization and Polarization b. Religious Fractionalization and Polarization

Figure 2.3: Correlation Plots - Fractionalization and Polarization Indices

Note: Migration figures used to construct our Birthplace Diversity indices are taken from the World Bank bilateral migration matrix, 1970-2013. Religious information are retrieved from Maoz et al. (2013).

are available. Countries reporting budgetary data are noted in the country metadata. Because budgetary accounts may not include all central government units (such as social security funds), they usually provide an incomplete picture. In federal states, the central government accounts provide an incomplete view of total public finance. Data on government revenue and expense is collected by the International Monetary Fund (IMF) through questionnaires to member countries and by the Organization for Economic Co-operation and Development (OECD).

Also data on *migrant stocks* is taken from the World Bank[4]. We define international migrant stocks as the number of people born in a country other than that in which they live. The estimates are derived from over 1,100 national individual census and population register records for more than 230 destination countries and territories over the last five decades (i.e., 1960-2000). This information takes the form of 226-by-226 bilateral matrices of migration stocks for each decade (therefore 5-by-226-by-226 matrices). As each census round was conducted during a 10-year window,[5] we linearly interpolated all missing data between two consecutive rounds, but we also report robustness checks where we used alternative approaches to deal

[4] `http://data.worldbank.org/data-catalog/global-bilateral-migration-database`

[5] According to Özden et al. (2011), most destination countries conducted their censuses at the turn of the decade.

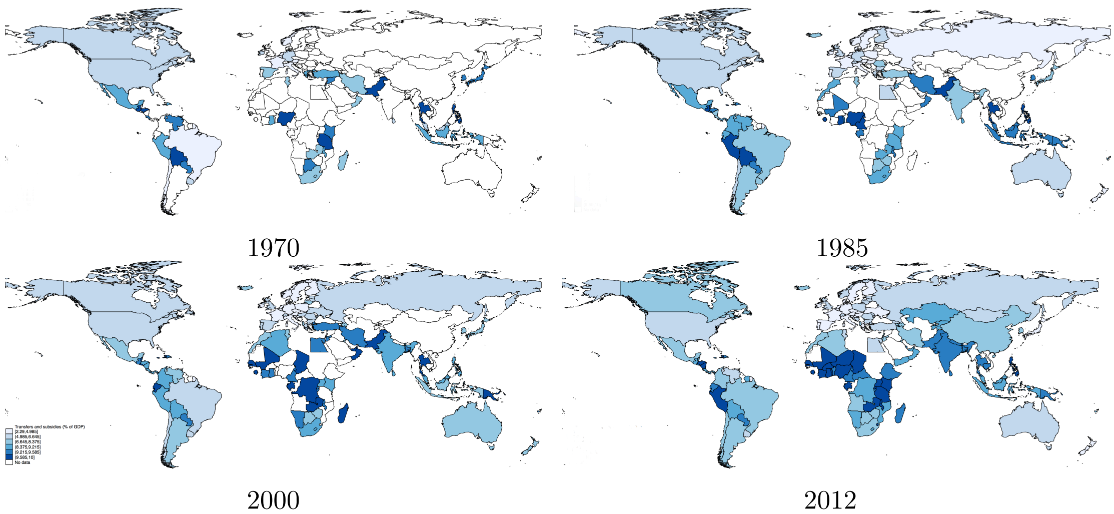


Figure 2.4: World maps of Redistribution density, 1970-2012

Redistribution is measured with yearly data on transfers and subsidies at country level (World Bank) as share of total spending. Transfers and subsidies include: subsidies, grants; all unrequited, nonrepayable transfers on current account to private and public enterprises; grants to foreign governments, international organizations, and other government units; and social security, social assistance benefits, and employer social benefits in cash and in kind.

with these missing data. Moreover, as the time period 1960-2000 was limiting, we added to these data a very recently released extension on migration flows published by the World Bank in collaboration with various other organizations (University of Sussex, UN, etc.). They provide two migration matrixes for the post-2000 decade. We include the most recent matrix in the analysis as it offers the widest coverage of countries. We also use data on the distribution of religious adherents across time and space that have been put together by Maoz and Henderson (2013) and the data are also available online[6]. They provide data at five-year intervals over the period of 1945-2010 on the religious adherents of states coded for 14 major religions: Christianity, Judaism, Islam, Buddhism, Zoroastrian Hinduism, Bahai, Sikh, Shintoism, Taoist, Confucian, Jain, Syncretic and Animism. Here, we also interpolated all missing data between two consecutive rounds. There are few states, like Haiti and Japan, where dual religion is a common practice. In those cases, the percentages of religious groups do not sum up to 100%, and we decided to drop

[6] `http://www.correlatesofwar.org/COW2\%20Data/Religion/Religion.htm`

them. Table 2.2 presents summary statistics.

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Transfers and subsidies	7.7	2.2	0	10	2159
Population	30779038.8	114718340	9004	1344130048	7630
GDP per capita (const. 2000 US$)	8539.1	14663.6	50	158802.5	7630
GDP growth (annual %)	3.9	6.5	-62.1	150	7596
Gross fixed K form. (% of GDP)	22	10.2	-2.4	219.1	6563
Trade (% of GDP)	76.2	48.3	0.3	531.7	7342
Migrants as % of pop	0.1	0.1	0	0.9	6234
Birthplace Fractionalization	0.1	0.2	0	0.9	732
Birthplace Polarization	0.2	0.2	0	1	732
Religious Fractionalization	0.3	0.2	0	0.8	1937
Religious Polarization	0.5	0.3	0	1	1937

Table 2.2: Summary statistics

Mean, Standard Deviation, Minimum & Maximum values and Sample Size are reported for our dependant variable Transfers and subsidies (i.e.redistribution), for our main control variables at country level: Population size, GDP per capita (in constant 2000$), GDP growth (annual %), Gross fixed capital formation (% of GDP) and Migrants as % of national population; for the time-varying indexes of Birthplace and Religious Diversity that we construct.

Before turning to the empirical strategy, we need to briefly address a possible concern: are birthplace and religious indices of diversity capturing the same underlying phenomenon, i.e., the degree of heterogeneity in the ethnic composition of a society? If, e.g., changes in the level of birthplace diversity in Europe are due to migration of Muslims into European states, then using two indices may be redundant. We remand the reader to Figure 2.5, (2.5.a: fractionalization measures and 2.5.b: polarization measures) for a comparison of birthplace diversity measures with their religious counterpart. A visual inspection of the scatterplots reveals that there is virtually no correlation between the two measures of diversity. Possibly, this is because the relative size of any given religious group in a state can reflect changes in religious affiliation of the same subjects. Islam, for example, has captured an increasingly larger share of the world's population over time. Moreover, the proportion of the nonreligious population has increased its size in Europe and Oceania, largely due to the modernization and secularization trends in these regions (Maoz and Henderson, 2013). Finally, inspecting the correlation between different dimensions of diversity we see how our novel measure of birthplace diversity does not seem to be correlated with other known measures of heterogeneity such as the index of ethnic fractionalization of Alesina et al.(2013).

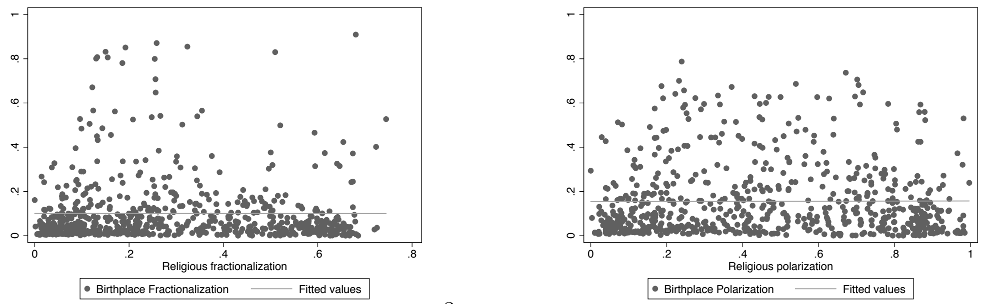
2.5 Empirical Strategy

2.5.1 Baseline Model

Our baseline specification relies on the panel fixed effect model described below. We estimate the following equation:

$$LnY_{it} = \alpha DIV_{it} + \sum_{m} \delta_m \ lnX_{imt} + \lambda_t + \mu_i + \epsilon_{it} \tag{2.1}$$

with $i = 1, . . . , 136$ (countries) and $t = 1, . .. , 40$ (years), as our dataset is from 1970 to 2010. LnY_{it} is the level of transfers and subsidies as % of GDP; DIV_{it} can be either the degree of fractionalization or polarization; X is a vector of explanatory variables and δ is the associated coefficient vector; ϵ_{it} is the error term. Our covariates include the share of migrants (as % of the population); the size of the population; the GDP per capita in constant 2000 US$ as well as its growth rate; the gross fixed capital formation in % of GDP which is meant to capture the level of investments; and trade openness (i.e., imports + exports) as share of the GDP. We also include a full set of year dummies, λ_t, and country fixed effects μ_i. We control for group-wise heteroskedasticity and serial correlation by reporting robust standard errors clustered on countries. The log-log regression specification of the model (both dependent and independent variables are log-transformed), facilitates the interpretation of α, which is that of a percentage change in the growth rate given a percentage change in fractionalization or polarization, holding all else constant. As we acknowledged above, fractionalization and polarization are highly correlated and therefore the interpretation of two highly correlated (and thus multicollinear) variables is ambiguous. In fact, when we try to include both



a. Birthplace and Religious Fractionalization

b. Birthplace and Religious Polarization

Figure 2.5: Correlation Plots - Birthplace and Religious Indices

Note: Migration figures used to construct our Birthplace Diversity indices are taken from the World Bank bilateral migration matrix, 1970-2013. Religious information are retrieved from Maoz et al. (2013).

indices in the regressions, the abnormal size of the coefficient of fractionalization and of its standard error is a clear indicator of the high degree of collinearity, which make us less confident in the validity of the results. This issue is also acknowledged in some of the recent literature on the topic (Ager and Brückner, 2013). In light of this issue, we do not include the models where both indices are included jointly.

2.5.2 IV Approach

Our findings are subject to additional caveats. First, one may be concerned about the bias stemming from the omission of important determinants of redistribution. This concern is only partially mitigated by the inclusion of country fixed effects if these omitted covariates vary over time. Second, a correlation between diversity and transfers can also arise from causality running both ways, although we could reasonably claim that high degrees of diversity should be driven by high levels of transfers, rather than the opposite. Not surprisingly, empirical studies support the intuition that better economic conditions in the destination country are important factors affecting the decision to emigrate. If anything then, the coefficient of diversity should suffer from downward bias. We address the above concerns by means of a novel instrumental variable approach. The Two Stages Least Squares (2SLS) that we develop date back to the contribution by Frankel and Romer (1999).The idea behind this identification strategy is to construct a gravity-based prediction of bilateral migration stocks from origin country i to destination j. This Gravity IV technique originates in the area of International Economics studies that focus on the determinants of trade patterns between countries. Only very recently the economic literature on migration has borrowed this device, for example the work by Docquier et al. (2016) and Alesina et al. (2016). To exploit the Gravity IV strategy, these latter contributions leverage the dyadic nature of a dataset on migration released from the World Bank for the first time in 2013. Previously, data on international migration flows was not available with global coverage and on a consistent basis, preventing the literature on the economics of migration from taking advantage of this IV strategy. To construct the gravity model further data is necessary for both its independent variable, i.e. *migrant stocks*, and the exogenous controls. The explanatory variables of the Gravity model are taken from the 'CEPII Gravity dataset', a "square" gravity dataset for all pairs of countries, allowing the estimation of international migration flows as a function of the time invariant variables: Common Currency, Common Official Language/s, Common Unofficial Language/s, Contiguity, Common Legal System, Geographical Distance, whether part of the same Hegemony and whether both a Colony under the same Empire up to 1945[7]. Country-level information for second stage controls including Population, GDP per capita, GDP growth, Trade, Investments and Share of Migrants are retrieved from a variety of sources. Population and GDP per capita variables are obtained by Gleditsch (2002), as online updated in 2013 to cover the time window 1950-2011[8]. Gleditsch (2002) retains Penn World Tables (PWT) (Heston et al., 2012) populations estimates when available while compiling missing data with a range of alternative sources. GDP growth, Trade, Investments and International migrant stock (% of population) controls are instead taken from

[7] http://www.cepii.fr/CEPII/en

[8] See `http://privatewww.essex.ac.uk/~ksg/exptradegdp.html`

the World Bank (WB) dataset on World Development Indicators (WDI) (World Bank, 2015)[9].

Gravity specification and issues

The gravity model takes the following form:

$$m_{ijt} = \sum_{k} \delta_k \; X_{kij} + f_i + f_j + f_t + \epsilon_{ijt} \tag{2.2}$$

where m_{ijt} is the number of people born in country i but living in j at time t; X is our vector of exogenous dyadic variables i.e., contiguity, colonial relationship, same colonizer, common language, if part of the same country in the past and capital-to-capital distance; f_i, f_j and f_t are country of origin, country of destination and year fixed-effects. The interactions between distance and time dummies improve predictive power and capture changes in transportation costs (Docquier et al., 2016).

As noted by Docquier et al. (2016), one of the issue with this approach is that most of our exogenous predictors of migration, such as the capital-to-capital distance, do not change over time. We therefore use interactions between geographic distance and year dummies to flexibly improve the quality of the first stage. At the same time, interacting year dummies and geographic distance takes into account common shocks in communication and transportation technologies and "[a]s long as changes in technologies are common to all countries, these time series changes will be exogenous with respect to any particular country, but they will have different effects perhaps across country pairs, depending on the relative geographic position" (Docquier et al. 2016, p.212).

There are a number of additional issues that merit consideration. First, seminal studies such as Frankel (1999) use a log-linear OLS model. Yet, migration flows are often zero, and the classical log-gravity model is unsuitable in this case. In fact,

[9] `http://data.worldbank.org/data-catalog/world-development-indicators`

dropping all the observation with no bilateral migration as if they were uniformative induces a sample selection issue. At the same time, using the logarithm of $Y_{ijt} + 1$ as the dependent variable can generate inconsistency in the parameter of interest (Silva, 2006). Second, our dependent variable is highly heteroskedastic: we have small deviation when i and j are small countries, distant and without particular relations, while large values of immigration flows as well as large dispersions around the mean are observed when i and j are big neighbouring economies, perhaps connected by political or historical links. Under heteroskedasticity, estimating log-linearized equation by OLS leads to significant biases. We therefore use the Poisson pseudo maximum likelihood estimator (PPML) developed by Silva (2006), which is robust to different patterns of heteroskedasticity, resilient to measurement error of Y_{ijt} and also deals with the zero values in migration data[10]. Another potential issue is the inclusion of country of destination fixed effects. Ortega et al. (2014), for example, claim that such fixed effects introduce endogeneity by absorbing all country-specific factors that explain bilateral flows. As a robustness check, we drop fixed effects, although this results in a deacrese in the goodness of fit of the model.

2.6 Results

Our baseline empirical results from the panel fixed effect model in equation (3) are reported in Tables 2.3 - 2.6[11]. To begin with, note that the signs of our explanatory variables are consistent with previous studies on the determinants of redistribution (see e.g., Desmet et al., 2009). As one would expect, both the GDP level and its growth rate are positively associated with the level of redistribution, as government transfers increase with a country's level of development. Population

[10]For a discussion of the advantages of the PPML over alternative models see: Silva (2006) and Silva (2011).

[11]We carry out the standard specification test for this sort of exercise, the Haussman test, and test the null hypothesis that the coefficients estimated by the efficient random effects estimator are the same as the ones estimated by the consistent fixed effects estimator. Random effects are rejected against fixed effects by the Haussman test ($Prob > \chi^2 = 0.00$). Therefore, the FE specification seems to be the most appropriate choice.

size is also positively signed and significant, which runs counter to previous studies finding that transfers (as a share of GDP) are unrelated to population size, given that this portion of government expenditure should not have the nature of a public goods (Alesina and Wacziarg (1998) and Desmet et al. (2009)). Investments have a positive association with redistribution, whereas trade openness is insignificant. Note however that our models are very conservative, and the presence of clusters at country level, combined with country and time fixed effects, might result in lack of significance at conventional levels for some of the control variables.

—— Tables 2.3, 2.4 ,2.5 and 2.6 about here ——

Reading across the last three rows of results in Tables 2.3 and 2.4, we find that birthplace diversity, measured by either fractionalization or polarization, is consistently negative and significant. Note that fractionalization and polarization have also similar coefficients.

As concerns our variables of main interest, recall that our model specification allows for direct reading of the coefficients, and the substantive interpretation is similar to an elasticity. Hence, e.g., in models (ii), a 10 % increase in the level of birthplace fractionalization is estimated to decrease redistribution by 7.8%, whereas a 10 % increase in birthplace polarization reduces the level of transfers by 5.8%. Therefore in columns (iv) and (v) we add the number of migrants as an additional control variable and our results hold up well to this inclusion. This means that, conditional on a given share of immigrants within the population, more diversity decreases government transfers. In fact the size of fractionalization is now larger than in the previous specification and a 10 % increase in its level is associated to a 2.3% reduction in redistribution. The coefficient of polarization retains a similar magnitude but decreases in significance.

These results stand in contrast to a number of previous studies on this topic, which have suggested that i) diversity does not actually have any effect on redistribution unless we control for distances between subgroups (e.g., Desmet et al.,

2009) and that ii) fractionalization and polarization have an opposite impact development indicators (see Section 2.3).

In Tables 2.3 and 2.4 - column (iii), we find that religious diversity has no effects on the level of redistribution. This is somewhat surprising. Among social scientists the awareness of how religion is a determinant of socio-economic outcomes dates back to *The Protestant Ethic* by Weber (1905 [1930]), whose analysis has outspoken religiosity as an independent variable influencing economic outcomes. Accordingly, among other things, religious beliefs affect the economy by fostering traits such as honesty (and hence trust), charity, hospitality to strangers, thrift and work ethic. Recent data confirm that the importance of religion in one's life did not fade away during the last century and still features across nowadays societies. In the 2006 wave of the World Values Survey (WVS), over 71% of the respondents reported that religion is either very or rather important in their life, and more than half of them ranked the importance of God in their life at the maximum allowed score in that question. WVS data also report how the relative shares of adherents across religions and beliefs have notably changed over the last three decades. Hence it might well be that due to the changing character of religion adherence, that may change over one's lifetime, our religious diversity measures fail to capture the actual degree of religious fractionalization and polarization at country level. In the same fashion, some issues may concern the data provided by Maoz and Henderson (2013) as calculating convert numbers is tricky. As instance the census in UK does not ask people about their past religions. In America calculating conversion rates is even harder as the census does not ask about religion. Moreover some new believers keep their conversions secret, worried about the reactions of friends and family, left alone that common misreporting problems could have more room to play a role as devotion is not a visible character. If anything then, the results in Tables 2.3 and 2.4, column (iii) do not mirror the expected extent at which observed changes in beliefs across national populations might have affected social trust and redistributive policies. Our results for religious diversity indices may underestimate or overestimate the impact on the generosity of governmental transfers. Which direction prevails boils down to whether larger shares of conversions have benefited religions already featuring numerous devouts or not. This in fact would turn to affect differently both religious fractionalization and polarization. As instance, a prevailing number of individuals moving from a less popular belief to Islam would decrease religious fractionalization and increase religious polarization (up to the bipolar case of two major religions, then it would decrease). In 2007 the Pew Research Centre estimated that there were around 2.4m American Muslims with just under a quarter converts. However, according to a new analysis of the 2014 Religious Landscape Study, a substantial share of adults who were raised Muslim no longer identify as members of the faith. In contrast, Christianity as a whole loses more people than it gains from religious switching (conversions in both directions) in the U.S.. It is also worth noticing how the inclusion of both religious fractionalization and polarization measures coincides with the downsizing in magnitude of population coefficients, with respect to columns (ii) and (iii). In the same fashion, population coefficients exhibit comparatively lower significance levels. This suggests potential collinearity. As a consequence our measures still describe the national population composition they refer to, making their sign more reliable even if not significant at conventional level.

An important and fair criticism would be to point at the difficulty in interpreting the very meaning of the birthplace diversity indices: what kind of heterogeneity within a society are they capturing? We therefore now compare the results in Tables 2.3 and 2.4 with those in Tables 2.5 and 2.6, where we basically replace birthplace diversity with ethnic and ethnolinguistic diversity. The last three rows in Tables 2.5 and 2.6, present our estimates for the impact of ethnic and ethnolinguistic fractionalization and polarization, respectively.

Even though with our data we can fairly replicate Alesina et al. (2003) and

Desmet et al. (2009) findings, our estimates go in the opposite direction. All coefficients are positive and highly significant across specifications. As discussed in Section 2.3, measurement errors due to both cross-sectional analysis and time invariant proxies of volatile variables could explain previous results. In particular, these baseline results suggest that temporal variation allows birthplace diversity to capture the degree of social mistrust - if any -, that ethnicity and language fail to detect. Hence, ultimately the diversity driving lower redistributive outcomes stems from most recent migration flows. (see also OECD, 2015) As robustness checks we also estimate the model in 2.1 using the diversity *within the migrant community* only, as well as the general index of *population* diversity i.e., it includes the natives. We drop all linearly interpolated values of the two diversity variables and then re-estimate our model with actually observed cases only. Both checks do not bring substantially different results and are therefore not reported.

—— Tables 2.7 and 2.8 about here ——

In Tables 2.7 and 2.8 instrumental variable strategy results are provided. In Table 2.7, four different gravity regression models are performed. Columns (i), (ii) and (iii) report OLS estimates and column (iv) shown results for a PPML gravity model with country of origin and destination and time fixed effects. Consistently with the previous literature on this topic reviewed in Section 2.3, column (iv) is our preferred specification. The control variables included are all significant at 1% for both OLS and PPML estimates. As robustness, we have performed gravity models with same controls but using PPML respectively: without two-ways fixed effects; including only country-of-destination fixed effects and including only year dummies (results are not reported). In the same way, Negative Binomial Regression (NBER) results are available upon request. Each gravity model performed ultimately serves to predict fitted shares of migration inflows, for every year from 1970 up to 2010, for all the countries in the world. We have used these predicted figures on worldwide migration flows to construct fitted birthplace fractionalization and polarization indeces. Estimates for instrumented variables of interest are shown in Table 2.8. All regressions replicate the fixed model from 2.1, with the same time window 1970-2010. The first two columns are reported for a matter of comparison with Frankel (1999), who uses a log-linear OLS model. The magnitude of birthplace diversity coefficients confirms a potential sample selection issue. In fact, variable instrumented by using the FE PPML gravity model predictions are much smaller for both the the fractionalization and the polarization indices. All other controls have comparable magnitude and significance levels across the two specifications. Results from our preferred specification largely confirm sign and significance of baseline regressions estimates. In particular, reading across the first row, third column, the instrumented coefficient matches closely its baseline counterpart in Table 2.3, specification (iii). Looking at the last row, fourth column, the coefficient for birthplace polarization exhibits now a lower magnitude than across baseline specifications, yet featuring higher significance.

Table 2.3: FE Models. Redistribution and Birthplace and Religious *Diversity* - Fractionalization Indeces (1970-2010)

	(i)	(ii)	(iii)	(iv)	(v)
Population	0.148**	0.268***	0.252***	0.166**	0.304***
	(0.072)	(0.080)	(0.079)	(0.073)	(0.085)
GDP per capita	0.020	0.022	0.019	0.016	0.018
	(0.027)	(0.034)	(0.033)	(0.028)	(0.034)
GDP growth rate	0.010**	0.007**	0.007**	0.009**	0.007**
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Investments	0.031**	0.037***	0.037***	0.037**	0.044***
	(0.014)	(0.014)	(0.014)	(0.015)	(0.016)
Trade	-0.025	-0.023	-0.023	-0.029	-0.027
	(0.026)	(0.026)	(0.026)	(0.027)	(0.027)
Birthplace FRA		-0.776***	-2.268**		
		(0.280)	(1.041)		
Migrants(% pop)			2.369		-1.167***
			(1.511)		(0.437)
Religious FRA				0.219	0.263
				(0.183)	(0.244)
Observations	3482	2196	2196	3300	2164

Fixed Effect Models of the impact of Birthplace and Religious Diversity Indeces on Redistribution. *Note* Redistribution is measured with yearly data on transfers and subsidies at country level (World Bank) as share of total spending. Transfers and subsidies include: subsidies, grants; all unrequited, nonrepayable transfers on current account to private and public enterprises; grants to foreign governments, international organizations, and other government units; and social security, social assistance benefits, and employer social benefits in cash and in kind. Figures for Population, GDP per capita (constant USD), GDP growth (annual %), Investments and Migrants (% pop) are also taken from the World Bank. Religious adherents data are provided at five-year intervals by Maoz and Henderson (2013). All missing data between two consecutive rounds are interpolated. All the variables are in logarithmic form, included fractionalization and polarization indexes of Birthplace and Religious diversity. Year dummies are included but not reported. Standard errors are clustered at country level. Significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table 2.4: FE Models. Redistribution and Birthplace and Religious *Diversity* - Polarization Indeces (1970-2010)

	(i)	(ii)	(iii)	(iv)	(v)
Population	0.148**	0.258***	0.253***	0.160**	0.297***
	(0.072)	(0.078)	(0.079)	(0.074)	(0.084)
GDP per capita	0.020	0.021	0.019	0.015	0.018
	(0.027)	(0.032)	(0.032)	(0.028)	(0.034)
GDP growth rate	0.010**	0.007**	0.007**	0.009**	0.007**
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Investments	0.031**	0.036***	0.037***	0.035**	0.043***
	(0.014)	(0.013)	(0.014)	(0.015)	(0.016)
Trade	-0.025	-0.023	-0.022	-0.029	-0.026
	(0.026)	(0.026)	(0.026)	(0.027)	(0.027)
Birthplace POL		-0.581***	-0.761*		
		(0.192)	(0.411)		
Migrants(% pop)			0.472		-1.149***
			(0.907)		(0.437)
Religious POL				0.126	0.136
				(0.121)	(0.153)
Observations	3482	2196	2196	3300	2164

Fixed Effect Models of the impact of Birthplace and Religious Diversity Indexes on Redistribution.

Note Redistribution is measured with yearly data on transfers and subsidies at country level (World Bank)as share of total spending. Transfers and subsidies include: subsidies, grants; all unrequited, nonrepayable transfers on current account to private and public enterprises; grants to foreign governments, international organizations, and other government units; and social security, social assistance benefits, and employer social benefits in cash and in kind. Figures for Population, GDP per capita (constant USD), GDP growth (annual %), Investments and Migrants (% pop) are also taken from the World Bank. Religious adherents data are provided at five-year intervals by Maoz and Henderson (2013). All missing data between two consecutive rounds are interpolated. All the variables are in logarithmic form, included fractionalization and polarization indexes of Birthplace and Religious diversity. Year dummies are included but not reported. Standard errors are clustered at country level. Significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table 2.5: FE Models. Redistribution and Ethnic and Ethno-linguistic *Diversity* - Fractionalization Indeces (1970-2010)

	(i)	(ii)	(iii)	(iv)	(v)
Population	0.148**	0.023	0.063**	0.008	0.037
	(0.072)	(0.019)	(0.026)	(0.019)	(0.026)
GDP per capita	0.020	-0.064***	-0.073***	-0.047***	-0.039*
	(0.027)	(0.015)	(0.023)	(0.015)	(0.024)
GDP growth rate	0.010**	0.010**	0.007*	0.008**	0.006*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Investments	0.031**	0.049***	0.064***	0.051***	0.053***
	(0.014)	(0.019)	(0.017)	(0.017)	(0.016)
Trade	-0.025	-0.047*	-0.033	-0.032	-0.022
	(0.026)	(0.028)	(0.028)	(0.027)	(0.026)
Migrants(% pop)			-0.580		-0.866
			(0.561)		(0.532)
Ethnolinguistic FRA (A/D)		0.491***	0.452***		
		(0.108)	(0.157)		
Ethnic FRA (RQ)				0.515***	0.553***
				(0.133)	(0.165)
Observations	3482	3112	1948	3145	2111

Fixed Effect Models of the impact of Birthplace and Religious Diversity Indeces on Redistribution. *Note* Redistribution is measured with yearly data on transfers and subsidies at country level (World Bank)as share of total spending. Transfers and subsidies include: subsidies, grants; all unrequited, nonrepayable transfers on current account to private and public enterprises; grants to foreign governments, international organizations, and other government units; and social security, social assistance benefits, and employer social benefits in cash and in kind. Figures for Population, GDP per capita (constant USD), GDP growth (annual %), Investments and Migrants (% pop) are also taken from the World Bank. Time invariant measures of Ethnic and Ethnolinguistic diversity are respectively provided by Reynal-Querol (2002) and Alesina et al. (2003)-Desmet et al. (2009). All the variables are in logarithmic form, included fractionalization and polarization indexes of Birthplace, Ethnic and Ethnolinguistic diversity. Year dummies are included but not reported. Standard errors are clustered at country level. Significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table 2.6: FE Models. Redistribution and Ethnic and Ethno-linguistic *Diversity* - Polarization Indeces (1970-2010)

	(i)	(ii)	(iii)	(iv)	(v)
Population	0.148**	0.023	0.063**	0.013	0.046*
	(0.072)	(0.019)	(0.026)	(0.019)	(0.026)
GDP per capita	0.020	-0.064***	-0.073***	-0.058***	-0.046**
	(0.027)	(0.015)	(0.023)	(0.014)	(0.023)
Investments	0.031**	0.049***	0.064***	0.051***	0.054***
	(0.014)	(0.019)	(0.017)	(0.017)	(0.016)
GDP growth rate	0.010**	0.010**	0.007*	0.008**	0.006*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Trade	-0.025	-0.047*	-0.033	-0.032	-0.022
	(0.026)	(0.028)	(0.028)	(0.028)	(0.026)
Ethnolinguistic POL (A/D)		0.300***	0.276***		
		(0.072)	(0.106)		
Migrants(% pop)			-0.583		-0.877*
			(0.562)		(0.513)
Ethnic POL (RQ)				0.524***	0.678***
				(0.147)	(0.198)
Observations	3482	3112	1948	3145	2111

Fixed Effect Models of the impact of Birthplace and Religious Diversity Indexes on Redistribution.

Note Redistribution is measured with yearly data on transfers and subsidies at country level (World Bank)as share of total spending. Transfers and subsidies include: subsidies, grants; all unrequited, nonrepayable transfers on current account to private and public enterprises; grants to foreign governments, international organizations, and other government units; and social security, social assistance benefits, and employer social benefits in cash and in kind. Figures for Population, GDP per capita (constant USD), GDP growth (annual %), Investments and Migrants (% pop) are also taken from the World Bank. Time invariant measures of Ethnic and Ethnolinguistic diversity are respectively provided by Reynal-Querol (2002) and Alesina et al. (2003)-Desmet et al. (2009). All the variables are in logarithmic form, included fractionalization and polarization indexes of Birthplace, Ethnic and Ethnolinguistic diversity. Year dummies are included but not reported. Standard errors are clustered at country level. Significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table 2.7: Gravity Regression Models - First Stage

	OLS			PPML
	(i)	(ii)	(iii)	(iv)
Model	Country-year FE (origin and destination)	Origin-year interaction, 10-years dummies	10-years dummies	Country-year FE (origin and destination)
Contiguity	4.066***	4.334***	4.301***	1.954***
	(0.033)	(0.044)	(0.045)	(0.084)
Common official language	0.802***	0.973***	0.947***	0.804***
	(0.014)	(0.017)	(0.017)	(0.073)
Ever in colonial relationship	2.178***	3.435***	3.990***	1.689***
	(0.042)	(0.053)	(0.053)	(0.073)
Common colonizer post 1945	0.679***	-0.174***	-0.305***	1.294***
	(0.017)	(0.021)	(0.020)	(0.094)
Currently in colonial relationship	1.372***	1.788***	1.839***	1.745***
	(0.299)	(0.396)	(0.408)	(0.215)
Country of origin population (log)	0.532***	0.616***	0.403***	3.815***
	(0.021)	(0.034)	(0.003)	(1.237)
Same country (were or are)	2.155***	2.186***	2.176***	1.515***
	(0.048)	(0.063)	(0.065)	(0.135)
Observations	195120	195120	195120	194940

First stage regression models.
Ordinary Least Squares estimates from (i) to (iii) and Poisson-Pseudo Maximum Likelihood estimates in (iv). Dependent variables: migrants (log) from (i) to (iii) and migrants in units (rescaled) in (iv).
Note: 10-Years dummies are included in (ii) and (iii) but not reported. Two-ways fixed-effects for both countries of origin and destination are included in (i) and (iv) but not showed. Interactions between country of origin and decades dummies (from 1960 to 2010) are performed in (iii) and (vi) but not presented. Capital-to-Capital distance (in km) is included in (i), whereas the interaction between this distance and decades dummies is included in (ii), (iii) and (iv). Yet the resulting coefficients resent from multicollinearity issues across all specifications. Variables at pair-of-countries level related to bilateral distance, area, common language and colonies (time-invariant) come from the CEPII GeoDist database. Population figures are obtained from Penn World Table 9.0. Standard errors in parentheses. Significance levels conventionally represented by: (*) for $p < 0.10$, (**) for $p < 0.05$ and (***) for $p < 0.01$.

Table 2.8: Gravity Regression Models - Instrumented Results

Gravity-based IV Regressions		Fixed Effects	Models	
IV obtained from:		OLS Gravity Model w/ country-year FE (origin and destination)		PPML Gravity Model w/ country-year FE (origin and destination)
	(i)	(ii)	(iii)	(iv)
Birthplace FRA	-0.858***		-0.296***	
	(0.191)		(0.076)	
Population	0.139***	0.134***	0.162***	0.165***
	(0.020)	(0.020)	(0.019)	(0.019)
GDP per capita relationship	0.049***	0.053***	0.038***	0.036***
	(0.011)	(0.011)	(0.010)	(0.010)
GDP growth	0.005***	0.004	0.006**	0.006**
	(0.003)	(0.003)	(0.003)	(0.003)
Investments	0.013	0.005	0.021**	0.021**
	(0.010)	(0.010)	(0.009)	(0.009)
Trade	-0.030***	-0.027**	-0.025**	-0.023**
	(0.011)	(0.011)	(0.010)	(0.010)
Birthplace POL		-0.842**		-0.172***
		(0.168)		(0.062)
Observations	3329	3330	3329	3330

Gravity-based Instrumental Variable Models of the impact of Birthplace Diversity on Redistribution (1970- 2010).
Birthplace Diversity indeces have been instrumented using the measures of Fractionalization and Polarization respectively built on the predicted values of migration inflows obtained from the first stage. Columns (i) and (ii) report results for two-ways OLS Fixed Effects, for both origin and destination countries. Columns (iii) and (iv) report results for instrumented indexes of Birthplace Diversity using PPML regressions.
Note: Redistribution is measured with yearly data on transfers and subsidies at country level (World Bank) as share of total spending. Transfers and subsidies include: subsidies, grants; all unrequited, nonrepayable transfers on current account to private and public enterprises; grants to foreign governments, international organizations, and other government units; and social security, social assistance benefits, and employer social benefits in cash and in kind. Figures for Population, GDP per capita (constant USD), GDP growth (annual %), Investments and Migrants (% pop) are also taken from the World Bank. All the variables are in logarithmic form. Standard errors in parentheses. Significance levels conventionally represented by: (*) $p < 0.10$, $(**) p < 0.05$, $(***) p < 0.01$.

2.7 Mechanisms

In what follows, we provide a number of insights into the mechanisms that can explain the relation between birthplace diversity and social transfers. In more details, we explore whether the results are driven by changes in preferences for tax rates or changes in interpersonal trust. First, Razin et al. (2002) suggest that in presence of higher immigration, the so-called "fiscal leakage" from the native population to the migrant population may change the attitude of the natives against high taxes. In fact, they find that a higher number of low-skilled immigrants is followed by a decrease in social transfers and thus less redistribution (see also Speciale, 2012, for a review). In a similar vein, a recent and novel work by Belmonte et al. (2017) explores how aversion to ethnic diversity, the degree of fiscal and political decentralization, and tax morale interact. Their argue that individuals who are averted to ethnic diversity are more reluctant to contribute to the provision of public goods, because this can benefit other groups. This is less of a problem in decentralized countries, where individuals' welfare losses are mitigated because the provision of public goods is administrated by jurisdictions where communities are more homogeneous than the whole country; this increases the individuals' intrinsic motivation to pay taxes. Accordingly, they find that a negative attitude toward ethnic diversity reduces tax morale in centralized political systems, whereas it does not seem to affect significantly decentralized ones. Moreover, the negative effect of ethnic aversion on tax morale is lower in more homogenous countries[12]. Similarly, Guiso et al. (2006) show that different religious affiliations and ethnic background are associated with different preferences for redistribution. They also show how different preferences for redistribution affect actual redistribution in state-level fiscal policy in the United States. Recall that Alesina and Ferrara (2005) also claim

[12]Note that, although economic gains are widely accepted, immigrants' impact on fiscal contributions is a highly debated issue. In a recent work, Dustmann and Frattini (2014) find that immigrants overall make a positive fiscal contribution in the United Kingdom. Hansen et al. (2017) argues that although the second-generation non-Western immigrants make a negative contribution of almost twice the level of natives (who also make a negative net contribution), the first-generation makes a net cost of three times the level of natives.

that ethnic heterogeneity affects individual behaviour, preferences and economic policies.

—— Tables 2.9 and 2.10 about here ——

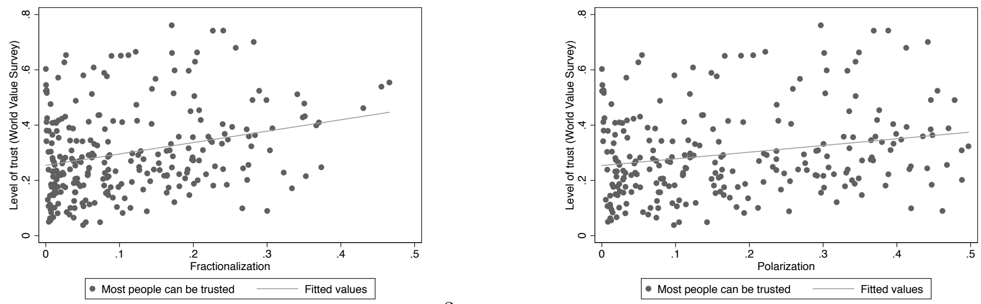
We use a newly released dataset by Cagé and Gadenne (2017), who assembles a new panel data set on tax revenues and government expenditures covering 130 countries between 1792 and 2006. In Table 2.9 we first run a simple model of taxation in percentage of the GDP, which is defined as central government tax revenues excluding social security contributions. We use again log-log regression models where all variables are log-transformed, to facilitate the interpretation of the variables of interest. We use two-way fixed effects models where country effects are added to account for the unobserved heterogeneities in preferences of taxation that are specific to each country and the time effects are entered to control for time-specific global shocks or systemic effects that might affect taxation, such as globalization. These effects capture cross-sectional dependence to the extent that the impacts of common factors are the same across countries.

We explain taxation using only diversity, and country and year fixed-effects and find that, in line with the expectations, in Table 2.9 birthplace diversity is indeed negatively correlated with taxation at conventional levels. Two additional Tables are provided in the Appendix of this Chapter. We add a battery of control variables, in particular population size, GDP per capita and government expenditure in percentage of the GDP. We also control for the share of migrants, to make sure that changes in ethnic diversity is not simply picking an increase in foreign population, rather than the degree of heterogeneity of a society. Our diversity measures are robust to the inclusion of these additional aggregated economic indicators and population controls at country level. As birthplace diversity performs as a significant negative predictor of tax revenues (as % of GDP), taxation can be considered as one of the transmission mechanisms through which birthplace diversity decreases redistribution.

Finally in Table 2.10 we only look at trade tax. The measure of trade is imports as a share of GDP, as most trade tax revenues come from tariffs levied on imports, only levied by federal governments and never in the form of contributions to social security funds.

The rationale behind this last table is that we should not expect to find a significant impact of heterogeneity on trade taxes as the latter should mostly mirror trade liberalization episodes and the evolution of a country's trade over time. As such, we could treat this as a sort of placebo. In fact, in Table 2.10 we can see that there is no significant association between our measures of birthplace fractionalization and polarization and trade taxes. This is true for both diversity indices measured *within the migrant community* only, as well as for general indices of *population* diversity. Note however that some of the results become insignificant when we use standard errors cluster on countries.

Second, we investigate whether adjustments to redistribution levels occur as a consequence of a decline in the level of interpersonal trust. Previous literature suggests that ethnic barriers can act as an important barrier to trust among individuals as people trust people who look like them more than those who do not (see e.g., DeBruine, 2002). This explanation is related to the fact the migrants might erode the social capital within a community, which in turn leads residents to decrease their demand for public goods provision. Putnam's (1993) is perhaps the most important empirical study on social capital, and he finds a strong correlation between civic engagement and government quality in Italian regions. Optimal investments in social capital can increase trust (Glaeser et al., 2002) thus the higher social capital the higher the level of trust toward others (Guiso et al., 2004). Furthermore, Guiso et al. (2009) convincingly show how the perception of trust, measured using surveys from the Eurobarometer, improves trade across a sample of European countries. In a global sample, finding reliable measures of social cohesion and interpersonal trust is not straightforward, and we rely on data



a. Birthplace Fractionalization and level of Trust

b. Birthplace Polarization and level of Trust

Figure 2.6: Correlation Plots - Birthplace Indices and Trust

Note: Migration figures used to construct our Birthplace Diversity indices are taken from the World Bank bilateral migration matrix, 1970-2013. Trust information are retrieved from the World Values Survey Association, 2015.

from the World Value Survey, a global network of social scientists studying changing values and their impact on social and political life.[13] In particular, we use the variable *Most people can be trusted*, which is based on answers to the following question *Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?*. The answers are “0. Need to be very careful" or "1. Most people can be trusted". By graphically inspecting Figure 2.6.a, a spurious positive correlation between our overall measure of social trust and birthplace fractionalization emerges. At a lower incidence, a similar relation is depicted for the birthplace polarization index in Figure 2.6.b. However, even if counterintuitive with respect to most of the arguments discussed across social sciences on the drivers of the negative impacts of diversity on aggregated economic outcomes, these relations are not insignificant. Although we cannot entirely dismiss this interpretation, this preliminary evidence suggests that they seem unlikely to be the primary source of our findings.

---

[13]World Values Survey Association, 2015, see `http://www.worldvaluessurvey.org/`

Table 2.9: Diversity and Tax to GDP ratio: baseline regressions.

	Model A	Model B	Model C	Model D
Birthplace FRA (Tot)	0.052***			
	(0.012)			
Birthplace POL (Tot)		0.050***		
		(0.012)		
Birthplace FRA			0.004	
			(0.006)	
Birthplace POL				0.004
				(0.006)
Observations	3680	3682	3682	3682

Fixed-effects models.
Note: Taxation data are combined by Cagé and Gadenne (2017) covering 130 countries between 1792 and 2006 using different sources [International Monetary Funds Government Finance Statistics (GFS); Mitchell's International Historical Statistics (2007); Baunsgaard and Keen (2010)]. Taxation (in percentage of the GDP) is defined as central government tax revenues excluding social security contributions. Migration figures used to construct our Birthplace Diversity indexes are taken from the World Bank bilateral migration matrix, 1970-2013. All the variables are in logarithmic form. Standard errors in parentheses. Year dummies are included but not shown. Conventional significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table 2.10: Diversity and Trade Tax to GDP ratio. Placebo Test.

	Model A	Model B	Model C	Model D
Population	1.263***	1.239***	1.274***	1.273***
	(0.092)	(0.093)	(0.097)	(0.097)
GDP per capita	-0.121**	-0.123***	-0.128***	-0.128***
	(0.048)	(0.048)	(0.048)	(0.048)
Government exp. to GDP ratio	0.146***	0.149***	0.145***	0.145***
	(0.034)	(0.034)	(0.034)	(0.034)
Migrants(% pop)	-2.210**	-0.711**	-0.224***	-0.226***
	(1.074)	(0.353)	(0.075)	(0.075)
Birthplace FRA (Tot)	1.986*			
	(1.094)			
Birthplace POL (Tot)		0.471		
		(0.368)		
Birthplace FRA			-0.017	
			(0.033)	
Birthplace POL				-0.016
				(0.033)
Observations	3516	3518	3518	3518

Fixed-effects models.
Note: Trade data are assembled by Cagé and Gadenne (2017) covering 130 countries between 1792 and 2006. Trade is measured in imports as a share of GDP at country level. Data for Population, GDP per capita and Government Expenditure in percentage of the GDP are taken from the World Bank, World Development Indicators. Migration figures used to construct our Birthplace Diversity indexes and the Migrant (% pop) variable are taken from the World Bank bilateral migration matrix, 1970-2013. All the variables are in logarithmic form. Standard errors in parentheses. Year dummies are included but not shown. Conventional significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

2.8 Conclusions

In this Chapter we have sought to contribute to the debate on diversity and public goods provisions by examining how time-varying measures of birthplace diversity affect the level of redistribution. We thus go beyond existing research on ethnic diversity and social transfers as we provide a systematic study of how variations in birthplace diversity alter the incentives to redistribute public goods following the arrival of immigrants. Our findings suggest that birthplace diversity reduces government redistribution. The coefficient of polarization retains a similar magnitude but decreases in significance. Results are robust across baseline specifications and fairly confirmed by the novel instrumental variable strategy we exploited. These evidences stand in contrast to a number of previous studies on this topic, which have suggested that i) diversity does not actually have any effect on redistribution unless we control for distances between subgroups (e.g., Desmet et al., 2009) and that ii) fractionalization and polarization have opposite impact on development indicators. Moreover, we replicate Alesina et al. (2003) and Desmet et al. (2009) analysis with our data, obtaining opposite findings: all coefficients are positive and highly significant across specifications. Measurement errors due to both cross-sectional analysis and time invariant proxies of diversity could explain previous results. In particular, results suggest how it is the time dimension that allows birthplace diversity to capture the degree of social mistrust at play, that ethnicity and language fail to depict. We do recognize that immigration usually has a large positive effect on economic outcomes, and there are a number of valuable economic opportunities and gains for both migrants and host societies through a variety of channels, for example through the “immigration surplus" accruing to native factors of production (see e.g., Borjas, 1999). Moreover, an increase in the level of heterogeneity in host countries, in terms of e.g., skills and perspectives, stimulate economic growth (Alesina et al., 2016; Bove and Elia, 2017). Yet, simply ignoring possible negative economic implications stemming from population movements more generally is unhelpful for research or informing policy.

Nevertheless, to the best of our knowledge there is no empirical work directly exploring the consequences of birthplace diversity on redistribution, and this study is a step in this direction. If anything, then, this research underscores the need for attention to how different aspects of immigration can lead to distinct types of economic gains and costs, in particular the support for redistribution.

Chapter 3

Reassessing the impact of Melting-pot on Economic Prosperity: only time can tell.

3.1 Introduction

Cross-country differences in GDP per capita are much larger than differences within countries (IMF, 2017). This suggests that any individual's standard of living is much more strongly determined by randomness of one's country of birth, as opposed to one's own individual talent and dedication (Milanovic, 2013). There are a number of factors that seem to contribute to economic growth, such as human capital, investments, and the quality of institutions. Yet, a new era of mass migration across Europe has reminded us that the makeup of modern societies has been quickly changing and this can have important effects on the rate of economic growth.

This Chapter attempts to explore the relation between cultural diversity and economic growth over-time. Economic growth has long been seen as a consequence of technological innovation and human capital. Yet, a fast-growing number of studies suggest that cultural diversity, the range of citizens with different origins, religions and traditions living and interacting together, plays a pivotal (and mostly positive) role in determining patters of economic growth. Implicitly, the central premise of the “optimistic view" is that a diverse range of societal norms, customs, and ethics can nurture technological innovation and the spread of ideas. To put it differently, cultural diversity can positively affect economic growth if a greater variety of skills is associated with the production of a greater variety of goods and services (Ottaviano and Peri, 2006; Alesina and Ferrara, 2005). On the other hand, however, cultural barriers represent a major hurdle to economic prosperity and trade between countries (Gokmen, 2017). Moreover, heterogeneous work environments may give rise to coordination problems (e.g. due to language diversity) and thus raise transaction costs, create incompatible expectations while cultural barriers and lack of trust may reduce the overall performance of a team (Horwitz and Horwitz, 2007). In fact, the “optimistic view" is also somewhat at odds and difficult to reconcile with the recent conflict literature, which has long argued that ethnic divisions have a positive effect on the incidence of civil war (Reynal-Querol, 2002).

In this Chapter we build on seminal studies by Easterly and Levine (1997) and Alesina et al. (2003) and address the following question: to what extent does the impact of cultural diversity on economic prosperity change over-time? As we discussed in Chapter 1 and Chapter 2, a new era of mass migration across Europe has forcefully reminded us how the makeup of modern societies has been changing. This could have important consequences for a number of economic outcomes, including economic development, and an increasing number of academics, policymakers and alike have debated the consequences of cultural change. Yet, in the words of Alesina and Giuliano (2015), “cultural economics is in its infancy" and empirical investigation of the relevance of culture on economic outcomes is fairly new in economics (Alesina and Giuliano, 2015, p.5). Against this background, we attempt to quantify the substantive impact of culture on economic growth overtime and make comparisons between different markers of identity. This Chapter also explores the role of a synthetic measure of cultural diversity. After providing new evidence on the effects of diversity on economic growth over-time, we seek to explore some of the underlying transmission channels. First, past work on economic growth has emphasized the lack of physical investments as one of the main impediment to economic growth Barro (1991). Therefore, we check whether the impact of diversity of economic growth may occur as a by-product of a decrease in investments because of e.g., lack of trust. We find that this is indeed the case and the effect of ethnic diversity on economic development work through a deterioration in the level of physical investments, regardless of the measure of investments we use. This seems to be one of the main transmission mechanisms. Second, a recent study by Alesina et al. (2016) finds a positive effect of diversity on innovation and production; the authors argue that the effect of birthplace diversity should affect GDP per capita through Total Factor Productivity (TFP). We therefore explore whether our battery of indices of heterogeneity produce a similar positive correlation with total factor productivity, taken from the Penn World Table. Our results suggest that this is indeed the case and one of the underlying monetary mechanisms is the one that relates productivity to diversity.

We proceed as it follows. In Section 3.2 an overview if the relevant literature is provided. Then Section 3.2.1 discusses methodological concerns in investigating the impact of time-invariant diversity measures using average-effects models. Section 3.3 presents the array of indices we compare throughout this study. Our empirical strategy is described in Section 3.4. In Section 3.5 we show baseline findings. Then Section 3.5.1 provides our new synthetic measure of diversity obtained *via* Principal Component Analysis (PCA). To dig deeper into the channels connecting diversity to economic prosperity, we add Section 3.6 and Section 3.7. The former investigates the intermediating role played by investments and Total Factor Productivity. The latter exploits a dataset newly assembled by the author to outline the role played by different dimensions of social cohesion in affecting economic growth. The rationale behind this extension stems from Putman's view over the mitigating *versus* exacerbating role that trust and social-cohesion can have in determining the sign and magnitude of the impact of diversity on socio-economic outcomes[1]. Finally, Section 3.8 briefly concludes this Chapter.

3.2 Literature review

The extensive body of literature on the effect of diversity on economic performances has so far provided mixed evidence. To some extent, seemingly conflicting findings can be explained by different approaches to the problem, and thus different empirical strategies. Studies vary significantly in terms of sample, unit of analysis (with beneficial effects mostly found in studies of US cities) and measures of diversity (both in terms of what makes societies different [ethnicity, language, genetics, birthplace] and diversity of which actors are salient, i.e. all or just workers and/or immigrants). Broadly speaking, diversity brings along both adversarial and beneficial effects on economic outcomes. As commonly noted, diversity is a double-edged sword (Horwitz and Horwitz, 2007, p.988).

On the one hand, although team diversity can potentially create a positive organizational synergy, and hence positive team outcomes, the same idiosyncratic expertise and experience can result in irreconcilable divisions and intra/intergroup conflict. In fact, heterogeneity within societies produces conflicting preferences and coordination problems (Alesina and Ferrara, 2005). Not only individuals' preferences are linked to preferences of other group members, but transaction costs with in-group members are also more efficient (e.g. because of lower communication barriers) (Alesina and Ferrara, 2005; Fearon and Laitin, 1996). These micro-level dynamics encourage rent-seeking behaviours at the group level and exacerbates disagreements over public goods (Alesina et al., 1999). Accordingly, a recent strand of economic literature has found that diversity, in particular polarization, leads to excessive taxation, and hence reductions in the return to physical capital and in-

[1]See also Alesina (2016)

vestment rates, which slows down growth (e.g., Azzimonti, 2011). It can also negatively affect economic development by increasing government consumption and the probability of a civil conflict (Montalvo and Reynal-Querol, 2005). Indeed, each group will allocate important resources to gain access to power (Montalvo and Reynal-Querol, 2005). The non-productive use of time, capital and labour has nefarious effects on economic performances and is, according to Easterly and Levine (1997), at the core of Africa's tragedy. In their seminal study on economic growth, the authors find that ethnic diversity explains a large set of economic indicators and poor public policies in Sub-Saharan countries. These include low levels of schooling, political instability, poor financial systems, high government deficits and inadequate infrastructures (Easterly and Levine, 1997). Such indicators and policies are, in turn, deemed responsible for negative per capita growth in African countries during 1965-1990.

On the other hand, diversity can also produce beneficial effects on economic outcomes. A mostly parallel area of research, in management studies, seems to support the notation that diversity - at a more disaggregated level i.e., within a team - may improve its performance. This is because, if a pool of workers stem from different backgrounds, they bring along their various skills, experiences, and abilities in the day-to-day interactions (see e.g., Fisher Ellison et al., 2010; Van Praag and Hoogendoorn, 2012; Trax et al., 2012; Kahane et al., 2013). This positive impact seemes indeed related to innovation and productivity. Alesina et al. (2000) propose a model where skill complementarities increase production. Ottaviano and Peri (2005, 2006) corroborate this model providing evidence that diversity in birthplace among workers in some US cities boosts productivity of all workers and results in higher wages. Importantly, though, skills complementarity boosts productivity mostly in advanced economies because it is in this context that the production process is indeed diversified (Alesina and Ferrara, 2005). With regard to innovation,Hong and Page (2004) argue that a group of individuals with different cognitive skills and heuristics may have stronger problem-solving skills than more homogenous groups. Although most studies use cross-sectional data to test for beneficial effect of diversity on innovation and production, Alesina et al. (2016) report consistent findings comparing 195 countries in 1990 and 2000. Furthermore, Bove and Elia (2017) use panel data with 135 countries from 1960 to 2010 and find extensive support for the hypothesis that birthplace diversity fosters economic growth, especially in developing countries. This result is seemingly in contradiction with Alesina and Ferrara (2005) who find a positive effect of diversity in countries with high democracy scores and per capita income. However the two studies measure diversity using different sources. While Alesina and Ferrara (2005) measure ethnic fractionalization cross-sectionally using a combination of sources (see Alesina et al., 2003, p. 159-160), Bove and Elia (2017) use census data to measure changes in migrant stocks from 1960 to 2000. So the measures of ethnic fractionalization used in these two studies are different in terms of primary sources, temporal coverage, and the traits that define population as diverse (race/language versus birthplace).

It is interesting to note that the above-mentioned studies highlighting a positive influence of diversity devote particular attention to measuring heterogeneity among non-native population. While measurement choices can be responsible for inconsistent or non-comparable findings, the numerous indices used in the literature reviewed above allow to observe how the effect of diversity has changed over-time but also to possibly separate economically beneficial dimensions of diversity from detrimental ones. Hence the effect of diversity found in extant scholarship depends on how the concept is measured, suggesting that different ethnic, linguistic, cultural and genetic attributes may have a discernible effect on economic growth. Furthermore, the effect of diversity is not homogenous across countries. Highly advanced economies seem to be better equipped at mitigating the potential negative effect of ethnic diversity through functioning institutions (Alesina and Ferrara, 2005; Gören, 2014). This means that context shapes the salience of diversity and on which trait defines a ‘diverse’ population. In this regard, Posner (2004) presents an interesting illustrative case. The author argues that institutional frameworks in which groups are embedded and the existing power configurations define groups’ relations. He shows that institutional frameworks explain why Chewas and Tumbuka tribes have friendly relationships in Zambia but are foes in the neighbouring Malawi. More importantly, though, institutions change over-time, and in turn shape the effect of diversity in different ways as they undergo such transformations. As argued in the next section, this justifies the intuition that the effect of diversity on growth varies not only across countries but also over-time, and institutional changes may mitigate or amplify it.

3.2.1 The issue of time-variation and average effects

A common feature of most studies reviewed above is that the relationship between economic outcomes and diversity (ethnic, cultural, or genetic) is assumed to be constant over-time. More specifically, the underlying assumption is that whether diversity is beneficial or adverse to economic performances does not depend on the temporal window selected for the analysis. This is interesting because several studies indicate that the effect of diversity varies across countries, but there is no attention to the possibility that it could also vary over-time. Alesina et al. (2003) point toward this possibility when explaining how the shift from ethnicity to clan-based identity transformed the country from a homogenous one (85% Somalis) to a fragmented one (numerous clans). Probably the most relevant study to this chapter is Gokmen’s work (2016) on how cultural differences have shaped trade during and after the Cold War. Borrowing from key propositions of the Clash of Civilization theory, Gokmen argues that the bipolarity of the Cold War International System significantly reduced the salience of cultural differences, thus reducing the negative effect of cultural diversity on trade and favouring exchanges among countries within the same bloc, regardless of cultural differences. With the end of the Cold War rivalry, cultural diversities regained relevance over ideology and became an obstacle to trade within culturally different dyads of countries. The effect of diversity on trade, indeed, turns out to be consistently negative but significantly stronger after the end of the Cold War. In a similar vein, this Chapter presents an investigation of the dynamic effect of most used diversity measure on countries' economic growth. The focus on economic growth adds a level of complexity in formulating clear directional expectations on the effect. The idea that the end of the Cold War and the dissolution of the bipolar system led to clashes over a variety of issues can be directly linked to worsening interstate relations among diverse states and, consequently, worsening trade exchanges. However, formulating expectations on how changes within the International System affect economic growth is less intuitive. The appropriate unit of analysis here is not a dyad, rather a single country; and the conceptualization of diversity does not capture distance between two states, rather intra-state diversity.

But why would we expect the effect of cultural, ethnic and linguistic diversity to vary over-time (in magnitude and, possibly, in direction)? First, processes of globalization and regional integration have also been accompanied by cultural convergence, or cultural homogenization. Relatedly, interpersonal cultural exchanges and information flows in the "Global Village" (Dreher et al., 2008) occur on a daily basis as consequence of lower transportation and communications costs. These trends toward cosmopolitanism suggest that differences in cultural and ethnic backgrounds and perceived distance, which is a function of familiarity, have become less and less salient in the last decades. This does not mean that absolute levels of diversity have decreased (in fact, many countries are now more diverse than in the past (Norris and Inglehart, 2009; Dreher et al., 2008), rather that its effect is less pronounced. Second, obstacles produced by linguistic diversity as identified in the economic literature should have been mitigated by the spread of English as *lingua* *franca*. So we could hypothesize that the negative effect of cultural, linguistic and ethnic diversity on economic growth - if any -, decreased in magnitude as an effect of globalization and regional integration. On the other hand, however, the perception of cultural globalization as Westernization or Americanization has resulted in a reaction to this convergence. Norris and Inglehart (2009) point out that the rejection of global cultural standards in traditional societies in Africa, Asia and Middle East exacerbated cultural cleavages. This process of identitarian entrenchment may not be unique to traditional societies; Alesina and Spolaore suggest that economic integration in Europe may produce disintegration as “linguistic, ethnic, and cultural minorities feel that they are economically ’viable’ in the context of a truly European common market, thus they can ’safely’ separate from the home country" (Alesina and Spolaore, 2005, p. 201). It is also possible that the effect of diversity varies over-time in terms of both magnitude and direction. Research that identifies diversity as beneficial to economic productivity focuses on diversity in workers’ birthplace. In other words, it seems that diversity within immigrant population drives the positive effect. Birthplace diversity among immigrant population results in economic growth (Bove and Elia, 2017) and higher wages and productivity for both native and non-native workers (Ottaviano and Peri, 2006; Alesina and Ferrara, 2005).

A related issue is the identification of how different traits or dimensions of diversity affect economic development and in which way. For example, measures of birthplace diversity proposed by Alesina et al. (2016) are orthogonal to measures of ethno-linguistic fractionalization and genetic diversity. The fact that they also find a positive rather than a negative effect further stresses the need for more nuanced understanding of what is captured by commonly used measures of diversity. In a study on the effect of diversity on international trade, Kónya (2006) posits that physical (geographic), cultural and linguistic distance impact trade in differing ways. In particular, linguistic diversity creates barriers to effective communication that, however, can be completely overcome through learning. Whereas Konya only focuses on physical and linguistic barriers, the argument can be extended to distance based on racial and cultural traits that are more difficult (if not impossible in the case of race) to change. Hence, we could expect that the effect of linguistic diversity on economic development varies more quickly than the effect of cultural and racial diversity, whose traits are stickier. This issue is further complicated when we generally refer to ethnicity because ethnic kinship is defined by traits that vary depending on the context. For example, ethnicity in the context of US cities is operationalized in terms of race (black and white individuals), but in African communities it may refer to religious creed or tribal affiliation (Alesina and Ferrara, 2005). In the previously mentioned study by Alesina et al. (2003), the authors construct an index of ethnic fractionalization based on racial and linguistic attributes. It turns out that in Latin America the main differences among groups followed racial features, since the majority of the population speaks the same language; in Europe and, to a lower extent, Sub-Saharan Africa, on the other hand, ethnic fractionalization mostly reflected linguistic diversity, while racial traits had no weight on the index.

To summarize, this Chapter contributes to the literature on economic growth and diversity in two crucial ways. First, it is the first exploratory endeavour that aims at describing over-time variation in the effect of diversity on economic growth. Second, it provides insights about diversity over which trait is more desirable with regard to economic growth. It examines the over-time effect of several diversity indices to assess which aspects of cultural, ethnic or linguistic diversity better explains variations in economic growth. Finally, it tackles the delicate issue of the endogenous determination of culture by proposing a new synthetic measure of cultural distance.

3.3 Data

In order to investigate to what extent the impact of cultural diversity on economic prosperity changes over-time, we collect a wealth of data from several different sources. Table reports summary statistics of the variables employed in this study whereas in what it follows details concerning data description and sources are provided. Our dependant variable - Economic Prosperity, is obtained using World Bank data on GDP per capita, in constant 2010 U.S. dollars. These figures are publicly available for the time window 1960 - 2016 across 146 countries (World Bank, 2016)[2]. To focus our analysis on the impact of diversity measures on economic prosperity, we choose the most conservative set of controls used across economic growth models. In doing so, we retrieve information on Educational Attainment from Barro & Lee (2013). Their data set provides educational attainment data for 146 countries in 5-year intervals from 1950 to 2010. The estimates used for this study refers to the latest edition of the Barro-Lee data-set, which is constructed using most recently available census/survey observations from consistent census data and featuring improved accuracy[3]. Dummy variables on world regions are instead taken from "The Authoritarian Regime" Dataset (Wahman et al., 2013) (Hadenius & Teorell, 2007), which is particularly suited for regional level analysis and covers the period 1972-2010[4]. We define culture as the amalgam of customs, beliefs, values and social organization. To effectively capture cultural diversity, we rely on several markers of identity. First, we use data from Desmet et al. (2009) and we re-build his overall Herfindal index:

- *Fractionalization Index* exploits Ethnologue data on linguistic threes, introducing distances across so defined cultural groups by referring to linguistic threes and to lexicostatistical studies (Dyen et al., 1992). By adding implicit weights to his Herfindal index, he partially addresses the group identification

[2]http://data.worldbank.org/data-catalog/world-development-indicators.
[3]http://www.barrolee.com/.
[4]https://sites.google.com/site/authoritarianregimedataset/data.

issue.

Second, we extract relevant information from the database "Ethnic and Cultural Diversity by Country" provided by Fearon (2003)[5]. The dataset contains information on 822 ethnic groups that made up at least one percent of the population in 160 countries in the 1990s. In more details, we use:

- *Cultural Diversity*, a measure that takes into account the cultural distances between groups, measured as the distance between languages spoken by different groups in a country. There are similarities between this index and Ethnic Fractionalization, as when two groups in a country speak structurally unrelated languages, their cultural diversity index will be the same as their level of ethnic fractionalization.

- *Ethnic Fractionalization*, based on the same 822 ethnic and "ethnoreligious" groups in 160 countries, measures the probability that two randomly selected people from a given country will belong to different such groups. The variable thus ranges from 0 (perfectly homogeneous) to 1 (highly fragmented). This is the same as the Ethnic Fractionalization index of other authors, although it is based on a different dataset for a different time period.

Third, we use data from Alesina et al. (2003). Their indices have been built using Enciclopedia Britannica. These data are supplied at a higher level of aggregation with respect to those available on Ethnologue, across all its editions. A consequence of this is that Alesina et al. (2003) did not have to choose which group represents an 'ethno-linguistic group', hence avoiding related controversities. In more details, we use:

- *Ethnic Fragmentation*, that involves a combination of racial and linguistic characteristics. Interestingly, Alesina et al.,'s index results in a higher degree of fractionalization than the commonly used ELF-index that we review below.

[5] See also `http://www.stanford.edu/~jfearon/`.

- *Linguistic Fragmentation*, that captures the chances that two randomly selected people from a country do not belong to the same linguistic group.

- *Religious Fragmentation*, that captures the chances that two randomly selected people from a country do not belong to the same religious group. Since religion has always played a central role in social and economic issues, we expect religious affiliations to affect the degree of cohesion within societies.

Fourth, we use Philip G. Roeder's data on Ethnolinguistic Fractionalization (ELF) Indices, 1961 and 1985[6]. The indices are computed from population estimates of different sources. We refer the interested reader to Roeder (2001) for more information and a more accurate depiction that we can possibly give here[7]. In more details, we use:

- *Ethnolinguistic Fractionalization* (Mira, 1964), that measures the odds that two randomly selected people from a country do not belong to the same ethnolinguistic group. This is a reprint from the index published in Taylor and Hudson (1972, 271-274). Yet, the original source is: Mira (1964).

- *Ethnolinguistic Fractionalization (ELF) Indices*, 1961 and 1985, computed from population estimates of different sources[8]. These are:

  - *Ethnolinguistic Fractionalization* (1961), which is similar to the one above introduced by Mira (1964), yet this is defined without collapsing any sub-groups in the sources (see Roeder, 2001, for more information)[9].

- *Ethnolinguistic Fractionalization* (Muller, 1964). This is a reprint from the

[6]`http://weber.ucsd.edu/~proeder/elf.htm.`

[7]In this study we use the main ELF specification, as presented in Roeder (2001).

[8]Computed by Philip G. Roeder using: Bromlei (1988),Bruk (1986),Bruk and Apenchenko (1964), USSR (1992) and Europa World Yearbook (for the Czechoslovakian and Yugoslavian successor states and for Bulgaria).

[9]In the main of the Chapter we focus on ELF indices referring to 1961. Estimates for ELF indices referring to 1985 - i.e. reflecting the composition in 1985 - are available upon request. For a discussion over this choice we refer the interested reader to `http//:weber.ucsd.edu\~proeder\elf.htm`.

index published in Taylor and Hudson (1972, 271-274) . Yet, the original source is Muller (1964).

- *Ethnolinguistic Fractionalization, (Roberts, 1962).* This is also a reprint from the index published in Taylor and Hudson (1972, 271-274). Yet, here the original source is Roberts (1962).

3.4 Empirical strategy

Following Easterly and Levine (1997) and Alesina et al. (2003), we focus on long-run growth and try to "abstract from business cycle fluctuations by studying economic performances over decades"(Easterly and Levine, 1997, p. 1208). As such, we follow their empirical specification and estimate a simple OLS where the dependent variable is 10-year GDP per capita growth rate. In fact, their baseline empirical model builds on a large literature that uses country-level data and cross-country regressions to explore the drivers of economic growth, in particular the growth models of Barro (1991). We thus add one of the several measures of diversity to a model of the following form:

$$g_i = \alpha + \gamma_{i,t0} + \lambda D_i + x_i\prime\beta + \epsilon_i \tag{3.1}$$

where g_i is the annual percentage growth rate of the (PPP Converted) per capita GDP at 2010 constant prices in country i over a specific time interval (e.g., between 1970 and 1980, between 1971 and 1981 etc); D_i is i's level of diversity, measured primarily by fractionalization, over the same period; $x_i\prime$ is a vector of explanatory variables that includes the log of initial income, the log of initial income squared, the log of schooling and dummy variables for Sub-Saharan Africa, Latin America and the Caribbean. The control variables are all measured in the initial year of each sub-period. α is a constant and ϵ_i is the error term. As the empirical growth literature suggests that human capital is a key determinant of output growth (Barro, 1991), we also add the average years of school attainment of the population aged 25 and over from Barro and Lee (2013). We transform all continuous variables into logs, except the growth rate and the measures of diversity, to scale down the variance and reduce the effect of outliers. We ask whether the coefficient of interest, λ, which captures the relationship between diversity and economic performances of country i, is stable across various time periods. To address this question, we estimate this model every year, from 1970 to 2016 to closely check the evolution of the coefficients of diversity.

Table 3.1: Summary statistics - baseline regressions

Control Variables	**Mean**	**Std. Dev.**	**N**
GDP per capita (constant 2010 US$)	10117.9	1533 5.1	7527
Average Schooling Years, Female & Male (25+)	5.3	3.3	1446
Sub-Saharan Africa Region - dummy	0.3	0.4	12384
Latin America and the Caribbean Region - dummy	0.2	0.4	12384
Cultural Diversity Measures	**Mean**	**Std. Dev.**	**N**
A: Fractionalization (Desmet, 2009)	0.4	0.3	12384
B: Ethnical Fragmentation (Alesina et al., 2003)	0.4	0.3	12384
C: Ethnic Fractionalization (Fearon, 2003)	0.5	0.3	10800
D: Cultural Diversity (Fearon, 2003)	0.3	0.2	10728
E: Religious Fragmentation (Alesina et al. 2003)	0.4	0.2	12384
F: Linguistic Fragmentation (Alesina et al. 2003)	0.4	0.3	11808
G: Ethnolinguistic Fractionalization (Atlas-1964)	0.4	0.3	5454
H: Ethnolinguistic Fractionalization - ELF (1961)	0.4	0.3	5467
I: Ethnolinguistic Fractionalization (Roberts, 1962)	0.5	0.3	2184

Table 3.1 contains the summary statistics of our measures of cultural distance and Table 3.2 gives information on the correlation between them. As we can see, the correlations among our classes of distance are not large, and are actually moderate when we look at religious distance, ensuring that they account for some distinct element of culture that are not captured by the remaining measures.

Table 3.2: Cross-correlation table - *Diversity* measures

Variables	A	B	C	D	E	F	G	H	I
A: Fractionalization (Desmet, 2009)	1.0								
B: Ethnic Fragmentation (Alesina et al., 2003)	0.5	1.0							
C: Ethnic Fractionalization (Fearon, 2003)	0.5	0.9	1.0						
D: Cultural Diversity (Fearon, 2003)	0.7	0.7	0.8	1.0					
E: Religious Fragmentation (Alesina et al., 2003)	0.0	0.2	0.3	0.2	1.0				
F: Linguistic Fragmentation (Alesina et al., 2003)	0.6	0.7	0.7	0.7	0.3	1.0			
G: Ethnolinguistic (Atlas-1964)	0.7	0.7	0.8	0.9	0.3	0.9	1.0		
H: Ethnolinguistic - ELF (1961)	0.6	0.8	0.8	0.7	0.3	0.8	0.9	1.0	
I: Ethnolinguistic (Roberts, 1962)	0.7	0.6	0.6	0.8	0.3	0.9	0.9	0.8	1.0

3.5 Results

Before turning to the evolution of the coefficient of diversity over-time, we start with Table 3.3, where we explore how diversity affects long-run growth using a pooled OLS for all countries between 1970 and 2016. We build on equation 3.1 but also add year dummies (which are then excluded when we turn to year-by-year equations). As we can see, with the only exceptions of religious diversity, all our indicators are negative and statistically significant at conventional levels.

—— Table 3.3 about here ——

This confirms that diversity has mostly adversarial effects on economic prosperity and that heterogeneity within societies produces conflicting preferences and coordination problems. As we said, the only exception is religious fragmentation. It is worthy to recall that although religiosity has long played a central role in social and political issues, as in Alesina et al. (2003), we do find that whereas ethnic fractionalization and linguistic fractionalization are inversely related to growth, religious fractionalization is not. This result runs against well-established evidences pointing out how people's beliefes play a key role in promoting socio-economic development (see e.g., Guiso et al., 2003; Montalvo and Reynal-Querol, 2003; Barro and McCleary, 2003; Barro, 2004) and democraticization (Barro, 1999; Künkler and Leininger, 2009). However, two stylized facts may help in reconciling this finding with previous contributions. First, religious affiliation is mainly an invisible cultural feature and might be absorbed by other individual cultural dimensions, such as ethnicity and language. In terms of the perception individuals may have of the surrounding religious diversity, associations can be made with respect to common religious adherence and ethnic group on a national or local basis. For instance, in continental European countries where the muslim community matches closely the geographical provenience of its adherents, one might infer an individual is muslim if she is North African. By the same fashion, across the US being African-American could be easily associated with catholic belief. Moreover, in contrast with visible traits of cultural diversity, religious adherence mights well change over one's lifetime. Consistently, religious beliefs may also be more sensitive to misreporting. Second, attitudes toward religion have significantly changed in Western countries over the 20th century. The phenomenon can be tracked down by retrieving cross-country information on “Religious Denomination" from World Values Survey (WVS) data[10]. In fact, answers to the WVS Integrated Questionnaire reveal a common decreasing trend in religious adherents across Western countries since the early eighties up to 2014[11]. On the analysis of this matter a consensus seems to be established among sociology scholars which include the decline in the share of devotees in the framework of the erosion of traditional social norms. In particular Turner (2008) identifies a link between the rise in mass consumption and the declining trend in religiousness. Maystre et al. (2014) posit on the analysis by Turner (2008) to argue how globalization decreases the relative utility of religion by increasing the supply of “secular goods". In Figure 3.1, we reproduce the model for different years from 1970 to 2016. In particular, we use Fractionalization Index (Desmet et al., 2009) - Figure 3.1.a, Ethnical Fragmentation (Alesina et al.

[10] World Values Survey 1981-2014 Longitudinal Aggregate v. 20150418. World Values Survey Association (www.worldvaluessurvey.org). Aggregate File Producer: JDSystems, Madrid SPAIN.

[11] It has been asked from wave one (1981-1984) to wave six (2010-2014) about : “Do you belong to a religious domination?" (the binary answer is “Yes" or “No").

2003) - Figure 3.1.b, Ethnic Fractionalization (Fearon, 2003) - Figure 3.1.c, Cultural Diversity (Fearon, 2003) - Figure 3.1.d and Religious fragmentation (Alesina et al. 2003) -Figure 3.1.e. Overall, we find that whereas the effect of diversity is again mostly negative - as also suggested by Table 3.3, it is significant mainly up to 1994. Perhaps more interestingly, however, the size of the coefficient increases over-time. A notable exception is religious fractionalization, which is never significant. This is consistent with the absence of correlation between religious diversity and the other indices as well as with the stylized facts concerning religious adherence outlined above. Also, ethnic fractionalization measured using Fearon (2003) is insignificant between 1970 and 1980. As the information that Fearon (2003) retrieves on ethnic groups belonging across the globe dates back to the nineties, this result might reflect how the relative share of these groups have changed in the two decades preceding data collection. This notwithstanding Fearon (2003) runs regressions using post-dated information without discussing this concern. Figure 3.1.b explores the effect of ethnolinguistic heterogeneity on economic growth. Interestingly, the results are overall similar to those in Figure 3.1.a. Yet, one might expect an accelerated speed of technological progress in more recent times and the effects of globalization. This might indicate that our time-invariant measures of diversity could not be well-suited to describe economies in post-globalization periods.

—— Figure 3.1 about here ——

3.5.1 A synthetic measure of *Diversity*

Cultural diversity is a catch-all and elusive concept, and conveys various information on differences in customs, beliefs, morals, laws, trust and information costs, among others. To dig deeper into the evolution of the impact of cultural diversity on economic growth over-time, we also construct a synthetic measure of cultural diversity. In more details, based on the cultural diversity variables listed in Table

3.1, we create a synthetic cultural diversity measure, using their first principal components. We use the first principal components as the loadings. We then run growth models of equation 3.1. In Appendix C we provide an alternative specification plotting residuals' coefficients instead of PCA results. Not surprisingly, we find analogous patterns. Interesting results emerge. First, since 1985 we observe a quite relevant decreasing trend in the negative impact of diversity over-time. Second, as we can see the 90s coincide with a common loss in significance across indices. More importantly, the small time window of significance across our plotted coefficients confirms the reason being of this study. As confidence intervals cross the zero line for most of the observed decades, previous findings relying on estimations averaged over-time may turn to be questionable at best. Results in this last figure suggest that there is definitely a need to operationalize more nuanced and effective measures of cultural diversity. We thus make a case for the inclusion of cultural diversity measures as a standard determinant in growth models, just like human capital or investments.

—— Figure 3.2 about here ——

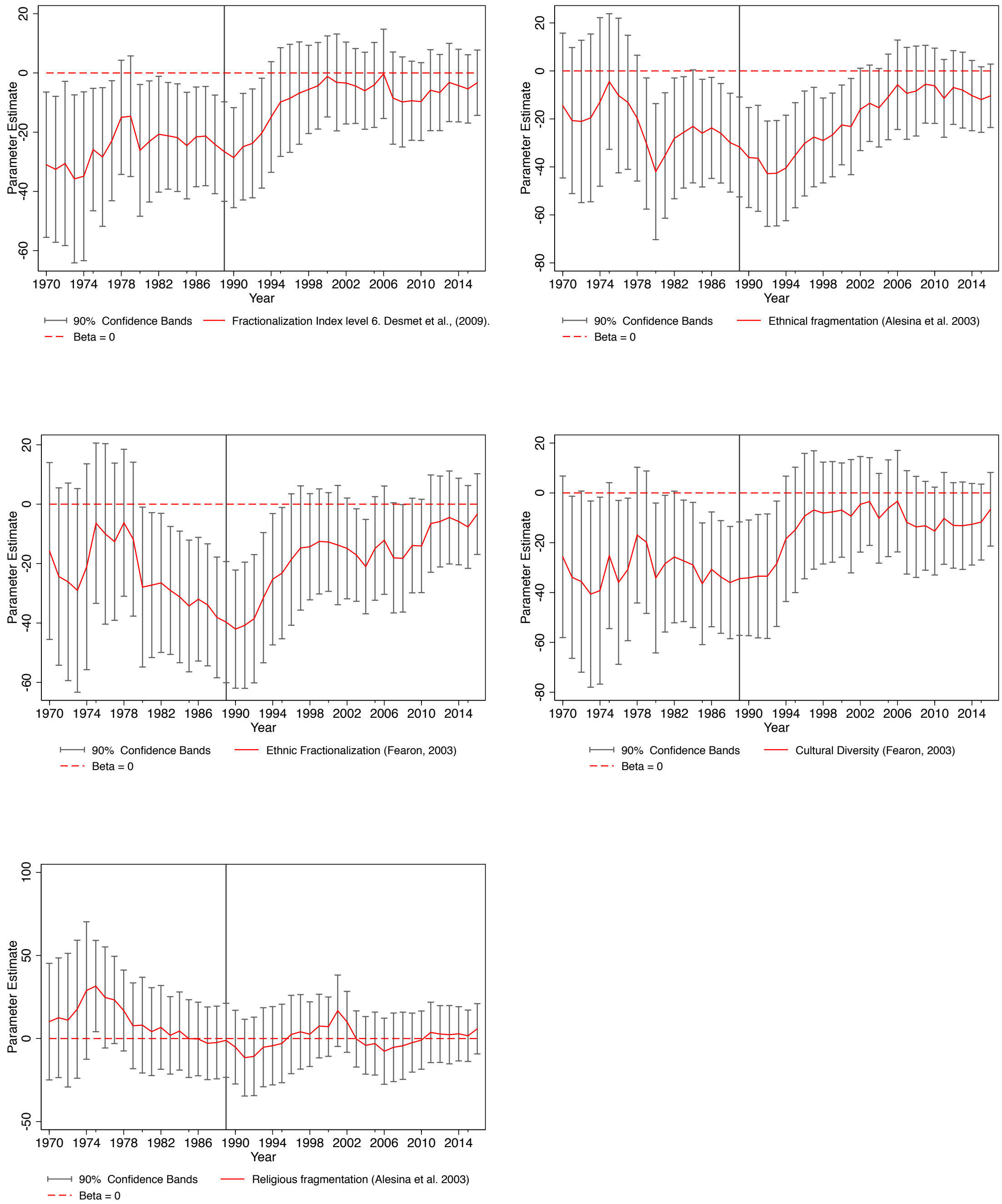


Figure 3.1: *Diversity* measures and Economic Prosperity (10-year GDP growth rate)

Figure 3.2: The effect of our synthetic measure of *Diversity* on Economic Prosperity (10-year GDP growth rate)

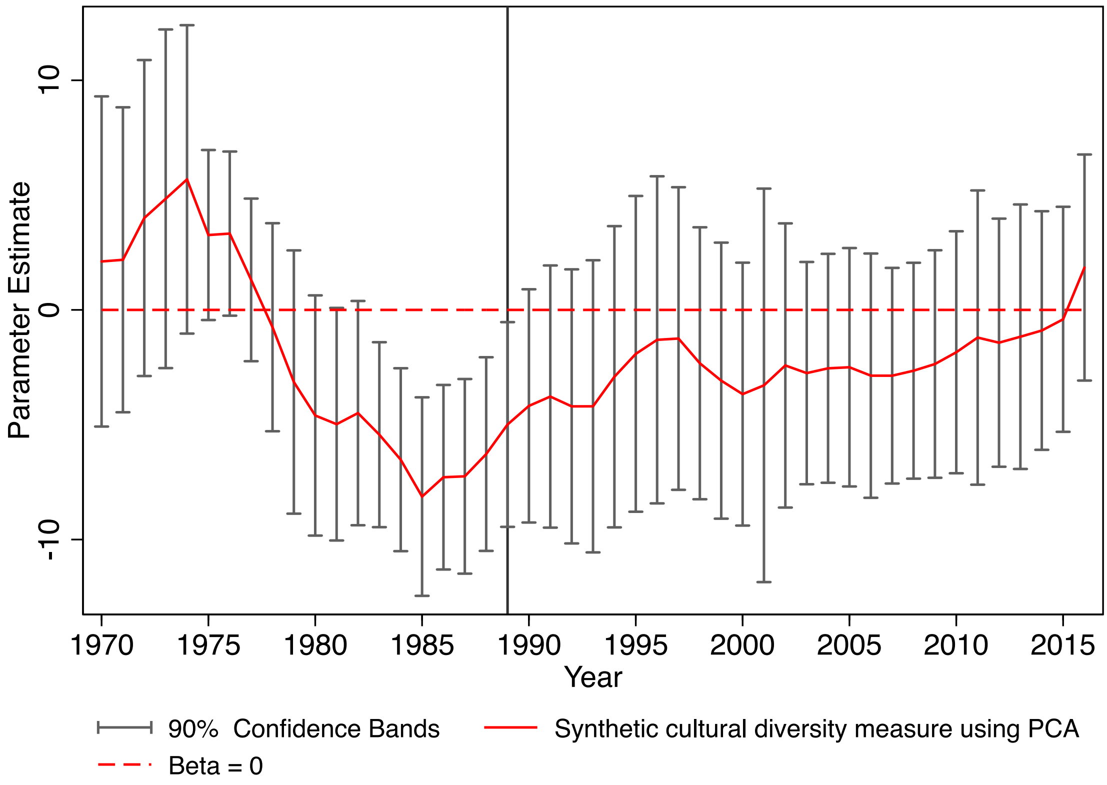


Table 3.3: *Diversity* and Economic Prosperity (dependent variable is long-run growth of per capita real GDP).

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)
A: Fractionalization (Desmet, 2009)	-14.355***								
	(1.514)								
B: Ethnic Fragmentation (Alesina et al., 2003)		-19.244***							
		(1.866)							
C: Ethnic Fractionalization (Fearon, 2003)			-18.678***						
			(1.835)						
D: Cultural Diversity (Fearon, 2003)				-18.245***					
				(2.054)					
E: Religious fragm (Alesina et al. 2003)					2.323				
					(1.976)				
F: Linguistic fragm (Alesina et al. 2003)						-18.395***			
						(1.791)			
G: Ethnolinguistic (Atlas-1964)							-12.357***		
							(1.769)		
H: Ethnolinguistic (1961)								-17.666***	
								(2.015)	
I: Ethnolinguistic (Roberts, 1962)									-23.859***
									(4.384)
Observations	4832	4832	4624	4599	4832	4701	3784	3531	1264
R^2	0.273	0.275	0.282	0.281	0.259	0.277	0.293	0.318	0.390

Note: Pooled OLS models for all countries between 1970 and 2016. The dependent variable is 10-year GDP per capita (PPP converted at 2010 constant prices),taken from the World Development Indicators. The set of control variables includes (log)initial income and initial income and initial income squared (World Bank, 2016); (log)schooling (Barro & Lee, 2013); Sub-Saharan Africa, Latin America and the Caribbean dummies (Wahman et al., (2013); Hadenius & Teorell, (2007)); year dummies. All controls are measured in the initial year of each sub-period.

Conventional significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

3.6 Mechanisms - I

After providing new evidence on the effects of diversity on economic growth overtime, we seek to explore some of the underlying transmission channels.

First, past work on economic growth has emphasized the lack of physical investments as one of the main impediment to economic growth Barro (1991). Therefore, we check whether the impact of diversity of economic growth may occur as a by-product of a decrease in investments because of e.g., lack of trust. We find that this is indeed the case and the effect of ethnic diversity on economic development works through a deterioration in the level of physical investments, regardless of the measure of investments we use. This seems to be one of the main transmission mechanisms.

Second, a recent study by Alesina et al. (2016) finds a positive effect of diversity on innovation and production; the authors argue that the effect of birthplace diversity should affect GDP per capita through Total Factor Productivity (TFP). We therefore explore whether our battery of indices of heterogeneity produce a similar positive correlation with total factor productivity, taken from the Penn World Table. Our results suggest that this is indeed the case and one of the underlying monetary mechanisms is the one that relates productivity to diversity. Table 3.4 reports summary statistics for the data employed in this Section. These include country-level data on 'Total Investment' (as % of GDP) provided by the IMF, covering the time window 1980-2016, across 173 countries.

We then extract from Penn World Table (PWT) - version 8, information on TFP and the 'Share of Gross Capital Formation - GCF', that is supplied for 182 countries, between 1950 and 2014. From the World Productivity Database (WPD) - provided by the United Nations Industrial Development Organization (UNIDO), we use 'Gross Capital Formation' (GCF) figures, which run from 1960 to 2000 for as many as 112 countries[12]. Covariates data for per capita GDP, per capita GDP

[12]All the data used are publicly available respectively at:
i) IMF: `https://www.imf.org/external/pubs/ft/weo/2018/01/`;

growth, population and trade are retrieved from the World Development Indicators (WDI) database[13].

Table 3.4: Summary statistics - transmission mechanisms

Alternative Dependant Variables	Mean	Std. Dev.	Min.	Max.	N
Total investment (Percent of GDP) [IMF]	23.8	9.5	-8.6	106.2	5080
GDP: GCF [WPD]	23.7	9.1	-13.4	95.2	7198
Share of GCF (at current PPPs) [PWT]	0.2	0.1	-0.1	0.9	7942
TFP (at constant national prices) [PWT]	0.9	0.3	0.2	4.4	5505

Control Variables [WDI]	Mean	Std. Dev.	Min.	Max.	N
GDP per capita (constant 2010 US$)	10117.9	15335.1	115.8	113682	7527
GDP per capita growth (annual %)	2.1	6.2	-65	140.5	7517
Population (total)	31928569.9	119037947.4	40834	1378665000	8422
Trade (% of GDP)	75.5	48.3	0	531.7	7538

3.6.1 The intermediate effect of Investments

A first channel may originate from the mechanics of physical investments. Therefore, in Table 3.5 we show the relation between heterogeneity and investments. We extract relevant information from the International Monetary Fund (IMF)[14]. The results clearly suggest that diversity decreases investments.

—— Table 3.5 about here ——

Given some of the theoretical ambiguities associated with the concept of physical investments, we use an array of measures[15]. As above mentioned, inherent information are retrieved from two alternative data sources: the UN WPD dataset[16]

ii) WPD: `https://www.unido.org/data1/wpd/Index.cfm`;
iii) PWT: `https://www.rug.nl/ggdc/productivity/pwt/`.

[13] Figures are publicly available at: `https://datacatalog.worldbank.org/dataset/world-development-indicators`.

[14] See Aiyar and Dalgaard (2005) for IMF data sources description and data set-up criteria.

[15] For a discussion refer to Breton (2015).

[16] See Isaksson (2007) for WPD data sources description and data set-up criteria.

and the Penn World Table[17]. We report OLS baseline estimates in the Appendix to this Chapter[18].

3.6.2 The intermediate effect of Total Factor Productivity

To offer further insights into the mechanism underlying the results reported in the previous section, we explore whether our findings are driven by changes in the level of total factor productivity. We follow Alesina et al. (2016) and replace our measure of GDP per capita with a measure of TFP per capita at constant national prices (2005=1) from the Penn World Table (ver. 8). Table 3.6 shows the results and confirm that diversity affects income also *via* total factor productivity.

—— Table 3.6 about here ——

Note that Ashraf and Galor (2013) claim that higher diversity in a population may have opposite effects on productivity and growth. On the one hand, technological advancement driven by diversity can have a positive impact. On the other hand, however, diversity can reduce cooperation, which in turn can decrease productivity and development. Particularly important for this research, the effect of diversity on growth can be 'hump-shaped', and the positive effects can be found at lower levels of diversity whereas the negative ones prevail at higher levels[19] .

---

[17]See Feenstra et al. (2015) for PWT data sources description and data set-up criteria.
[18]See Tables D6 - D7.
[19]For these reasons Ashraf and Galor (2013) include a quadratic effect.

Table 3.5: *Diversity* measures and Total Investment (% of GDP)

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)
A: Fractionalization (Desmet, 2009)	-3.805**								
	(1.817)								
B: Ethnic Fragmentation (Alesina et al., 2003)		-3.872**							
		(1.810)							
C: Ethnic Fractionalization (Fearon, 2003)			-5.592***						
			(1.868)						
D: Cultural Diversity (Fearon, 2003)				-3.722**					
				(1.606)					
E: Religious Fragmentation (Alesina et al., 2003)					-2.549				
					(1.727)				
F: Linguistic Fragmentation (Alesina et al., 2003)						-2.822*			
						(1.475)			
G: Ethnolinguistic (Atlas-1964)							-3.291**		
							(1.551)		
H: Ethnolinguistic - ELF (1961)								-4.344**	
								(1.868)	
I: Ethnolinguistic (Roberts, 1962)									-5.819*
									(3.107)
Observations	4813	4813	4254	4254	4813	4589	3085	2963	1120

Note: OLS models. The dependant variable is 'Total Investment (Percentage of GDP)' (IMF). Control variables include: per capita GDP, per capita GDP growth, population and trade (WDI). Year dummies are included but not reported. Standard errors in parentheses are clustered by country. Conventional significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table 3.6: *Diversity* measures and Total Factor Productivity

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)
A: Fractionalization (Desmet, 2009)	0.119*								
	(0.068)								
B: Ethnic Fragmentation (Alesina et al., 2003)		0.241***							
		(0.062)							
C: Ethnic Fractionalization (Fearon, 2003)			0.232***						
			(0.069)						
D: Cultural Diversity (Fearon, 2003)				0.153**					
				(0.061)					
E: Religious Fragmentation (Alesina et al., 2003)					-0.111*				
					(0.059)				
F: Linguistic Fragmentation (Alesina et al., 2003)						0.083			
						(0.061)			
G: Ethnolinguistic (Atlas-1964)							0.098*		
							(0.059)		
H: Ethnolinguistic - ELF (1961)								0.193**	
								(0.074)	
I: Ethnolinguistic (Roberts, 1962)									0.238**
									(0.110)
Observations	4656	4656	4490	4490	4656	4621	3670	3618	1322

Note: OLS models. The dependant variable is Total Factor Productivity (TFP) at constant national prices from (PWT ver. 8). Control variables include: per capita GDP, per capita GDP growth, population and trade (WDI). Year dummies are included but not reported. Standard errors in parentheses are clustered by country. Conventional significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

3.7 Mechanisms - II

To explore how exactly economic growth is affected by diversity, we ask whether social cohesion or attitudes towards other individual can constitute a transmission channel. There are no readily available data on people's sentiments towards diversity, and therefore we use data from the European Social Survey, in particular public attitudes towards people outside Europe, and trust into social interactions. We use the integrated data files of all eight rounds of the ESS covering 2002-2016 (including ESS round 8, edition 2.0) with the usual country-year as unit of analysis[20]. Variable values in years not included in the ESS between 2002 and 2016 are linearly interpolated. With these specifications, our sample includes 31 European countries. The first variable based on the ESS survey question "[t]o what extent do you think that your country should allow immigrants from poorer countries outside Europe.". Possible answers include "allow many to come and live here", "allow some", "allow a few" and "allow none". We first deleted all individuals who have not responded to this question or expressed no opinion ("do not know") before transforming this item into a binary variable capturing attitudes in favour of outside migration (1) or not (0); the "allow many" and "allow some" categories are merged into a single value of 1, while the "allow a few" and "allow none" categories pertain to the value of 0 of the new dichotomous item. We then collapse this individual-level variable to the country level by taking the mean across respondents. This allows us to get a reliable measure of the public mood towards outside-Europe migration in each country-year between 2002 and 2016, which ranges in [0; 1] with higher values indicating that a larger proportion of respondents approves migration from outside Europe. As an additional measure of positive attitudes towards others, we focus on trust using the following question from the ESS: "generally speaking, would you say that most people can be trusted, or that you can?t be too careful (i.e., need to be wary or always somewhat suspicious) in dealing with peo-

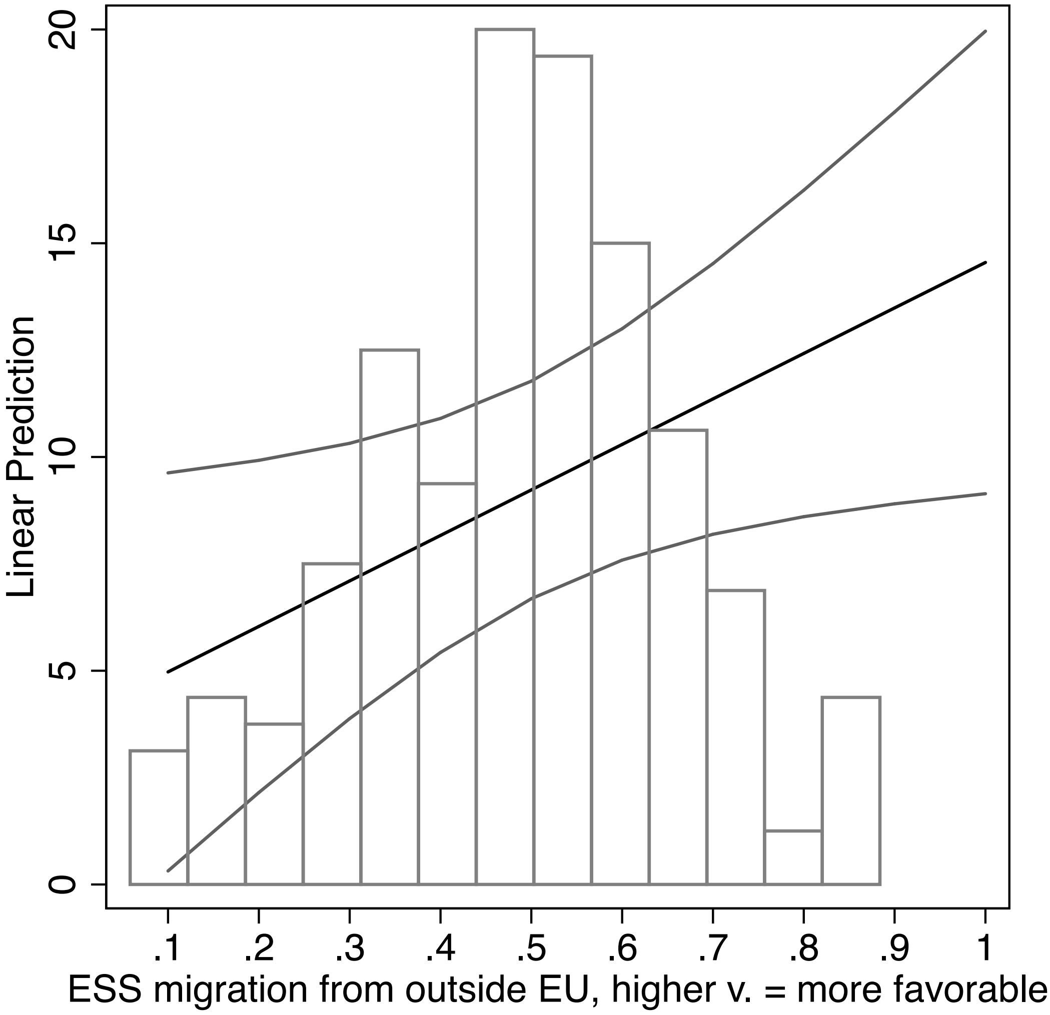
[20]This dataset has been assembled by the author at country level, requiring a considerable amount of time. As such, we hope it can be exploited for future research.

ple?" Individuals could reply on a scale from 1 to 10 with higher values standing for more trusting attitudes. We again collapse this variable to the country level by taking the average across respondents.

We expect to find a positive and statistically significant correlation between economic growth and either attitudes towards diversity/migration outside Europe or trust. We replicate the models in equation 3.1. We show the linear predictions for economic growth in light of the different values of public opinion towards immigrants and trust in Figure 3.3 below. As we can see, when moving from a low to high values of migration attitudes, our prediction for the outcome variable changes from about 0.1% to almost 20%. Similarly Figure 3.4 underlines that moving from a value of 2.3 to a value of 3.1 for Trust, economic growth is predicted to increase from about 0.1% to 0.46. Hence, we find strong and robust support for our theoretical expectations: social cohesion and public hostility towards non-native groups matters for economic growth.

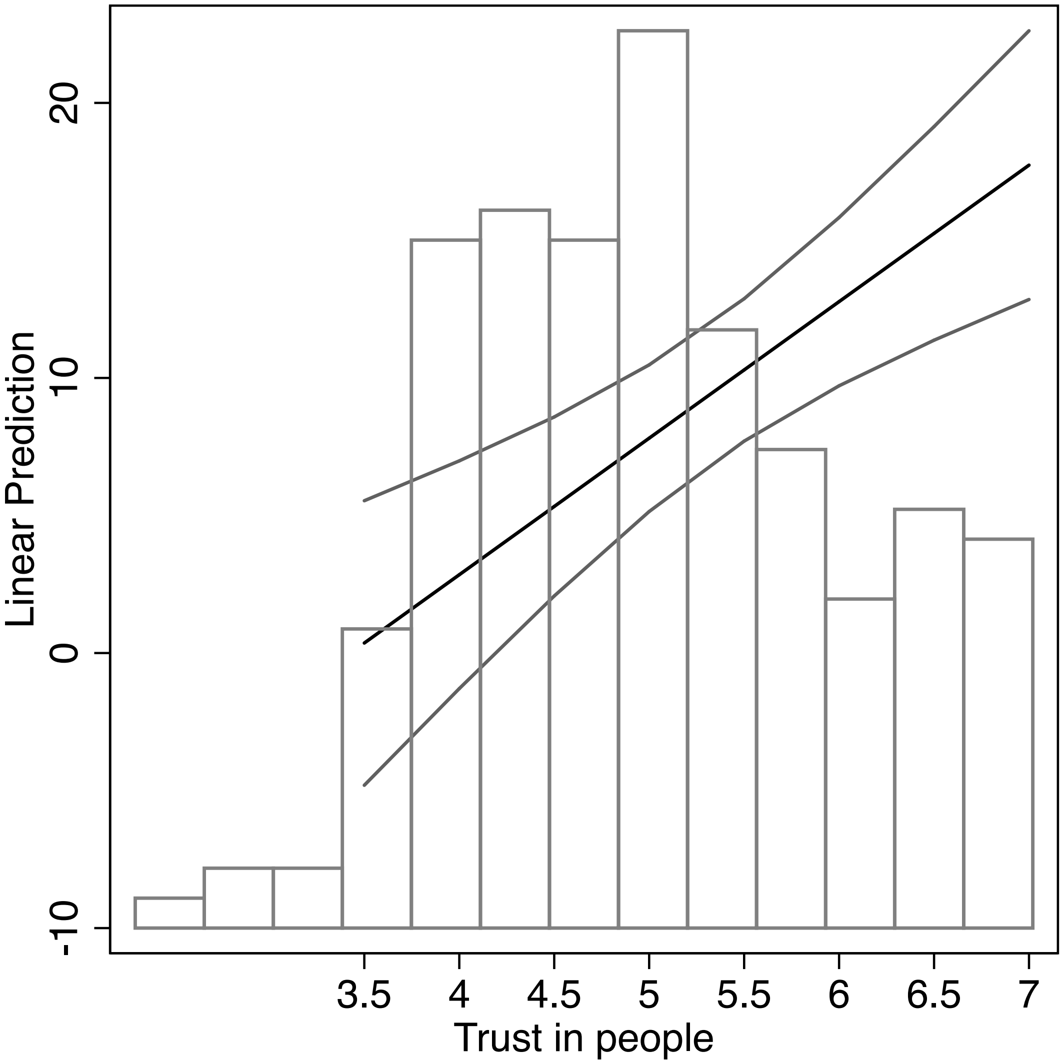
Accordingly with our last findings countries with higher levels of trust and more favourable with respect to immigrants tend to have higher rates of long-run growth. Reconciling these sketched evidences with the main of this Chapter, the negative impact of alternative measures of diversity on economic prosperity may well be sustained by low level of trust and un favourable attitudes towards migration inflows. As we know, nothing interesting is ever completely one-sided and - in accordance with Putnam (2007) and - in the long-run successful diverse societies can overcome initial decreases in trust, social solidarity and social capital that in turn negatively affect economic growth. However we put it, the advantages that a diverse range of cultures and skills can bring to socio-economic organizations crucially depend on their ability to benefit from these. Hence the attitudes expressed towards immigrants and the impact of diversity on economic outcomes seem to be two sides of the same story. Once again, this tackles the delicate issue of the endogenous determination of culture.

Figure 3.3: Marginal effects of different values of Public Opinion towards Immigrants on Economic Prosperity. Linear predictions.



Note: The graph shows average marginal effects of the Public Opinion towards Immigrants on Economic Prosperity. Public opinion data are obtained from the ESS at country level (31 European countries) for the period 2002-2016 (interpolated). Results are obtained by replicating our baseline specification.

Figure 3.4: Marginal effects of Trust on Economic Prosperity. Linear predictions.



Note: The graph shows average marginal effects of the Trust on Economic Prosperity. Trust data are obtained from the ESS at country level (31 European countries) for the period 2002-2016 (interpolated). Results are obtained by replicating our baseline specification.

3.8 Conclusions

Achieving stable economic growth has been at the forefront of the world agenda since the end of the recent economic crisis in 2008-2009. There are a number of factors that seem to contribute to economic growth, such as human capital, investments, and the quality of institutions. Yet, a new era of mass migration across Europe has reminded us that the makeup of modern societies has been quickly changing and this can have important effects on the rate of economic growth. In light of this, we seek to contribute to a large and growing debate on the economic effects of cultural diversity by including a battery of indices of ethnic, religious and linguistic diversity in standard economic models of growth. Our analysis covers the period 1970-2016. We find that whereas the effect of diversity is mostly negative it is significant mainly up to 1994, suggesting a possible unsuitability of time-invariant indices to describe diversity in the fast-changing globalization era. Interestingly, our synthetic measure of cultural distance exhibits similar patterns. We hope that this research provides important insights into the evolution of the effects of different markers of identity on economic growth over-time. In particular we would stress the inner limitations of average effects' estimations when considering time-invariant measures of diversity. The over-time variability in significance and sign outlined by our findings should convince the reader about it. Moreover, the extensions we have provided to the main analysis of this study are meant to support intuitive interpretations of the reason being of our results and to open up to a new timely avenue for future research.

Chapter 4

As far as we exchange:

Culture, Genetic Distance and Trade.

4.1 Introduction

This Chapter attempts to quantify the substantive impact of culture on international trade with a focus on genetic distance, and make comparisons vis-a-vis geographic distance, an all timer among trade determinants. In recent years, scholars have documented the importance of language and culture in explaining patterns of international trade. We now know that language barriers represent a major hurdle to trade between countries. For example, Egger and Lassmann (2012) find that having a common (official or spoken) language increases trade by 44% on average.[1] We also know that the language effect is larger when we move from dichotomous to continuous measures of linguistic distance (Lohmann, 2011; Melitz and Toubal, 2014). Interestingly, according to Rauch and Trindade (2002), common ancestry should have effects similar to those of common mother tongue. Yet, although having a common language correlates with the existence of similar cultural traits, it also conveys information that has little to do with culture (Felbermayr and

[1] See also Egger and Lassmann (2015) and Egger and Toubal (2016) for the role of various components of languages in international trade. Similarly, by lowering transaction costs, linguistic similarity and language-in-education policies make a country more attractive to also foreign direct investments (Selmier and Oh, 2013; Kim et al., 2014).

Toubal, 2010). Alternatively, to overcome the elusiveness of culture, Felbermayr and Toubal (2010) use data from the Eurovision Song Contest across 21 countries and show that cultural proximity affects trade flows.[2] Maystre et al. (2014) use the World Value Survey to construct measures of time-varying bilateral cultural distance and investigates the empirical relation between trade and culture. They find that whereas, on average, bilateral cultural distance decreased over the 1989-2004 period, bilateral trade openness is linked to a reduction of bilateral cultural distance.[3] We follow in their footsteps but add a battery of additional measures of cultural distance, including genetic distance, and track the evolution of the coefficient over time.

Importantly, Spolaore and Wacziarg (2009) investigate what impedes the diffusion of technological and institutional innovations across societies. They employ genetic distance to capture a wide array of cultural traits transmitted intergenerationally within populations over the long run. They find that important differences in societal norms, customs, and habits, proxied by genetic distance, act as barriers to the diffusion of development from the frontier country. We argue that such cultural barriers to development may be mitigated or exacerbated through trade relations. If the institutional environment is such that cultural differences impede two countries' trade, then, it will also distance them in terms of technology adoption and development. Although Spolaore and Wacziarg (2009) allude to this hypothesis, they do not study it systematically. In a similar vein, Guiso et al. (2009) demonstrate how the perception of trust, taken from Eurobarometer surveys, increases trade across a sample of European countries. Guiso et al. (2006) eloquently summarizes why trust can affect economic decisions, in particular trade, "Trust is particularly relevant when transactions involve some unknown counterpart like a buyer or seller of goods in another country, when the transaction takes place over a period of time rather than being completed on the spot, and when the legal protec-

[2]See also Guiso et al. (2009); Gokmen (2017); Giuliano et al. (2014).

[3]Disdier et al. (2010) use trade in cultural goods, which has the advantage of moving over time, as a proxy for cultural preferences.

tion is imperfect. These considerations suggest that international trade is an area where trust should matter" (Guiso et al., 2006, p.34). Interestingly, when Guiso et al. (2009) instrument trust using its long-term cultural building blocks, such as the commonality in religion and somatic/genetic distance, their estimates show larger coefficients. This finding implies that additional channels, besides trust, are likely to explain the impact of culture on trade. Giuliano et al. (2014) criticize this choice of instrument and argue that genetic distance indicates geographic barriers rather than cultural differences. They show that once geography is properly taken into account, genetic distance fails to achieve statistical significance.[4] Finally, Gokmen (2017) validates Huntington's (1993) Clash of Civilizations hypothesis that in the post-Cold War period the leading source of conflict is cultural, and therefore cultural differences cause clashes over several issues including trade. He finds that the negative impact of cultural dissimilarities on trade is larger in the post-Cold War period than during the Cold War.

In this study, we first quantify the impact of culture on trade by comparing a number of markers of identity, including genetic, religious and linguistic distances as well as differences in values, whereas most of the previous studies only use one marker. By doing so, we establish to what extent cultural distance has a substantive, economically relevant, impact on bilateral trade using a nearly exhaustive global sample of 160 countries over the period 1962-2012. We find that the magnitude of the impact of cultural distances, in particular of those weighted by the shares of sub-populations within each country, is similar to that of geographic distance, arguably one of the most important determinants of trade (see e.g., Lendle et al., 2012). We also highlight that genetic distance has the greatest influence on trade among the markers of cultural similarity. When we look at the evolution of the effect of culture on trade over time, we find that the impact of cultural barriers (measured by genetic distance) on economic exchange in the last five decades

[4]See also Yu et al. (2015), where the authors show trust and rule of law are substitutes in facilitating trade flows.

is rather stable. We also construct a synthetic measure of *cultural distance* and show that its effect on trade is always greater than that of geographic distance. Especially in the 2000s, the substantive effect *cultural distance* on trade is almost twice as large as that of geographic distance. Therefore, we make a case for the inclusion of our new measure of cultural distance as a standard determinant in gravity models of international trade, just like geographic distance or contiguity.

We estimate our model for different time periods, and find that the evolution of the impact of cultural barriers on economic exchange in the last five decades does not exhibit major changes and is rather stable. We also show that the evolution of the impact of geographic distance and genetic distance is statistically indistinguishable.

There are three shortcomings in the studies on culture and trade. They all use a measure of cultural distance for subsamples of rather homogeneous European countries and over a limited number of years. Finally, it has not yet been established to what extent cultural distance has a substantive, economically relevant, impact on bilateral trade.

In the next Section we introduce and discuss the range of cultural distance measures employed. Section 4.3 spells out the econometric specification and points out the rest of the dataset. We discuss our results in Section 4.4. Section 4.5.1 provides a further investigation of the intermediating role of perception in supporting the impact of cultural distance on trade. Thereby we use a rich dataset collected by the author on the attitudes towards immigrants, considering the latter as a proxy for attitudes towards cultural distance. We present the underlying empirical specification in Section 4.5.1 and then present inherent results in Section 4.6. Section 4.7 provides conclusive remarks.

4.2 Cultural Distance Measures

We employ multiple proxies of cultural affinity such as genetic, religious and linguistic distances as well as distances in values. Genetic distance is our main variable of interest and it captures differences in allele frequencies across a range of neutral genes. Spolaore and Wacziarg (2015) convincingly show that genetic distance provides a useful summary of a wide array of cultural traits transmitted intergenerationally. There are several versions of this variable (see Cavalli-Sforza et al., 1994) and the one we use, from Spolaore and Wacziarg (2009) and called F_{ST}, is a measure of distance to the most recent common ancestors of two populations, i.e. their degree of genealogical relatedness, or equivalently, the length of time since two populations split apart.[5]

Yet F_{ST} is based on dominant groups. To better determine the expected genetic distance between two randomly selected individuals, we also use genetic distance weighted by the share of population belonging to each distinct ancestral group in each country (see Spolaore and Wacziarg, 2009). By measuring the time since two populations shared common ancestors, genetic distance provides an ideal summary of differences in slowly changing genealogically transmitted characteristics, including habits and customs (Spolaore and Wacziarg, 2009, p. 523).

We use two measures of religious distance, both taken from Spolaore and Wacziarg (2015). They base their indices on Fearon et al. (2006) and the World Christian Database (WCD)[6] on the prevalence of religion in each country, the former providing higher level of disaggregation. They calculate the number of common nodes between the dominant religions of each country in a pair and implement a simple transformation to obtain measures of religious distance bounded by 0 and 1. Religion has always played a central role in social and economic issues, and re-

[5] F_{ST} is constructed using information on 128 alleles related to 45 selectively neutral genes. It includes alleles coding for blood groups, immunoglobulin, hemoglobin, enzymes and lymphocyte antigens. We refer the interested reader to Spolaore and Wacziarg (2009) for more information and the formal definition.

[6] `http://www.worldchristiandatabase.org/wcd/`

ligious affiliations can affect the degree of cohesion within societies. We therefore include also weighted distances using the share of each religious sub-group within each country. In Spolaore & Wacziarg 's (2015) version, all value-related questions appearing in the WVS 1981- 2010 Integrated Questionnaire are converted into distances by category. The categories are seven: a) Perceptions of Life; b), Environment; c) Work; d) Family; e) Politics and Society; f) Religion and Morale; and g) National Identity.

Table 4.1: Summary statistics

	Mean	Std. Dev.	Min	Max	Obs
Genetic Distance	0.095	0.070	0	0.29	549711
Genetic Distance, Weighted	0.094	0.058	0	0.30	549711
Cognate Distance	0.444	0.226	0	0.65	134187
Cognate Distance, Weighted	0.423	0.208	0	0.65	68547
Linguistic Distance	0.656	0.133	0	0.69	447613
Linguistic Distance, Weighted	0.666	0.091	0	0.69	447613
Religious Distance, Fearon	0.531	0.240	0	0.69	451252
Religious Distance, Fearon Weighted	0.595	0.103	0.08	0.69	451252
Religious Distance, WCD	0.441	0.265	0	0.69	542534
Religious Distance, WCD Weighted	0.550	0.102	0.11	0.69	542534
Cultural Distance, WVS (Traditional/Survival)	0.310	0.136	0	0.60	1879

To establish a close link with recent works on linguistic distances, we use two indices, one based on language trees (Fearon, 2003) and another one based on lexicostatistics (Dyen et al., 1992). In the former languages are grouped into families based on similarities between them and it is therefore based on a discrete number of common nodes. The latter is constructed using 200 common meanings and provides the percentage of words between dominant languages spoken in each country-pair which originate from the same ancestor word (the so-called "cognate words"). Again, we rely on Spolaore & Wacziarg's (2015) transformation into distances ranging from 0 to 1 as well as on the weighted versions of both distances, where sub-populations within each country are duly taken into account[7].

[7]We refer the interested reader to the original papers for a discussions of the properties of each variable.

Table 4.2: Correlations between Cultural Distance Variables

	A	B	C	D	E	F	G	H	I	J
A: Genetic D.										
B: Genetic D.(Weighted)	0.600***									
C: Cognate D.	-0.184***	-0.374***								
D: Cognate D.(Weighted)	-0.220***	-0.403***	0.976***							
E: Linguistic D.	-0.219***	-0.450***	0.878***	0.855***						
F: Linguistic D.(Weighted)	-0.249***	-0.501***	0.854***	0.872***	0.966***					
G: Religious D.(Fearon)	-0.151**	-0.157**	0.520***	0.608***	0.393***	0.445***				
H: Religious D.(Fearon Weighted)	-0.130*	-0.227***	0.556***	0.620***	0.440***	0.479***	0.899***			
I: Religious D.(WCD)	-0.138**	-0.118*	0.509***	0.597***	0.376***	0.429***	0.953***	0.838***		
J: Religious D.(WCD Weighted)	-0.275***	-0.388***	0.658***	0.715***	0.583***	0.642***	0.828***	0.880***	0.830***	
K: Cultural D.(WVS) (Traditional/Survival)	-0.0595	-0.00231	0.406***	0.412***	0.315***	0.284***	0.497***	0.544***	0.441***	0.432***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We also retrieve information from the World Values Survey (WVS),[8] which provides standardized and time-varying data for a range of cultural issues, e.g., gender roles, family values, communal identities, civic engagement, ethical concerns, environmental protection, and scientific and technological progress (see Inglehart and Welzel, 2005). The surveys, conducted between 1998 and 2006, are available for 74 countries. We use composite value of two dimensions, traditional vs. secular-rational values, which capture the difference between societies in which religion is very important and those in which it is not; and survival vs. self-expression values, linked to the transition from industrial society to post-industrial societies. The two dimensions account for more than 70% of the cross-cultural variance. We transform the WVS values to obtain distances ranging from 0 to 1.

4.3 Estimation

We estimate the standard log-linear gravity equation *à la* Anderson and van Wincoop (2003):

$$\log Y_{ijt} = a + \gamma \log C_{ij} + \alpha_k \tau_{kijt} + R_i * Year_t + R_j * Year_t + \epsilon_{ijt} \tag{4.1}$$

[8] `http://www.worldvaluessurvey.org/wvs.jsp`

where Y_{ijt} is imports from country i to j in year t; a is a constant; C_{ij} is our variable of interest, the cultural distance between i and j; τ_{kijt} represents the k bilateral trade barriers other than culture; R_i and R_j are exporting and importing country fixed effects, respectively; $Year_t$ is yearly time fixed effects; and ϵ_{ijt} is the error term. Our empirical strategy likely soaks up much of the effects of country-specific variables. $R_{i/j} * Year_t$ account for multilateral resistance terms, whose exclusion bias estimates (Anderson and van Wincoop, 2003), and flexibly account for time-varying country-specific characteristics (e.g., per capita GDP of i and j). The inclusion of exporting and importing country fixed effects is also shown to produce consistent estimates (see Feenstra, 2002). Lastly, γ, our parameter of interest, represents the elasticity of Y with respect to C, as both are log-transformed.

Trade Data are from UN ComTrade data set that includes aggregate yearly trade flows across dyads. We include a dummy for land or water contiguity between two countries as well as the great circle (geodesic) distance between the major cities of the countries. We transform the geographic distance into log to scale down the variance, reduce the effect of outliers and provide a coefficient which is directly comparable to that of cultural distance. To control for institutional and historical links we include dummies for the same legal origin, which can lower transaction costs, due to legal and regulatory systems, and improve mutual trust (Guiso et al., 2009). The inclusion of this variable ensures also that our cultural distances are not simply capturing differences in the legal origin. We also control for the existence of a colonial relationship, i.e., whether one country was a colony of the other at some point in time.

We strive to control for a host of economic and political relations, and include indicators for free trade agreements (FTA), GATT/WTO membership, common currency and generalized system of preferences agreements (GSP). Finally, throughout the models, we include the presence of a common language, to isolate the impact of culture after controlling for simple communication costs.[9]

[9]The control variables can be accessed on CEPII's or Thierry Mayer's webpage. `http://`

4.3.1 Gravity model limitations and 'zero valued' trade flows

Gravity models are now a common practice the empirical literature in international trade (Linders and de Groot 2006). The pioneer in this sense was Jan Tinbergen (1962), who was followed by a great number of scholars (e.g. Linneman 1966; Anderson 1979; Deardorff 1984; Bergstrand 1985; or Frankel et al. 1997). There are, however, still discussions about the appropriate model specification (see e.g. Anderson and Van Wincoop 2003). Santos Silva and Tenreyro (2006) and Martínez-Zarzoso et al. (2013) propose to use the Poisson method, whose main advantage consists in the possibility of working with a continuous dependent variable and offers a solution to the displacement problem related to the heteroskedasticity caused by the log-linear form of the model. We have discussed most of the technicalities concerning gravity model's limitations in Chapter 2, to which we refer the interested reader. A less discussed issue concerns which strategy to choose to deal with 'zero valued' bilateral trade figures. This may turn to be an important factor in terms of results reliability as well as in bringing unfortunate consequences with respect to measurement errors. Some scholars sustain that this concern can be addressed by using Tobit models, where the unobserved part of the dependent variable is continuous and censored to some specific value. This procedure may then be useful when zero trade flows are a consequence of the applied methodology[10]. However, the Tobit model does not explain trade figures are missing (Linders and de Groot 2006). In this study we have implemented a new imputation strategy exploiting Least Squares (LS) prediction procedure with Least Absolute Shrinkage Operator (LASSO) technique. The latter - by augmenting the LS with a penality term - selects the subset of dyads whose linear combination best predicts the trade observed figures different from zero. After fitting, we have then replaced unobserved values using the out-of-sample prediction. We compare the resulting

econ.sciences-po.fr/node/131.

[10]See: Soloaga and Wintersb 2001; Rose 2004; Linders and de Groot 2006; Kuchar?uková et al. 2012; Gran?ay et al. 2015.

trade figures with both i) those obtained by implementing linear interpolation (by following Barbieri et al., 2009) and ii) those imputed by interpreting all zero valued figures as 'true zeros'. Therewith we find that our LS-LASSO procedure provides the best approximation. Hence trade figures used trhoughout this Chapter have had 'zero valued' cells imputes by the LS-LASSO prediction method.

4.4 Results

Table 4.3 includes genetic distance and two measures of linguistic distances, based on language trees and lexicostatistics (i.e., cognate distance). Recall that we control for geographic distance throughout the models to make sure that none of our cultural distances are picking up geographical impediments that can affect transportation costs. Genetic distance has the largest substantive impact and a 10% increase causes a 9.7% to 15% decrease in bilateral trade flows. As many countries are fragmented into a multitude of genetic groups, the weighted version of genetic distance provides a more refined measure of cultural distance between countries, where the relative weight that each group has in relation to the others within each country is explicitly taken into account. Accordingly, it also displays a relatively more meaningful effect on trade.

—— Tables 4.3 and 4.4 about here ——

By accounting for deeper cultural roots and divergence in characteristics transmitted across generations over the long-run, genetic distance is a large and important factor affecting trade. Although cognate distances are insignificant overall, linguistic distance based on trees has an effect smaller than in previous studies (e.g., Lohmann, 2011), even after correcting for within-country weights. Note however that when we do not control for common official language, cognate distance is negative and significant. Virtually all our control variables for economic and political relations exhibit the expected positive sign and are all significant at conventional levels.

Table 4.4 includes an array of measures of religious distance, as well as a more direct measure of cultural boundaries based on the World Value Survey. The lower end of the estimated impact of religious distance is -0.31, whereas the upper end is -1.25. Note again that weighted indices have more sizeable effects. This is not surprising as they move beyond the assumption that countries are culturally homogeneous and provide more nuanced measures of the distance between countries with heterogenous sub-populations. The coefficient of cultural distance based on the World Value Survey (column v) is about -0.9. It is remarkably significant and of the same magnitude of genetic distance, despite the fact that the sample size of the latter is around 290 times larger than the former. This provides further empirical support to the idea that cultural distance is indeed a critical barrier to trade.

Although geographic barriers, in particular geographic distance metrics, enjoy near-consensus support as a main deterrent of trade, note that the coefficient of (log) of geographic distance is about -1.3 on average. Therefore, the estimates of the impact of genetic and religious distances (weighted) as well as cultural distance constructed using the World Value Survey are similar to those of geographic distance, after explicitly controlling for a range of geographic metrics. Overall, Table 4.4 pins down the average impact of culture on trade and show its relevance and substantive impact on trade across a range of different measures.

—— Table 4.5 about here ——

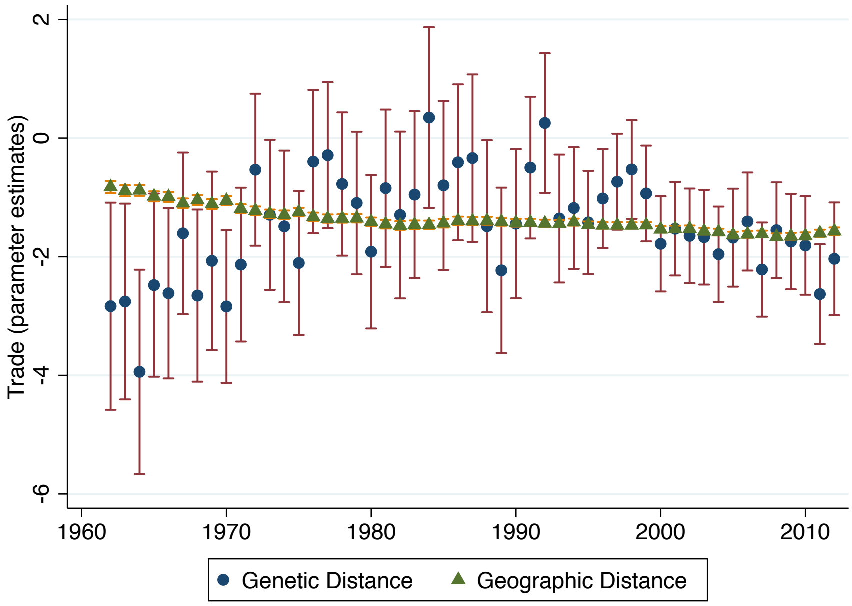
We then move to Table 4.5 where we reproduce the baseline model of column (ii) of Table 4.4 with genetic distance for five decades, from 1960s to 2000s. We find that the coefficients of genetic distance are consistently negative and significant, and overall of the same order of magnitude (within similar confidence intervals). There is only a slight decline in the effect of genetic distance from the 1960s until the first decade after the end of the Cold War. In fact, the coefficient moves from

-2.0 in the 1960s to -0.9 in the 1990s. In the last decade, however, the impact of the genetic distance variable doubles in absolute value, reaching -1.8, close to the magnitude of the coefficient in the 1960s, -2.0. Yet, given the size of the standard errors, the magnitudes of these decade-specific coefficients are statistically difficult to distinguish from each other.

In Figure 4.1 we track the magnitude of the coefficients of genetic distance and geographic distance, with their 95% confidence interval, from the regression in equation 4.1. As one moves across the x-axis in Figure 4.1, genetic distance has a negative and significant effect on trade from the 1960s until the 1970s. Then, from the 1970s until the end of the Cold War most of the coefficients are statistically indistinguishable from zero at the 5% level. From 1992 on the coefficient is again negative and significant and its effect gradually builds up, in particular after 1998. Whereas advances in transportation and communication technologies and the globalization of markets might have reduced the effect of cultural barriers on trade, the increase in genetic distance coefficient in the last decade could suggest a resurgence of the role played by cultural differences in economic exchange. In this context, advances in technology in recent decades could have failed to further reduce cultural frictions between countries, due to e.g., dissimilarity of preferences and tastes, trust and misunderstandings related to non-verbal communication (see e.g., Gokmen, 2017). Yet, the annual coefficients are imprecisely estimated, the standard errors are quite sizeable, and therefore this pattern should be interpreted with caution. When we turn to geographic barriers, although we observe a modest decreasing trend in the negative impact of distance over time, the coefficients are very similar to each other.

To dig deeper into the evolution of the impact of cultural distance on international trade over time, in Table 4.6, column (i), we first pick the distances with the higher relative impact, i.e., genetic, linguistic and religious distance (Fearon, 2003), all weighted. We then include them simultaneously in the same model and

Figure 4.1: Evolution of the Effect of Genetic Distance and Geographic Distance on Trade



find that their coefficients remain statistically different from zero at convention levels. If anything, this is further evidence that these markers of identity are indeed capturing distinct elements of culture, and they all have independent and discernible impacts on economic exchanges between countries. At the same time, this also means that their combined effect should be greater than that of geographic distance.

—— Table 4.6 about here ——

Subsequently, based on these three cultural distance variables, we create a synthetic cultural distance measure, called *cultural distance*, using their first principal components (with the first principal components as the loadings). We transform its values to obtain distances ranging from 0 to 1 and take the log to make the coefficient comparable to those of the other distances and to facilitate its interpretation. We then run gravity models for the entire period (column ii) and for different decades (columns iii to vii). Reading across the first row of results, we find that this new summary *cultural distance* measure has a very strong effect over the entire period (the coefficient is -1.6), and the impact is at least as large as that of geographic distance. Interestingly, in the 2000s the substantive effect of *cultural distance* on trade is almost twice as large as that of geographic distance.

Table 4.3: Cultural Distance and International Trade I

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Genetic Distance	-0.973***					
	(0.211)					
Genetic Distance, Weighted		-1.515***				
		(0.248)				
Cognate Distance			-0.259			
			(0.188)			
Cognate Distance, Weighted				0.066		
				(0.307)		
Linguistic Distance					-0.471***	
					(0.137)	
Linguistic Distance, Weighted						-0.742***
						(0.193)
Log Geographic Distance	-1.443***	-1.432***	-1.363***	-1.188***	-1.373***	-1.367***
	(0.020)	(0.020)	(0.032)	(0.043)	(0.024)	(0.024)
Contiguity	0.360***	0.364***	0.429***	0.223	0.671***	0.674***
	(0.089)	(0.089)	(0.136)	(0.176)	(0.093)	(0.093)
Common Official Language	0.555***	0.559***	0.470***	0.500***	0.522***	0.523***
	(0.038)	(0.038)	(0.093)	(0.133)	(0.048)	(0.047)
Common Legal Origin	0.355***	0.356***	0.377***	0.445***	0.362***	0.361***
	(0.026)	(0.026)	(0.059)	(0.097)	(0.028)	(0.028)
Colonial Link	1.047***	1.046***	0.936***	0.886***	0.833***	0.853***
	(0.085)	(0.085)	(0.111)	(0.134)	(0.093)	(0.092)
Free Trade Agreements	0.576***	0.564***	0.612***	0.849***	0.460***	0.464***
	(0.044)	(0.044)	(0.077)	(0.096)	(0.047)	(0.047)
GATT/WTO Membership	0.106**	0.109**	-0.170	-0.081	0.091*	0.095*
	(0.049)	(0.049)	(0.106)	(0.161)	(0.055)	(0.055)
Common Currency	0.399***	0.373***	0.131	0.295*	0.608***	0.605***
	(0.097)	(0.096)	(0.159)	(0.166)	(0.115)	(0.115)
Generalized System of Preferences	0.934***	0.936***	1.148***	1.099***	0.932***	0.931***
	(0.041)	(0.040)	(0.071)	(0.098)	(0.044)	(0.044)
N	549543	549543	134162	68537	447512	447512

Note: Regressand: Log of Imports. Each regression includes time-varying exporter and importer fixed effects. Import figures are retrieved from UN ComTrade data. Genetic Distance is taken from Spolaore and Wacziarg (2009). Linguistic indices are obtained by Fearon (2003) and Dyen et al. (1992). The other control variables are taken from the CEPII dataset. Results refer to a sample of 160 countries over the period 1962-2012. Robust standard errors clustered by dyad are given in parentheses. Significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table 4.4: Cultural Distance and International Trade II

	(i)	(ii)	(iii)	(iv)	(v)
Religious Distance, Fearon	-0.469***				
	(0.059)				
Religious Distance, Fearon Weighted		-1.248***			
		(0.155)			
Religious Distance, WCD			-0.317***		
			(0.049)		
Religious Distance, WCD Weighted				-1.206***	
				(0.151)	
Cultural Distance, WVS (Traditional/Survival)					-0.901**
					(0.398)
Log Geographic Distance	-1.374***	-1.366***	-1.444***	-1.435***	-1.410***
	(0.023)	(0.023)	(0.020)	(0.020)	(0.075)
Contiguity	0.623***	0.635***	0.348***	0.329***	0.257
	(0.093)	(0.093)	(0.090)	(0.089)	(0.223)
Common Official Language	0.557***	0.539***	0.548***	0.520***	0.404**
	(0.043)	(0.043)	(0.038)	(0.038)	(0.165)
Common Legal Origin	0.360***	0.358***	0.329***	0.331***	0.119
	(0.028)	(0.028)	(0.026)	(0.026)	(0.112)
Colonial Link	0.863***	0.864***	1.021***	1.016***	1.123***
	(0.092)	(0.092)	(0.084)	(0.084)	(0.378)
Free Trade Agreements	0.435***	0.444***	0.563***	0.576***	0.256*
	(0.047)	(0.047)	(0.045)	(0.045)	(0.140)
GATT/WTO Membership	0.083	0.074	0.059	0.046	0.210
	(0.055)	(0.055)	(0.050)	(0.050)	(0.315)
Common Currency	0.561***	0.546***	0.484***	0.495***	-0.863***
	(0.115)	(0.116)	(0.097)	(0.097)	(0.298)
Generalized System of Preferences	0.930***	0.943***	0.919***	0.929***	0.470***
	(0.044)	(0.044)	(0.041)	(0.041)	(0.129)
N	451149	451149	542371	542371	1879

Note: Regressand: Log of Imports. Each regression includes time-varying exporter and importer fixed effects. Import figures are retrieved from UN ComTrade data. Religious Distance measures are taken from Fearon et al. (2006) and the World Christian Database (WCD). Cultural Distance here is computed by the author using World Values Surveys (WVS) data. The other control variables are taken from the CEPII dataset. Results refer to a sample of 160 countries over the period 1962-2012. Robust standard errors clustered by dyad are given in parentheses. Significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table 4.5: Genetic Distance versus Geographic Distance over Time

	(i) 60s	(ii) 70s	(iii) 80s	(iv) 90s	(v) 2000s
Genetic Distance, Weighted	-2.020***	-1.065**	-1.275***	-0.887***	-1.765***
	(0.580)	(0.464)	(0.486)	(0.310)	(0.277)
Log Distance	-1.007***	-1.313***	-1.524***	-1.439***	-1.552***
	(0.039)	(0.030)	(0.031)	(0.023)	(0.024)
Contiguity	0.663***	0.429***	0.034	0.414***	0.500***
	(0.141)	(0.124)	(0.123)	(0.093)	(0.102)
Common Official Language	0.436***	0.460***	0.371***	0.557***	0.715***
	(0.073)	(0.060)	(0.060)	(0.047)	(0.042)
Common Legal Origin	0.224***	0.309***	0.309***	0.380***	0.391***
	(0.056)	(0.044)	(0.044)	(0.031)	(0.029)
Colonial Link	1.323***	1.350***	1.192***	0.895***	0.727***
	(0.124)	(0.100)	(0.110)	(0.096)	(0.096)
Free Trade Agreements	0.124	0.123	0.147	0.443***	0.567***
	(0.182)	(0.110)	(0.106)	(0.059)	(0.048)
GATT/WTO Membership	-0.173**	-0.038	0.219**	0.517***	0.186*
	(0.081)	(0.078)	(0.086)	(0.068)	(0.099)
Common Currency	0.912***	1.021***	0.625***	0.456***	-0.235*
	(0.127)	(0.149)	(0.191)	(0.159)	(0.126)
Generalized System of Preferences	1.269***	1.150***	1.209***	0.895***	0.686***
	(0.307)	(0.067)	(0.070)	(0.049)	(0.045)
N	42907	80265	79276	116399	230696

Regressand: Log of Imports. Each regression includes time-varying exporter and importer fixed effects.
Robust standard errors clustered by dyad are given in parentheses.
$*p < 0.10, **p < 0.05, ***p < 0.01$

Note: Regressand: Log of Imports. Each regression includes time-varying exporter and importer fixed effects. Import figures are retrieved from UN ComTrade data. Genetic Distance is taken from Spolaore and Wacziarg (2009). Control variables are taken from the CEPII dataset. Results refer to a sample of 160 countries per decade. Robust standard errors clustered by dyad are given in parentheses. Significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table 4.6: Cultural Distance versus Geographic Distance over Time

	(i) Full	(ii) Full	(iii) 60s	(iv) 70s	(v) 80s	(vi) 90s	(vii) 2000s
Genetic Distance, Weighted	-0.942***						
	(0.274)						
Linguistic Distance, Weighted	-0.434**						
	(0.198)						
Religious Distance, Fearon Weighted	-1.152***						
	(0.160)						
Cultural Distance		-1.597***	-0.865**	-1.264***	-1.273***	-1.394***	-2.474***
		(0.223)	(0.384)	(0.334)	(0.334)	(0.265)	(0.252)
Log Distance	-1.322***	-1.330***	-1.013***	-1.285***	-1.452***	-1.346***	-1.369***
	(0.025)	(0.025)	(0.042)	(0.036)	(0.036)	(0.028)	(0.030)
Contiguity	0.646***	0.666***	0.859***	0.653***	0.373***	0.673***	0.814***
	(0.093)	(0.093)	(0.143)	(0.131)	(0.129)	(0.099)	(0.108)
Common Official Language	0.497***	0.473***	0.382***	0.309***	0.241***	0.493***	0.653***
	(0.047)	(0.046)	(0.084)	(0.072)	(0.074)	(0.057)	(0.052)
Common Legal Origin	0.361***	0.362***	0.196***	0.301***	0.286***	0.390***	0.410***
	(0.029)	(0.028)	(0.060)	(0.050)	(0.049)	(0.034)	(0.031)
Colonial Link	0.847***	0.850***	1.294***	1.232***	0.972***	0.652***	0.467***
	(0.093)	(0.093)	(0.130)	(0.110)	(0.122)	(0.102)	(0.101)
Free Trade Agreements	0.447***	0.462***	0.230	-0.093	-0.375***	0.261***	0.548***
	(0.047)	(0.047)	(0.186)	(0.136)	(0.121)	(0.063)	(0.051)
GATT/WTO Membership	0.078	0.087	-0.132	-0.061	0.131	0.551***	0.187*
	(0.055)	(0.055)	(0.086)	(0.088)	(0.096)	(0.076)	(0.113)
Common Currency	0.521***	0.585***	1.027***	1.255***	0.877***	0.603***	-0.041
	(0.115)	(0.115)	(0.135)	(0.167)	(0.205)	(0.184)	(0.156)
Generalized System of Preferences	0.951***	0.945***	1.385***	1.189***	1.178***	0.883***	0.668***
	(0.044)	(0.044)	(0.314)	(0.079)	(0.079)	(0.052)	(0.049)
N	447512	447512	37981	66540	62684	95222	185085

Regressand: Log of Imports. Each regression includes time-varying exporter and importer fixed effects.
Robust standard errors clustered by dyad are given in parentheses.
$*p < 0.10, **p < 0.05, ***p < 0.01$

Note: Regressand: Log of Imports. Each regression includes time-varying exporter and importer fixed effects. Import figures are retrieved from UN ComTrade data. **Cultural Distance** is computed by the author *via* PCA using Genetic (Spolaore and Wacziarg, 2009), Religious (WCD Fearon et al., 2006, and) and Linguistic (Fearon, 2003) Distance measures. The other control variables are taken from the CEPII dataset. Results refer to a sample of 160 countries. In (i) and (ii) the analysis is carried over the period 1962-2012. In (iii) - (vii) results are per decade. Robust standard errors clustered by dyad are given in parentheses. Significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

4.5 Exploring the role of Attitudes towards Migrants

We now explore the transmission mechanism that could explain how cultural distance affects trade. The ties and relationships that bind members of a society, is frequently associated with positive outcomes. Trade and economic growth are just two examples. In fact, previous literature partially helps to clarify the specific channels through which cultural differences affect trade. According to Guiso et al. (2006, p.29) “the opening through which culture entered the economic discourse was the concept of trust". Guiso et al. (2006) summarize why trust can affect economic decisions: “Trust is particularly relevant when transactions involve some unknown counterpart like a buyer or seller of goods in another country, when the transaction takes place over a period of time rather than being completed on the spot, and when the legal protection is imperfect."(Guiso et al., 2006, p.34).

Yet, although we know that trust, *per se*, can be an impediment to economic growth and trade, we do not know what exactly reduces or improves interpersonal trust. In this Section, we contend that cultural diversity and distance can affect economic outcomes, in particular trade, by enhancing interpersonal trust, thus lower levels of cultural distance correspond to lower levels of trust toward individuals. While this brief overview cannot do justice to the broad knowledge generated by existing work, there is still limited evidence about the effect of cultural diversity on levels of trust. We address this issue by looking directly and systematically at one crucial aspect of cultural distance, namely the attitude towards immigrants. Public attitudes toward migration can be used as a reliable indicator of how diversity and cultural distance are perceived by native populations. In this context, public opinion on migration can be seen as a valuable barometer of the salience that citizens attach to the issue of cultural diversity and of the level of openness of native populations toward the arrival of foreign-born individuals. Not surprisingly, cosmopolitan attitudes and interculturalism are often associated with more pro-immigrant stances (Curtis, 2014; Bello, 2017). In general, although the broader public is often skeptical of immigration (see Abou-Chadi, 2016, e.g.), growing concerns about immigration have in fact recently contributed to the success of reactionary nationalist parties at local and national elections in Europe (Davis and Deole, 2017). We thus use this as an index of preference towards cultural distance and investigate whether it affects interpersonal trust.

4.5.1 A novel dataset of Attitudes towards Migrants

We assemble a novel and comprehensive dataset on trust and migration attitudes by drawing on all seven rounds (2002-2014) of the European Social Survey (ESS)[11]. The ESS is one of the most methodologically rigorous regional cross-national survey projects. Initiated in 2002, there are eight rounds so far covering more than 30 European states until 2016. The ESS's chief advantage is that survey practices are harmonized to reduce the likelihood that different results between countries are driven by alterations in how the survey is conducted per state. To this end, the ESS has developed strict guidelines for consistent methods of fieldwork. These practices require, among others, a random sampling design of residents 15 years and older (no quota sampling), one hour face-to-face interviews, a target response rate of 70 percent, and a minimum of 2,000 respondents per country. These characteristics make the ESS particularly useful for our purposes. We employ the integrated data files of all seven rounds of the ESS covering 2002-2014 and use the NUTS 2-year as unit of analysis. In other words, we create a panel dataset at the sub-national region level. We aggregate because individual-level relations are not the ultimate target of our study and to test the transmission mechanisms we need macro-level considerations in modelling. In fact, there are direct effects on individual behaviour beyond what we expect given the specific individual values

[11] Available at: `http://www.europeansocialsurvey.org/`.

when, e.g., the average economic prosperity of a region has “effects on an individual over and above the effects of the individual’s economic status” (Greenland, 2001, p.1343). We use the 2010 Nomenclature of Units for Territorial Statistics (NUTS) classification scheme. Accordingly, the aggregation accounts for changes in the NUTS classification, such as shifts in boundaries, mergers and/or splits. The outcome variable for the country-level analysis is based on the ESS survey question “[g]enerally speaking, would you say that most people can be trusted, or that you can‘t be too careful (i.e., need to be wary or always somewhat suspicious) in dealing with people?”. Individuals could reply on a scale from 1 to 10 with higher values standing for more trusting attitudes. We aggregate this variable to the NUTS2 level by averaging across respondents and look at the percentage of people reporting values above 5.

Our theoretical argument focuses on how attitudes towards foreigners, and therefore towards cultural difference, is associated with trust. We employ three variables to this end to measure sentiment towards immigrants, albeit we capture different components of the same underlying concept. First, the ESS has a survey question asking “[t]o what extent do you think [country] should allow people of the same race or ethnic group as most [country] people to come and live here?"; second, there is a question asking “[h]ow about people of a different race or ethnic group from most [country] people?"; third, there is a question asking “[h]ow about people from the poorer countries outside Europe?”. Possible answers include “allow many to come and live here", “allow some", “allow a few", and “allow none". We construct an “anti-immigration" variable, where scores are calculated by the weighted percentage of those who prefer either “allow a few" or “allow none". We also control for a series of other variables that may either be seen as alternative determinants of interpersonal trust. First, there is the population size (stock) of natives and the net migration; second, we control for education and employment; third, we control for age and gender. For the above variables, we use the weighted percentages of respondents at NUTS2 regions. In Section 4.6 we examine possible interaction effects of net immigration at the regional level with migration attitudes. In the appendix to this Chapter (Appendix D) we report baseline estimations of models focusing on an unconditional effect stemming from public opinion towards diversity. Table 4.7 summarizes the descriptive statistics of the variables we just discussed.

Table 4.7: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Against immigrants of the SAME race or ethnic group	33.5	16	0	90.5	968
Against immigrants of DIFFERENT race or ethnicity	45.8	18.6	4.3	100	968
Against POOR, NON-EUROPEAN immigrants	48.6	19	3.4	100	968
Trust	41.5	19.2	0	85.7	968
Native	92.8	7.1	40	100	968
Male	47.6	6.2	21.2	80	968
Age	46.8	3.4	29.5	62.8	968
Education	74.3	14.9	6.9	100	968
Unemployment	9.1	5.7	1.7	37	946

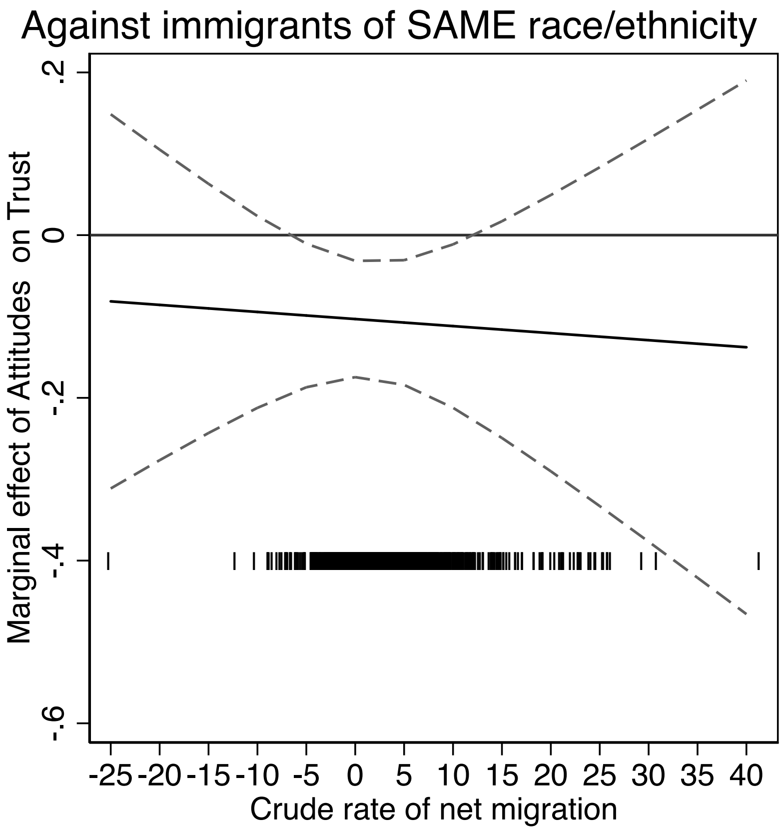
4.6 Results

Figures 4.2, 4.3 and 4.4 present the underlying models that comprise a multiplicative term for the migration variable and attitudes[12]. The theoretical rationale behind modelling such interactions is that net immigration could be a proxy for the salience of the migration issue, which increases with the size of the migrant population in a country (?). Theoretically, we may expect that larger inflows of foreign-born individuals reduce interpersonal trust. In times of crisis, as it may have been perceivably the case in 2015 with a significant number of migrants and refugees arriving in Europe, contact is more likely to occur under less favourable circumstances. Large inflows of immigrants and refugees in Europe can create situations of distress, especially in countries that are less able to manage such flows or

[12]We remand the interested reader to Table D8 in Appendix D.

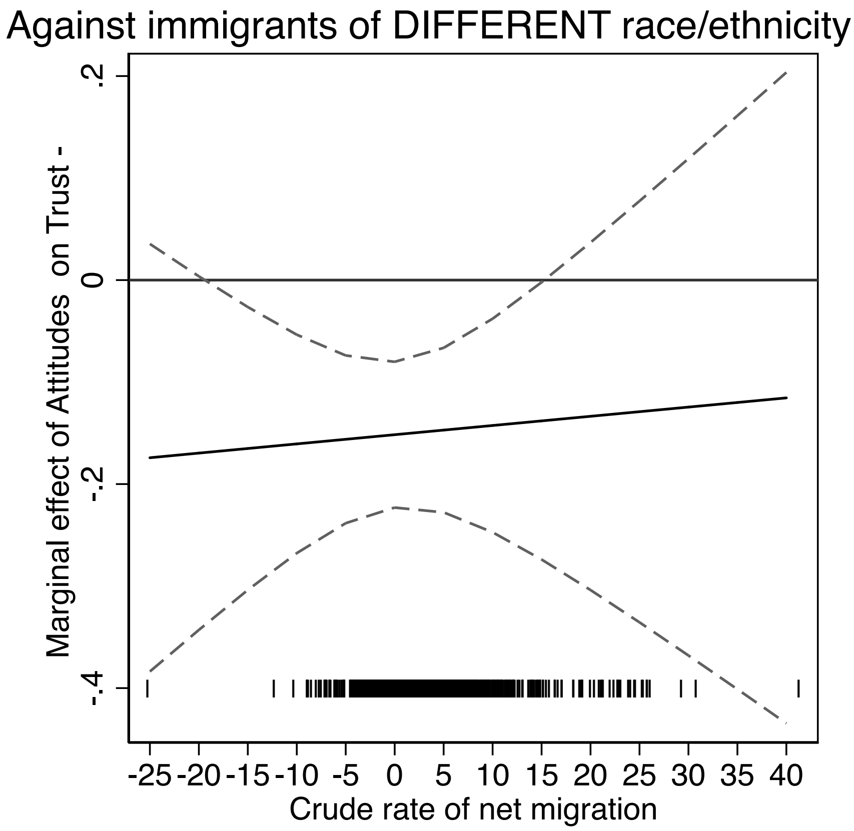
are unfamiliar with these emergencies. With a large number of migrants, contact itself could elicit negative stereotyping and increase prejudice and lack of trust (see e.g., Bello, 2017). On the other hand, however, research based on contact theory (Allport, 1979) showed that people living in diverse societies have more opportunity for inter-group contact and are less prejudiced towards individuals (**?**). Having said that, we find little evidence for positive interaction effect particularly in the case of attitudes agains immigrations of the same race. In 4.2 the effect is negative, and the crude rate of net migration seems to exacerbate the effect stemming from migration attitudes. On the contrary, in Figures 4.3 and 4.4 a positive effect prevails. Yet, given the small changes over the values of crude rate of net migration, we do not find a systematic mitigating effect of net migration.

Figure 4.2: Regional Net Migration and Attitudes towards Immigrants of the same ethnicity



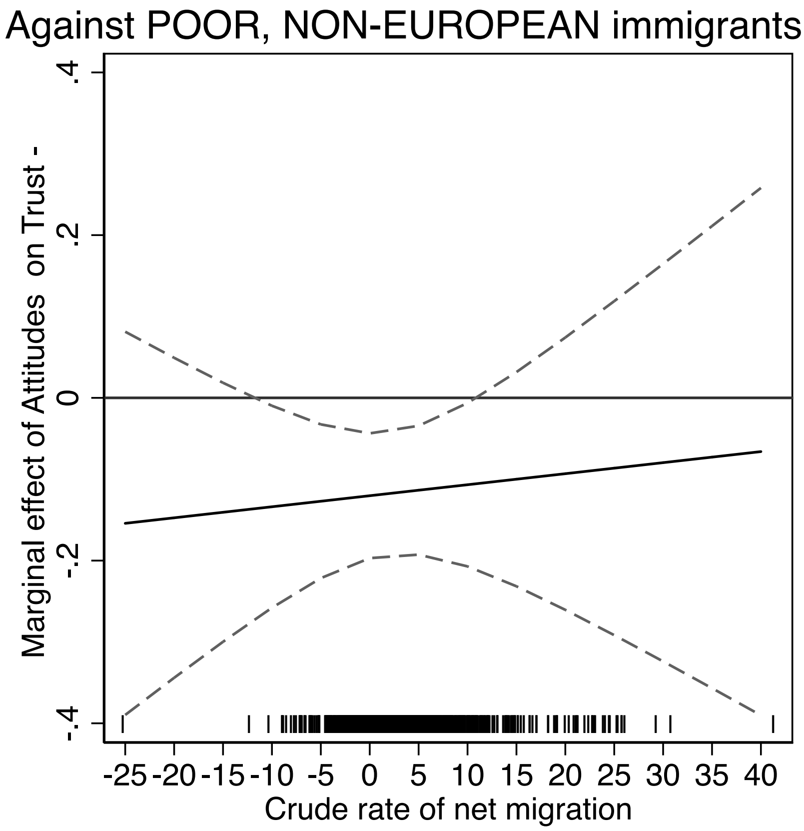
Note: The graph shows average marginal effects of the Migration Attitude variables conditional on Net Immigration, while holding all other covariates constant at their means; dashed lines signify 90 percent confidence interval; rug plot along horizontal axis illustrates distribution of Net Migration. Attitudes data are retrieved from the ESS covering 2002-2014 at NUTS 2 level.

Figure 4.3: Regional Net Migration and Attitudes towards Immigrants of different ethnicity



Note: The graph shows average marginal effects of the Migration Attitude variables conditional on Net Immigration, while holding all other covariates constant at their means; dashed lines signify 90 percent confidence interval; rug plot along horizontal axis illustrates distribution of Net Migration. Attitudes data are retrieved from the ESS covering 2002-2014 at NUTS 2 level.

Figure 4.4: Regional Net Migration and Attitudes towards poor/non-european Immigrants



Note: The graph shows average marginal effects of the Migration Attitude variables conditional on Net Immigration, while holding all other covariates constant at their means; dashed lines signify 90 percent confidence interval; rug plot along horizontal axis illustrates distribution of Net Migration. Attitudes data are retrieved from the ESS covering 2002-2014 at NUTS 2 level.

4.7 Conclusions

We look to contribute to the debate on the economic effects of culture by including a battery of indices of cultural distance in a gravity model of trade between 1962 and 2012. We also investigate the evolution of the impact of cultural barriers on economic exchange over time. We find that the elasticity of bilateral trade flows with respect to genetic and culture distance ranges from -0.9 to -1.6. This implies that a 10 percent increase in cultural distance reduces trade by about 9 to 16 percent. Measures of genetic and religious distance as well as distances computed on differences in values exhibit fairly large marginal effects and are of the same order of magnitude of geographic distance. Linguistic distance is the class with the smallest average impact on trade. Overall, the impact of cultural distance on trade relations is stable and does not display substantive changes over time.

Cultural distance conveys various information on differences in customs, beliefs, morals, laws, trust and information costs, among others. If trading partners have a similar culture, a shared understanding and common identities reduce the coordination costs. In fact, when the cultural distance between them is high, there might be different norms, different perceptions and more misunderstandings between them. Less challenging coordination between actors, however, could make it easier to communicate and agree on some standards and it facilitates the decision-making process due to a lower likelihood of misunderstanding and higher levels of trust. In turn, this should facilitate economic transactions. Our results suggest that cultural distances are important factors affecting bilateral trade and their omission in standard models of international trade is all the more problematic in light of the substantive impact that they have on bilateral flows.

Finally, we have explored a transmission mechanism that could explain how cultural distance affects trade. To do so we have investigated an intermediate channel considering attitudes towards immigrants as an index of preference towards cultural distance. Analytically, public sentiments towards immigrants is perhaps the most critical and discernible aspect of the in-group/out-group positioning. In fact, natives and non-natives are two groups that are reciprocally related, as each is defined in terms of the other (de Figueiredo Jr and Elkins, 2003). We find that sentiments towards immigrants are negatively correlated with trust. The effects are conditional on the number of immigrants at regional (NUT2) level. These evidences corroborate the intuition that whether trust affects trade - as pointed out by Guiso et al. (2006) - a more diverse socio-economic context may hinder trust by triggering negative attitudes towards immigrants, at least in the short-run to medium-run.

The conceptualization of cultural distance remains an open question, and in this study we do not explore what are the specific mechanisms that make cultural distance a barrier to trade. This leaves many avenues for future research open. Substantial work has been undertaken in recent years to operationalize nuanced measures of cultural distance, ensuring that the nexus culture-trade will be a fertile area of research for the foreseeable future.

Chapter 5

Conclusive Remarks

The size of transnational migration has risen significantly worldwide over the last two decades. By one estimate (UN DESA, 2015), the global population of international migrants, i.e., people residing in a country other than their country of birth, has more than doubled since the year 2000 to about 244 million in 2015. The ongoing age of migration substantially increases advanced economies' exposure to cultural *diversity* and cultural change.

Yet, empirical research on whether culture is relevant for economic outcomes is "fairly new in economics" (Alesina and Giuliano, 2014, p.5), and "research seeking to quantify human barriers to socioeconomic interactions across populations is in its infancy" (Spolaore and Wacziarg, 2015, p.24).

Throughout this thesis we have investigated the varying impact of diversity on three economic dimensions: redistribution, economic prosperity and bilateral trade. Obviously - our analysis touches only the tip of the iceberg and several important issues remain to be investigated. We list few of these below whereas providing further conclusive remarks for Chapter 2, Chapter 3 and Chapter 4.

In Chapter 2 we have investigated the impact of birthplace diversity measures on transfers and subsidies. Our work suggests that social spending in the presence of large immigration inflows may be a pressing concern, and we shed new light on this issue. It is worth noticing here that the level of ethnic or birthplace diversity in receiving countries is going to dramatically change over the next years. The scale of the contemporary refugee crisis is undeniable: the global number of refugees has risen rapidly with the Syrian civil war, and there were more than 21 million refugees globally by the end of 2015 according to the UNHCR. In addition, the movement of people travelling across the Mediterranean Sea or overland through Southeast Europe into the EU is perceived as one of the biggest challenges ever to the Union (see also OECD, 2015). We would stress that although immigrants can pose challenges to preferences for redistribution, they are seldom a burden on public funds. Moreover, governments have a lot of instruments at their disposal for dealing with this issue and future work should explore how institutions can mitigate or exacerbate the negative effect of diversity on redistribution. We detail some of the potentially promising avenues for future research. First, much of the impact should depend on the ability of the state to manage immigrant populations. Negative economic implications largely depend on pre-existing conditions in the country of destination of immigration flows, in particular the domestic political context. In fact, domestic political dynamics influence the way in which immigrants are received by hosts and shape subsequent interactions between the two groups, natives and non-natives. Second, in weak states, criminal networks can monopolize the reception of immigrants and even replace the state in providing public goods, which can quickly induce resentment among the local population. In 2012 the Italian magazine L'Espresso has published an *ante litteram* journalistic inquiry on *Who speculates on refugees*, pointing out arising business possibilities for the organised crime[1]. It followed an investigation by the Italian police that has uncovered how mafia has infiltrated the national asylum-system. The content of revealed wiretaps still echoes across international press: "migrants more profitable than drugs"[2]. Moreover, a number of institutional arguments stress the role of state

[1] `http://espresso.repubblica.it/attualita/cronaca/2012/10/15/news/chi-specula-sui-profughi-1.47304`

[2] `https://www.theguardian.com/news/2018/feb/01/migrants-more-profitable?CMP=share_btn_link`

capacity for corruption (e.g., Shleifer and Vishny, 1993). Weak governments with limited administrative capacity are unable to effectively manage large numbers of people and sanction the bureaucracy for corrupt behaviour. Group resentment stemming from a sense of widespread corruption and lack of state response to emergency situations could be targeted against other groups perceived to be either privileged or undeserving. This can exacerbate existing tensions and decrease preferences for redistribution. In other words, countries could be more vulnerable to a reduction in public goods provision with a larger population of immigrants *and* in the presence of weak state institutions. Third, the balance of power within a country has important implications for the outcome of immigration inflows: a country with a secure and stable government is likely to experience different results than one whose hold on power is tenuous. By further exploring political dynamics in the countries into which immigrants go, we can better understand the possible outcome of the influx and the potential economic implications.

In Chapter 3 we have explored the multifaceted impact of alternative proxies for diversity on economic prosperity. Several important avenues for further research might emerge from our work, while it also points to critical implications for practitioners. First, a number of studies, such as Vandenbussche et al. (2006), claims that since rich countries are closer to the technological frontier, the strength of the catch-up effect with the frontier vanishes with the relative level of development. Therefore, we could expect developing economies to benefit more strongly from diversity than developed market economies. In other words, future works should explore whether there is actually an heterogeneous effect of cultural diversity on economic growth, depending on e.g., the initial level of per capita income. Second, in Chapter 3 we make the assumption that countries are culturally homogeneous, and therefore we identify cultural divides only across countries, i.e., we do not allow for within-country diversity. A fair criticism would point out to a simplistic categorization, because many countries, in particular less developed economies, are actually fragmented into a multitude of ethnic groups. Recall that we use data from Fearon (2003), which in a way measures ethnic distances across groups to obtain indicators of cultural diversity within countries. An important extension to our analysis would be therefore the inclusion of more refined measures of cultural diversity, where we take into account more directly the relative weight that each ethnic (or religious) group has in relation to the others within each country. To do so, one could sum up the dyadic distance between each ethnic group, weighted by the proportion of citizens belonging to each group in each country. Third, and related to this last point, a geo-referenced analysis of cultural zones, where we identify geographic areas which are more or less homogeneous in terms of identity, would allow us to explore inter-zone relations. This data could be coupled with data on local economic activities, proxied by e.g., nighttime illumination (Henderson et al., 2011; Weidmann and Schutte, 2017).

In Chapter 4 we have provided novel evidence over the impact of cultural distance on bilateral trade. A number of refinements to this study would be desirable, including the application of more recent techniques able to partially overcome gravity model limitations. For the time being we hope for the inclusion of our measure of cultural distance in standard gravity models of trade.

Finally, as perceptions rooted are rooted in culture, underlying interdependencies between the perception of diversity and its definition should be investigated across social sciences at large, as any further insight on this matter would better-off our understanding of the current functioning of socio-economic organizations.

A Appendix to Chapter 1

A.1 Measuring diversity

The degree of diversity (within a country in our case) is measured through two indices: fractionalization and polarization. The fractionalization index, also called “Ethnolinguistic fractionalization (ELF) Index", measures the probability of two randomly selected individuals in society belonging to different groups (see Desmet et al., 2009, for a thorough discussion). This index is a variation of the Herfindahl-Hirschman concentration index (HHI). In general, any index of fractionalization can be written as:

$$Fractionalisation = 1 - \sum_{i=1}^{N} \pi_i^2 = \sum_{i=1}^{N} \pi_i(1 - \pi_i) \tag{5.1}$$

where π_i is the proportion of people who belong to the group i, and N is the number of groups. In our case, π_i is the proportion of citizens from a certain county i, or the percentage of people that practice a given religion i, and N is the total number of world countries. Note that in our study we compute indices of population diversity (i.e., π_i includes the natives) as well as the degree of diversity within the immigrant group only. Yet, while this measure of heterogeneity has attracted a fair amount of attention, a number of scholars have suggested an alternative index of diversity, called polarization, and originally introduced by Reynal-Querol (2002) as:

$$Polarisation = 4 \sum_{i=1}^{N} \pi_i^2(1 - \pi_i) \tag{5.2}$$

Polarisation measures how far the distribution of the groups is from a bipolar distribution e.g. $1/2, 0, 0, ...0, 1/2$, and attains its maximum value when we have two groups of equal size. The polarization index is multiplied by 4 so as to make it range between 0 and 1. While in the case of two groups, the fractionalization and the polarization take up the same value,[3] when we move from two groups to three groups, the relationship between those indices breaks down. This is because in the fractionalization index, the size of each group has no effect on the weight of the probabilities of two individuals belonging to different groups, whereas in the polarization index these probabilities are weighted by the relative size of each group (Montalvo and Reynal-Querol, 2005).

B Appendix to Chapter 2

B.1 Mechanisms: extended baseline regressions

In Table D4 we add a battery of control variables, in particular population size, GDP per capita and government expenditure in percentage of the GDP. In Table D5 we add the share of migrants.

—— Tables D4 and D5 about here ——

C Appendix to Chapter 3

C.1 Measures of Genetic *Diversity*

Another interesting measure of diversity was proposed by Spolaore and Wacziarg (2009). The authors construct a genetic distance index to capture social and cultural differences among populations. The index measures the time elapsed since two groups had common ancestors and explains variations in income levels, human capital and institutions. Genetically diverse populations, they argue, exchanged technological innovations at significantly lower rates, with clear long-term implications for economic development. Ashraf and Galor (2013) use the same index to

[3]In case of two groups, polarization is equal to fractionalization up to a scalar.

show that genetic diversity within a population carries both social costs and social benefits, thus has an overall hump-shaped effect of development. More specifically, social benefits (e.g. skills complementarity) prevail at lower levels of diversity while costs (e.g. inefficiency, mistrust) become prominent when genetic diversity is high.

We take measures of genetic distance as proposed by Ashraf and Galor (2013). By doing so we replicate Equation 3.1 using respectively:

- *Observed Genetic Distance*, this measure refers to genetic diversity among contemporaneous indigenous population across the globe which are native to their geographical location and have been isolated from the inflows of other ethnic groups. The index builds on common measure of genetic diversity employed by population geneticists, the “expected heterozygosity", reporting the probability that two randomly selected individuals differ from one another with respect to a given spectrum of traits. It has been computed considering the 53 ethnic groups from the HGDP-CEPH Human Genome Diversity Cell Panel, spanning 21 countries. For a full discussion the interested reader may refer to Ramachandran et al. (2005).

- *Predicted Genetic Distance*, considers values of genetic diversity predicted using prehistoric migration distances, for all countries in the world, including those for which diversity data are currently unavailable. To do so the index accounts for the ethnic composition of contemporary national populations following migration flows in the post-1500 era, the genetic distance of the precolonial ancestral population of each ethnic group and the genetic distance between these ancestral populations. Ethnic composition information are retrieved from Putterman and Weil (2010), *World Migration Matrix ,1500-2000.*

- *Ancestry Adjusted Distance*, the measure posits on the Predicted Genetic Distance index whereas incorporating between-group differences across sub-national ethnic groups. In order to add the intra-group dimension the index uses the concept of genetic distance as borrowed from the field of population genetics. A step-by-step explanation over the construction of this measure is provided by Ashraf and Galor (2013) in the Section B of their online Appendix.

Table C.1 provides summary statistics for the above measures, whereas Table C2 outlines cross-correlations across all the the diversity variables employed in Chapter 2 and the above introduced Genetic Distance indices elaborated by Ashraf and Galor (2013). It clearly emerges that Genetic Distances are orthogonal to most of previously employed diversity measures. As exception to this, the reader should not as the measure for Observed Genetic Distance correlates with Ethnolinguistic measures dating back to the sixties, that were structured on traditional ethic belongings across countries (Atlas (1964) and Roberts (1962)). In the same fashion, the Observed Genetic Distance substantially correlates with the Linguistic Fragmentation index introduced by Alesina (2003). Not surprisingly, the latter has been build by mimicking Atlas (1964) criteria. It is also predictable the cross-correlation between Predicted Genetic Distance and Ancestry Adjusted Distance measures, as the latter is a refinement of the former.

Table C1: Summary statistics - Genetic Indices

Variable	**Mean**	**Std. Dev.**	**N**
i) Observed Genetic (Ashraf and Galor, 2013)	0.7	0.1	1512
ii) Predicted Genetic (Ashraf and Galor, 2013)	0.7	0.1	12384
iii) Predicted Genetic (Ancestry Adjusted)	0.7	0	11232

Figure C1 shows how the coefficients of genetic diversity evolves over time. The effect is mostly insignificant. However, the pattern depicted across the three graphs is of some interest. It features two peaks, a negative peak in 1994 and a positive peak in 2006. Especially in 2007 the substantive effect of genetic diversity on economic growth is almost twice as large as in 2002. If anything, this suggests

Table C2: Cross-correlation table - *Diversity* measures & Genetic Indices

Variables	A	B	C	D	E	F	G	H	I	L	K	L
A: Fractionalization (Desmet, 2009)	1.0											
B: Ethnic Fragmentation (Alesina et al., 2003)	0.5	1.0										
C: Ethnic Fractionalization (Fearon, 2003)	0.5	0.9	1.0									
D: Cultural Diversity (Fearon, 2003)	0.7	0.7	0.8	1.0								
E: Religious Fragmentation (Alesina et al., 2003)	0.0	0.2	0.3	0.2	1.0							
F: Linguistic Fragmentation (Alesina et al., 2003)	0.6	0.7	0.7	0.7	0.3	1.0						
G: Ethnolinguistic (Atlas-1964)	0.7	0.7	0.8	0.9	0.3	0.9	1.0					
H: Ethnolinguistic - ELF (1961)	0.6	0.8	0.8	0.7	0.3	0.8	0.9	1.0				
I: Ethnolinguistic (Roberts, 1962)	0.7	0.6	0.6	0.8	0.3	0.9	0.9	0.8	1.0			
J: Observed G. (Ashraf and Galor, 2013)	0.5	0.2	0.1	0.6	0.3	0.7	0.7	0.2	0.8	1.0		
K: Predicted G. (Ashraf and Galor, 2013)	0.2	0.2	0.2	0.2	-0.1	0.3	0.2	0.0	-0.1	1.0	1.0	
L: Predicted G. - Ancestry Adjusted	-0.0	0.1	0.1	0.1	0.2	0.2	0.1	0.0	-0.1	0.7	0.8	1.0

Table C3: Genetic Indices and Economic Prosperity (dependent variable is long-run growth of per capita real GDP).

	(i)	(ii)	(iii)
J: Observed genetic (Ashraf and Galor, 2013)	-197.496***		
	(42.142)		
K: Predicted genetic (Ashraf and Galor, 2014)		50.075***	
		(15.447)	
L: Predicted genetic (ancestry adjusted)			-19.599
			(18.608)
Observations	775	4832	4737
R^2	0.576	0.261	0.263

Note: Pooled OLS models for all countries between 1970 and 2016. The dependent variable is 10-year GDP per capita (PPP converted at 2010 constant prices),taken from the World Development Indicators. The set of control variables includes (log)initial income and initial income and initial income squared (World Bank, 2016); (log)schooling (Barro & Lee, 2013); Sub-Saharan Africa, Latin America and the Caribbean dummies (Wahman et al., (2013); Hadenius & Teorell, (2007)); year dummies. All controls are measured in the initial year of each sub-period.

Conventional significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

that whether the effect of genetic diversity on economic development is positive or negative needs to be determined from the data using year-by-year models.

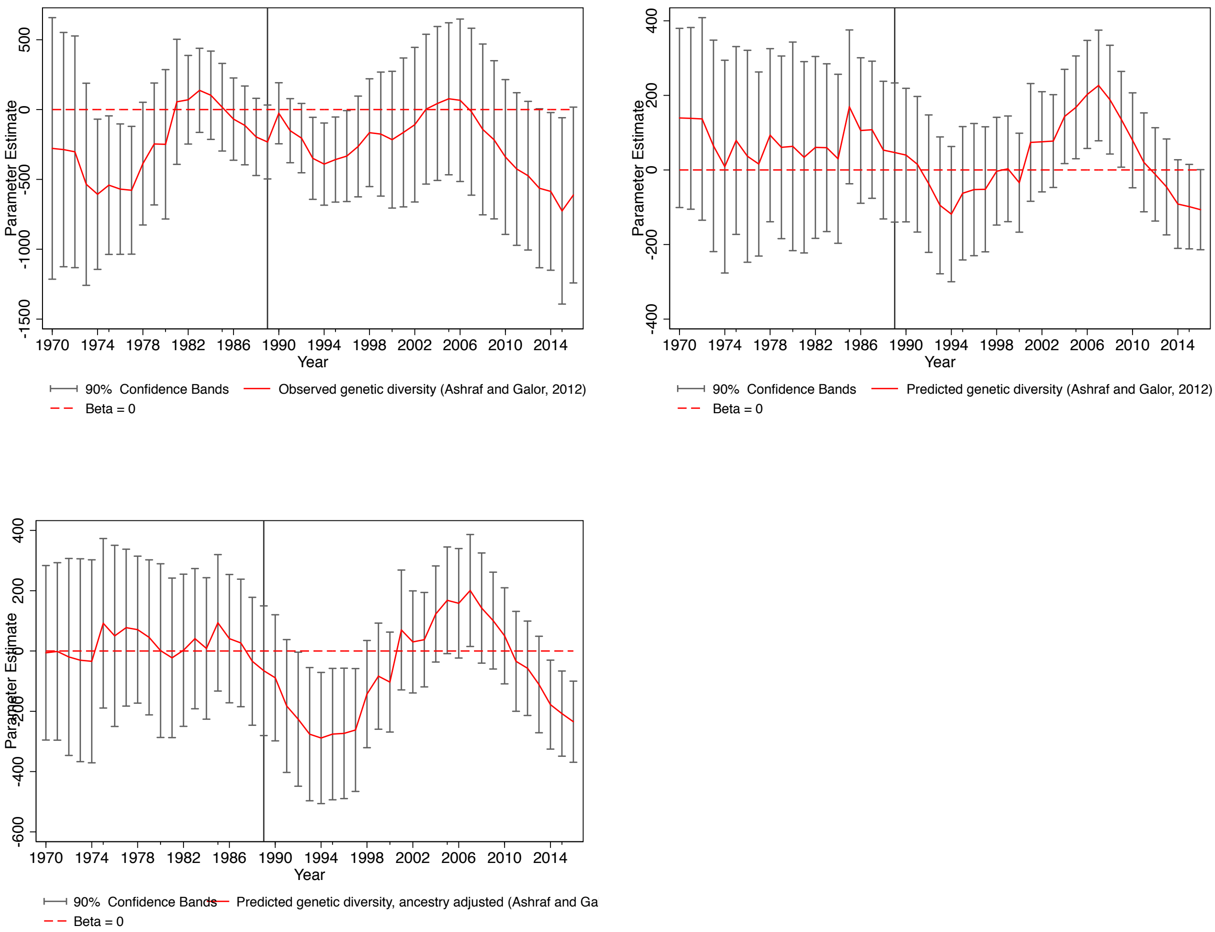


Figure C1: Measures of Genetic *Diversity* (Ashraf and Galor, 2013) and Economic Prosperity (10-year GDP growth rate)

The only index showing a positive coefficient (although never significant at conventional levels) is Predicted Genetic Diversity. One reason for its positive sign is that this index fails to capture the extent of genetic diversity in contemporary national populations. In facts it does not account for genetic diversity between subnational ethnic groups. However, when the measure is adjusted to incorporate inter-groups genetic diversity (i.e. the Ancestry Adjusted index), the plotted coefficients shift downwards - allowing for a longer lasting negative effect during the first-half of the nineties, while gaining in significance. If anything these evidences confirm the trade-off in negative and positive effects that diversity exerts on economic prosperity as discussed by Ashraf and Galor (2013). Our findings further support a significant negative role played by diversity among ethnic groups genetically distant. It is noteworthy that the Ancestry Adjusted index is the only significant (and negative) predictor for comparative economic development also for Ashraf and Galor (2013), as opposed to the unadjusted Predicted Genetic Diversity.

C.2 Mechanisms: alternative measures

In what it follows we provide baseline OLS regressions using alternative investment figures with respect to those used in Section 3.6.1. In Table refgcfun and Table D7 data sources are respectively the UN WPD dataset and Penn World Table (ver.8), as described in Section 3.6.1. The results showed below confirm that diversity affects income also *via* alternative forms of investment, as expected, with different signs.

—— Tables D6 and D7 about here ——

C.3 Residuals

We report below plotted coefficients of the residuals obtained by regressing each diversity measure presented in Table 3.1 on the others.

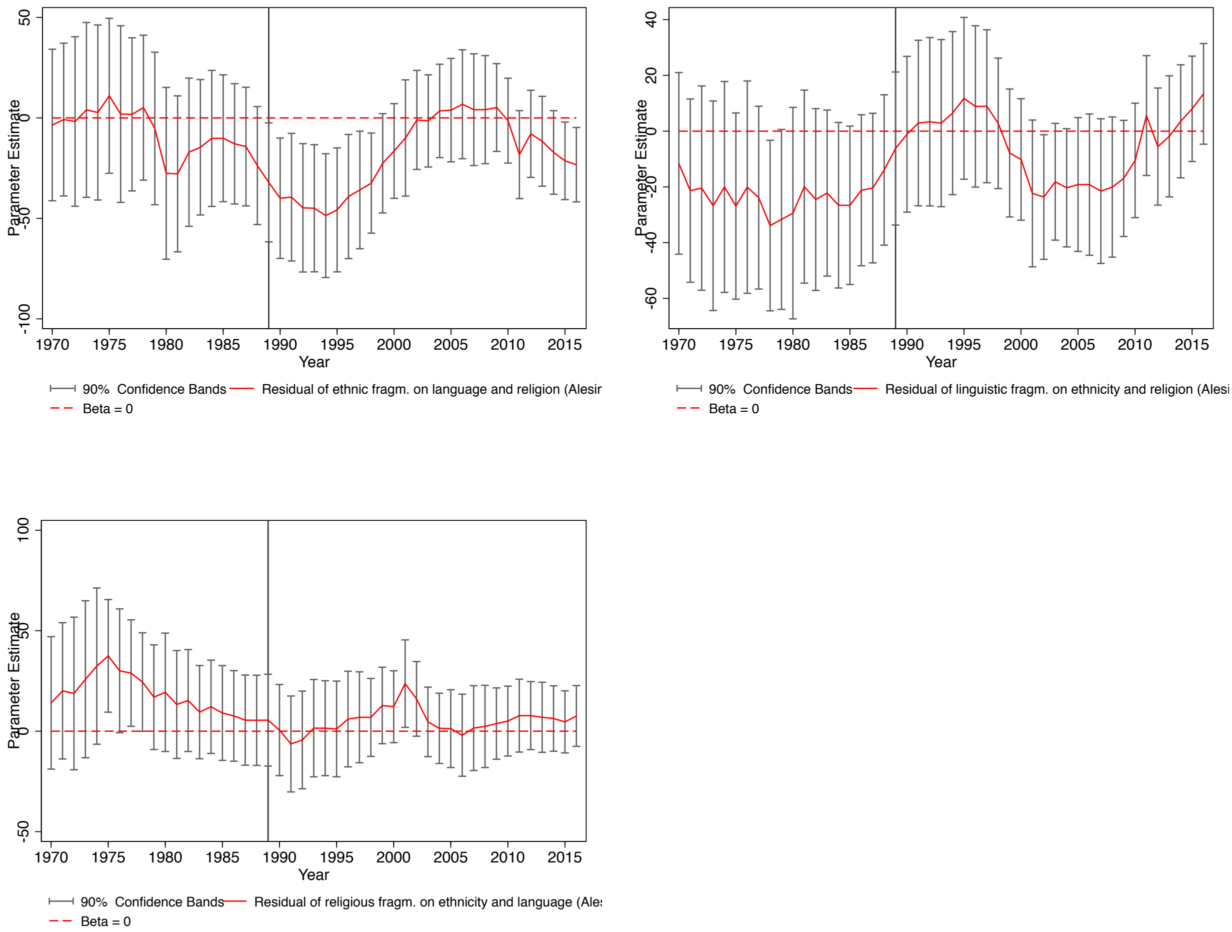


Figure C2: Plotted Residuals obtained by regressing a single *Diversity* measure on the others

D Appendix to Chapter 4

D.1 Trust and Attitudes towards Immigration-*naive* regressions

Table D8 summarizes the three main models of the ESS analysis. Each model uses a different a attitudinal variables representing the shares of respondents who oppose (a) immigrants of the same race or ethnic group, (b) immigrants of different race or ethnic group or (c) immigrants from poorer countries outside Europe. All models comprise the full set of control variables and the country and year fixed effects. Robust stander errors are clustered at the regional level. The table entries pertain to OLS regression coefficients and can be interpreted directly as marginal effects. With regard to our main variables of interest, Table D8 supports our theoretical expectations. The attitudes variables are negatively signed and significant at conventional levels. In substantive terms, the coefficient of attitudes toward immigration in model (i), for example, suggest that a one percentage point increase in the percentage of respondents with anti-immigrant attitudes against immigrants of the same race or ethnicity as the majority population is correlated with a decrease in the percentage of respondents with high levels of interpersonal trust by 0.11 percentage points. In sum, trust in other people is generally positively associated with more favourable views toward migration, as argued by our expectations.

—— Table D8 about here ——

—— APPENDIX TABLES ——

Table D4: Diversity and Tax to GDP ratio: extended baseline regressions.

	Model A	Model B	Model C	Model D
Population	-0.306***	-0.305***	-0.286***	-0.286***
	(0.040)	(0.040)	(0.038)	(0.038)
GDP per capita	0.260***	0.260***	0.257***	0.257***
	(0.021)	(0.021)	(0.021)	(0.021)
Government exp. to GDP ratio	0.455***	0.455***	0.454***	0.454***
	(0.015)	(0.015)	(0.015)	(0.015)
Birthplace FRA (Tot)	-0.047***			
	(0.011)			
Birthplace POL (Tot)		-0.049***		
		(0.011)		
Birthplace FRA			-0.022***	
			(0.005)	
Birthplace POL				-0.022***
				(0.005)
Observations	3548	3550	3550	3550

Fixed-effects models.

Note: Taxation data are combined by Cagé and Gadenne (2017) covering 130 countries between 1792 and 2006 using different sources [International Monetary Funds Government Finance Statistics (GFS); Mitchell's International Historical Statistics (2007); Baunsgaard and Keen (2010)]. Taxation (in percentage of the GDP) is defined as central government tax revenues excluding social security contributions. Data for Population, GDP per capita and Government Expenditure in percentage of the GDP are taken from the World Bank, World Development Indicators. Migration figures used to construct our Birthplace Diversity indexes are taken from the World Bank bilateral migration matrix, 1970-2013. All the variables are in logarithmic form. Standard errors in parentheses. Year dummies are included but not shown. Conventional significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table D5: Diversity and Tax to GDP ratio: extended baseline regressions controlling for Share of Migrants.

	Model A	Model B	Model C	Model D
Population	-0.303***	-0.302***	-0.282***	-0.284***
	(0.040)	(0.040)	(0.042)	(0.042)
GDP per capita	0.262***	0.259***	0.257***	0.257***
	(0.021)	(0.021)	(0.021)	(0.021)
Government exp. to GDP ratio	0.455***	0.454***	0.453***	0.454***
	(0.015)	(0.015)	(0.015)	(0.015)
Migrants(% pop)	-0.885*	0.066	0.008	0.004
	(0.466)	(0.154)	(0.032)	(0.032)
Birthplace FRA (Tot)	0.854*			
	(0.475)			
Birthplace POL (Tot)		-0.117		
		(0.160)		
Birthplace FRA			-0.025*	
			(0.014)	
Birthplace POL				-0.023
				(0.014)
Observations	3548	3550	3550	3550

Fixed-effects models.

Note: Taxation data are combined by Cagé and Gadenne (2017) covering 130 countries between 1792 and 2006 using different sources [International Monetary Funds Government Finance Statistics (GFS); Mitchell's International Historical Statistics (2007); Baunsgaard and Keen (2010)]. Taxation (in percentage of the GDP) is defined as central government tax revenues excluding social security contributions. Data for Population, GDP per capita and Government Expenditure in percentage of the GDP are taken from the World Bank, World Development Indicators. Migration figures used to construct our Birthplace Diversity indexes and the Migrant (% pop) variable are taken from the World Bank bilateral migration matrix, 1970-2013. All the variables are in logarithmic form. Standard errors in parentheses. Year dummies are included but not shown. Conventional significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table D6: *Diversity* measures and Gross Capital Formation

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)
A: Fractionalization (Desmet, 2009)	-3.334**								
	(1.529)								
B: Ethnic Fragmentation (Alesina et al., 2003)		-3.008*							
		(1.546)							
C: Ethnic Fractionalization (Fearon, 2003)			-4.015**						
			(1.640)						
D: Cultural Diversity (Fearon, 2003)				-2.863**					
				(1.377)					
E: Religious Fragmentation (Alesina et al., 2003)					-3.157*				
					(1.619)				
F: Linguistic Fragmentation (Alesina et al., 2003)						-2.352*			
						(1.280)			
G: Ethnolinguistic (Atlas-1964)							-2.436		
							(1.499)		
H: Ethnolinguistic - ELF (1961)								-4.898***	
								(1.652)	
I: Ethnolinguistic (Roberts, 1962)									-7.620***
									(2.705)
Observations	6394	6394	5630	5601	6394	6097	4183	3978	1566

Note: OLS models. The dependant variable is the ‘GDP: Gross Capital Formation’ (WPD). Control variables include: per capita GDP, per capita GDP growth, population and trade (WDI). Year dummies are included but not reported. Standard errors in parentheses are clustered by country. Conventional significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table D7: *Diversity* measures and Share of Gross Capital Formation

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)
A: Fractionalization (Desmet, 2009)	-0.056***								
	(0.017)								
B: Ethnical Fragmentation (Alesina et al., 2003)		-0.064***							
		(0.018)							
C: Ethnic Fractionalization (Fearon, 2003)			-0.045**						
			(0.020)						
D: Cultural Diversity (Fearon, 2003)				-0.043**					
				(0.017)					
E: Religious Fragmentation (Alesina et al. 2003)					-0.046**				
					(0.019)				
F: Linguistic Fragmentation (Alesina et al. 2003)						-0.046***			
						(0.015)			
G: Ethnolinguistic (Atlas-1964)							-0.049***		
							(0.018)		
H: Ethnolinguistic - ELF (1961)								-0.068***	
								(0.021)	
I: Ethnolinguistic (Roberts, 1962)									-0.057
									(0.036)
Observations	6607	6607	5956	5956	6607	6350	4453	4403	1710

Note: OLS models. The dependant variable is 'Share of Gross Capital Formation' (PWT v.8). Control variables include: per capita GDP, per capita GDP growth, population and trade (WDI). Year dummies are included but not reported. Standard errors in parentheses are clustered by country. Conventional significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table D8: Trust and Attitudes towards Immigration

	(i)	(ii)	(iii)
Against immigrants of SAME race/ethnicity	-0.106**		
	(0.046)		
Native	0.040	0.079	0.084
	(0.076)	(0.073)	(0.080)
Male	-0.034	-0.014	-0.029
	(0.066)	(0.065)	(0.061)
Age	-0.203	-0.179	-0.201
	(0.139)	(0.133)	(0.135)
Education	0.019	0.022	0.016
	(0.062)	(0.060)	(0.061)
Unemployment	-0.238**	-0.208**	-0.212**
	(0.093)	(0.096)	(0.096)
Against immigrants of DIFFERENT race/ethnicity		-0.148***	
		(0.048)	
Against POOR, NON-EUROPEAN immigrants			-0.116**
			(0.046)
Constant	50.576***	47.559***	47.802***
	(11.431)	(10.791)	(11.325)
Observations	944	944	944

$*p < 0.10, **p < 0.05, ***p < 0.01$. Standard errors in parentheses are clustered at NUTS2 level. Two-way fixed-effects OLS.

Bibliography

Abou-Chadi, T. (2016). Political and institutional determinants of immigration policies. *Journal of Ethnic and Migration Studies*, 42(13):2087–2110.

Ager, P. and Brückner, M. (2013). Cultural diversity and economic growth: Evidence from the us during the age of mass migration. *European Economic Review*, 64:76–97.

Aiyar, S. and Dalgaard, C.-J. (2005). Total factor productivity revisited: a dual approach to development accounting. *IMF Staff Papers*, 52(1):82–102.

Alesina, A., Baqir, R., and Easterly, W. (1997). Public goods and ethnic divisions. Technical report, National Bureau of Economic Research.

Alesina, A., Baqir, R., and Easterly, W. (1999). Public goods and ethnic divisions. *The Quarterly Journal of Economics*, 114(4):1243–1284.

Alesina, A., Devleeschauwer, A., Easterly, W., Kurlat, S., and Wacziarg, R. (2003). Fractionalization. *Journal of Economic growth*, 8(2):155–194.

Alesina, A. and Ferrara, E. L. (2000). The determinants of trust. Technical report, National bureau of economic research.

Alesina, A. and Ferrara, E. L. (2005). Ethnic diversity and economic performance. *Journal of economic literature*, 43(3):762–800.

Alesina, A. and Giuliano, P. (2014). Culture and institutions. *National Bureau of Economic Research*.

Alesina, A. and Giuliano, P. (2015). Culture and institutions. *Journal of Economic Literature*, 53(4):898–944.

Alesina, A., Harnoss, J., and Rapoport, H. (2016). Birthplace diversity and economic prosperity. *Journal of Economic Growth*, 21(2):101–138.

Alesina, A. and La Ferrara, E. (2000). Participation in heterogeneous communities. *The quarterly journal of economics*, 115(3):847–904.

Alesina, A. and Spolaore, E. (2005). *The size of nations*. Mit Press.

Alesina, A., Spolaore, E., and Wacziarg, R. (2000). Economic integration and political disintegration. *American Economic Review*, 90(5):1276–1296.

Alesina, A. and Wacziarg, R. (1998). Openness, country size and government. *Journal of public Economics*, 69(3):305–321.

Allport, G. W. (1979). The nature of prejudice new york.

Anderson, J. E. and van Wincoop, E. (2003). Gravity with gravitas: A solution to the border puzzle. *American Economic Review*, 93(1):170–192.

Ashraf, Q. and Galor, O. (2013). The “out of africa" hypothesis, human genetic diversity, and comparative economic development. *American Economic Review*, 103(1):1–46.

Azzimonti, M. (2011). Barriers to investment in polarized societies. *The American Economic Review*, 101(5):2182–2204.

Bakaki, Z., Böhmelt, T., and Bove, V. (2016). Barriers to coordination? examining the impact of culture on international mediation occurrence and effectiveness. *Political Studies*.

Baldwin, K. and Huber, J. D. (2010). Economic versus cultural differences: Forms of ethnic diversity and public goods provision. *American Political Science Review*, 104(04):644–662.

Banerjee, A., Iyer, L., and Somanathan, R. (2005). History, social divisions, and public goods in rural india. *Journal of the European Economic Association*, 3(2-3):639–647.

Barbieri, K., Keshk, O. M., and Pollins, B. M. (2009). Trading data: Evaluating our assumptions and coding rules. *Conflict Management and Peace Science*, 26(5):471–491.

Barro, R. J. (1991). Economic growth in a cross section of countries. *The quarterly journal of economics*, 106(2):407–443.

Barro, R. J. (1999). Determinants of democracy. *Journal of Political economy*, 107(S6):S158–S183.

Barro, R. J. (2004). Spirit of capitalism: Religion and economic development. *Harvard International Review*, 25(4):64.

Barro, R. J. and Lee, J. W. (2013). A new data set of educational attainment in the world, 1950–2010. *Journal of Development Economics*, 104(C):184–198.

Barro, R. J. and McCleary, R. (2003). Religion and economic growth. Technical report, National Bureau of Economic Research.

Bates, R. H. (1974). Ethnic competition and modernization in contemporary africa. *Comparative Political Studies*, 6(4):457–484.

Bello, V. (2017). Interculturalism as a new framework to reduce prejudice in times of crisis in european countries. *International Migration*, 55(2):23–38.

Belmonte, A., Dell'Anno, R., and Teobaldelli, D. (2017). Tax morale, aversion to ethnic diversity, and decentralization. *European Journal of Political Economy.*

Borjas, G. J. (1999). Immigration and welfare magnets. *Journal of labor economics*, 17(4):607–637.

Bove, V. and Elia, L. (2017). Migration, diversity, and economic growth. *World Development*, 89:227–239.

Bove, V. and Gokmen, G. (2016). Cultural distance and interstate conflicts. *British Journal of Political Science*, pages 1–11.

Breton, T. (2015). Changes in the effect of capital and tfp on output in penn world tables 7 and 8: Improvement or error?

Bromlei, I. V. (1988). *Narody mira: istoriko-etnograficheskii spravochnik.* Moscow: Sovetskaia Entsiklopediia.

Bruk, S. I. (1986.). *Naselenie mira: etnodemograficheskii spravochnik, 2d rev..* Moscow: Izdatelstvo "Nauka".

Bruk, S. I. and Apenchenko, V. S. (1964). *Atlas narodov mira.* Moscow: Glavnoe upravlenie geodezii i kartografii gosudarstvennogo geologicheskogo komiteta SSSR and Institut etnografii im. H. H. Miklukho-Maklaia, Akademiia nauk SSSR.

Cagé, J. and Gadenne, L. (2017). Tax revenues, development, and the fiscal cost of trade liberalization, 1792-2006.

Carnevale, P. J. and Choi, D.-W. (2000). Culture in the mediation of international disputes. *International Journal of Psychology*, 35(2):105–110.

Castles, S. and Miller, M. J. (2009). *The age of migration: International population movements in the modern world.* Palgrave Macmillan.

Cavalli-Sforza, L. L., Menozzi, P., and Piazza, A. (1994). *The history and geography of human genes.* Princeton University Press.

Chaudhuri, A. (2011). Sustaining cooperation in laboratory public goods experiments: a selective survey of the literature. *Experimental Economics*, 14(1):47–83.

Croson, R. T. (2007). Theories of commitment, altruism and reciprocity: evidence from linear public goods games. *Economic Inquiry*, 45(2):199–216.

Curtis, K. A. (2014). Inclusive versus exclusive: A cross-national comparison of the effects of subnational, national, and supranational identity. *European Union Politics*, 15(4):521–546.

Davis, L. and Deole, S. S. (2017). Immigration and the rise of far-right parties in europe. *ifo DICE Report*, 15(4):10–15.

de Figueiredo Jr, R. J. and Elkins, Z. (2003). Are patriots bigots? an inquiry into the vices of in-group pride. *American Journal of Political Science*, 47(1):171–188.

DeBruine, L. M. (2002). Facial resemblance enhances trust. *Proceedings of the Royal Society of London B: Biological Sciences*, 269(1498):1307–1312.

Desmet, K., Ortuño-Ortín, I., and Wacziarg, R. (2012). The political economy of linguistic cleavages. *Journal of development Economics*, 97(2):322–338.

Desmet, K., Weber, S., and Ortuño-Ortín, I. (2009). Linguistic diversity and redistribution. *Journal of the European Economic Association*, 7(6):1291–1318.

Disdier, A.-C., Tai, S. H., Fontagné, L., and Mayer, T. (2010). Bilateral trade of cultural goods. *Review of World Economics*, 145(4):575–595.

Docquier, F., Lodigiani, E., Rapoport, H., and Schiff, M. (2016). Emigration and democracy. *Journal of Development Economics*, 120:209 – 223.

Dreher, A., Gaston, N., and Martens, P. (2008). *Measuring globalisation: Gauging its consequences*. Springer Science & Business Media.

Dustmann, C. and Frattini, T. (2014). The fiscal effects of immigration to the uk. *The Economic Journal*, 124(580).

Dyen, I., Kruskal, J. B., and Black, P. (1992). An indoeuropean classification: A lexicostatistical experiment. *Transactions of the American Philosophical society*, 82(5):iii–132.

Easterly, W. and Levine, R. (1997). Africa's growth tragedy: policies and ethnic divisions. *The quarterly journal of economics*, 112(4):1203–1250.

Egger, P. H. and Lassmann, A. (2012). The language effect in international trade: A meta-analysis. *Economics Letters*, 116(2):221–224.

Egger, P. H. and Lassmann, A. (2015). The causal impact of common native language on international trade: Evidence from a spatial regression discontinuity design. *The Economic Journal*, 125(584):699–745.

Egger, P. H. and Toubal, F. (2016). *Common Spoken Languages and International Trade*, pages 263–289. Palgrave Macmillan UK, London.

Esteban, J. and Ray, D. (2011). Linking conflict to inequality and polarization. *The American Economic Review*, 101(4):1345–1374.

Fearon, J., Laitin, D., and Mecham, R. Q. (2006). Religious classification and data on shares of major world religions. *unpublished, Stanford University*, 1(5):18.

Fearon, J. D. (2003). Ethnic and cultural diversity by country*. *Journal of Economic Growth*, 8(2):195–222.

Fearon, J. D. and Laitin, D. D. (1996). Explaining interethnic cooperation. *American political science review*, 90(4):715–735.

Feenstra, R. C. (2002). Border effects and the gravity equation: consistent methods for estimation. *Scottish Journal of Political Economy*, 49:491–506.

Feenstra, R. C., Inklaar, R., and Timmer, M. P. (2015). The next generation of the penn world table. *American economic review*, 105(10):3150–82.

Fehr, E. and Gachter, S. (2000). Cooperation and punishment in public goods experiments. *American Economic Review*, 90(4):980–994.

Felbermayr, G. J. and Toubal, F. (2010). Cultural proximity and trade. *European Economic Review*, 54(2):279–293.

Fisher Ellison, S., Greenbaum, J., and Mullin, W. (2010). Diversity, social goods provision, and performance in the firm. *MIT Department of Economics Working Paper*.

Gibson, C. C. and Hoffman, B. D. (2013). Coalitions not conflicts: Ethnicity, political institutions, and expenditure in africa. *Comparative Politics*, 45(3):273–290.

Gisselquist, R. M., Leiderer, S., and Niño-Zarazúa, M. (2016). *World Development*, 78:308–323.

Giuliano, P., Spilimbergo, A., and Tonon, G. (2014). Genetic distance, transportation costs, and trade. *Journal of Economic Geography*, 14(1):179–198.

Glaeser, E. L., Laibson, D., and Sacerdote, B. (2002). An economic approach to social capital. *The Economic Journal*, 112(483).

Gleditsch, K. S. (2002). Expanded trade and gdp data. *Journal of Conflict Resolution*, 46(5):712–724.

Gokmen, G. (2017). Clash of civilizations and the impact of cultural differences on trade. *Journal of Development Economics*, 127:449–458.

Gören, E. (2014). How ethnic diversity affects economic growth. *World Development*, 59:275–297.

Greenland, S. (2001). Ecologic versus individual-level sources of bias in ecologic estimates of contextual health effects. *International journal of epidemiology*, 30(6):1343–1350.

Guiso, L., Sapienza, P., and Zingales, L. (2003). People's opium? religion and economic attitudes. *Journal of monetary economics*, 50(1):225–282.

Guiso, L., Sapienza, P., and Zingales, L. (2004). The role of social capital in financial development. *The American Economic Review*, 94(3):526–556.

Guiso, L., Sapienza, P., and Zingales, L. (2006). Does culture affect economic outcomes? *Journal of Economic perspectives*, 20(2):23–48.

Guiso, L., Sapienza, P., and Zingales, L. (2009). Cultural biases in economic exchange? *The Quarterly Journal of Economics*, 124(3):1095–1131.

Habyarimana, J., Humphreys, M., Posner, D. N., and Weinstein, J. M. (2007). Why does ethnic diversity undermine public goods provision? *American Political Science Review*, 101(04):709–725.

Hansen, M. F., Schultz-Nielsen, M. L., and Tranæs, T. (2017). The fiscal impact of immigration to welfare states of the scandinavian type. *Journal of Population Economics*, 30(3):925–952.

Henderson, V., Storeygard, A., and Weil, D. N. (2011). A bright idea for measuring economic growth. *American Economic Review*, 101(3):194–99.

Heston, A., Summers, R., and Aten, B. (2012). Penn world table version 7.1. center of comparisons of production, income and prices at the university of pennsylvania.

Hong, L. and Page, S. E. (2004). Groups of diverse problem solvers can outperform groups of high-ability problem solvers. *Proceedings of the National Academy of Sciences of the United States of America*, 101(46):16385–16389.

Horowitz, D. L. (1985). *Ethnic groups in conflict*. Univ of California Press.

Horwitz, S. K. and Horwitz, I. B. (2007). The effects of team diversity on team outcomes: A meta-analytic review of team demography. *Journal of management*, 33(6):987–1015.

IMF (2017). Seeking sustainable growth: Short-term recovery, long-term challenges. *International Monetary Fund. Washington, DC, October.*

Inglehart, R. and Welzel, C. (2005). *Modernization, cultural change, and democracy: The human development sequence.* Cambridge University Press.

Isaksson, A. (2007). World productivity database: a technical description. *Research and Statistics Staff Working Paper*, 10:2007.

Iyer, L. and Do, Q.-T. (2007). Poverty, social divisions, and conflict in nepal.

Kahane, L., Longley, N., and Simmons, R. (2013). The effects of coworker heterogeneity on firm-level output: assessing the impacts of cultural and language diversity in the national hockey league. *Review of Economics and Statistics*, 95(1):302–314.

Kim, M., Liu, A. H., Tuxhorn, K.-L., Brown, D. S., and Leblang, D. (2014). Lingua mercatoria: Language and foreign direct investment. *International Studies Quarterly.*

Kónya, I. (2006). Modeling cultural barriers in international trade. *Review of International Economics*, 14(3):494–507.

Künkler, M. and Leininger, J. (2009). The multi-faceted role of religious actors in democratization processes: empirical evidence from five young democracies. *Democratization*, 16(6):1058–1092.

La Porta, R., Lopez-de Silanes, F., Shleifer, A., and Vishny, R. (1999). The quality of government. *Journal of Law, Economics, and organization*, 15(1):222–279.

Lendle, A., Olarreaga, M., Schropp, S., and Vézina, P.-L. (2012). There goes gravity: how ebay reduces trade costs. *CEPR Discussion Paper No. DP9094.*

Letki, N. (2008). Does diversity erode social cohesion? social capital and race in british neighbourhoods. *Political Studies*, 56(1):99–126.

Lohmann, J. (2011). Do language barriers affect trade? *Economics Letters*, 110(2):159–162.

Maoz, Z. and Henderson, E. A. (2013). The world religion dataset, 1945–2010: Logic, estimates, and trends. *International Interactions*, 39(3):265–291.

Maystre, N., Olivier, J., Thoenig, M., and Verdier, T. (2014). Product-based cultural change: Is the village global? *Journal of International Economics*, 92(2):212–230.

Melitz, J. and Toubal, F. (2014). Native language, spoken language, translation and trade. *Journal of International Economics*, 93(2):351–363.

Miguel, E. and Gugerty, M. K. (2005). Ethnic diversity, social sanctions, and public goods in kenya. *Journal of public Economics*, 89(11):2325–2368.

Milanovic, B. (2013). Global income inequality in numbers: in history and now. *Global Policy*, 4(2):198–208.

Mira, A. N. (1964). Atlas of the peoples of the world. *Moscow: Glavnoe Upravlenie Geodezii i Kartografii.*

Montalvo, J. G. and Reynal-Querol, M. (2003). Religious polarization and economic development. *Economics Letters*, 80(2):201–210.

Montalvo, J. G. and Reynal-Querol, M. (2005). Ethnic polarization, potential conflict, and civil wars. *The American Economic Review*, 95(3):796–816.

Muller, S. H. (1964). *The world's living languages.* New York: Frederick Ungar.

Norris, P. and Inglehart, R. (2009). *Cosmopolitan communications: Cultural diversity in a globalized world*. Cambridge University Press.

OECD, M. P. (2015). *Is This Humanitarian Migration Crisis Different?* OECD Migration Policy.

Ottaviano, G. I. and Peri, G. (2005). Cities and cultures. *Journal of Urban Economics*, 58(2):304–337.

Ottaviano, G. I. and Peri, G. (2006). The economic value of cultural diversity: evidence from us cities. *Journal of Economic geography*, 6(1):9–44.

Özden, Ç., Parsons, C. R., Schiff, M., and Walmsley, T. L. (2011). Where on earth is everybody? the evolution of global bilateral migration 1960–2000. *The World Bank Economic Review*, 25(1):12–56.

Piketty, T. (2014). *Capital in the twenty-first century*. Harvard University Press.

Posner, D. N. (2004). The political salience of cultural difference: Why chewas and tumbukas are allies in zambia and adversaries in malawi. *American Political Science Review*, 98(4):529–545.

Putnam, R. D. (2007). E pluribus unum: Diversity and community in the twenty-first century the 2006 johan skytte prize lecture. *Scandinavian political studies*, 30(2):137–174.

Putnam, R. D., Leonardi, R., and Nanetti, R. Y. (1994). *Making democracy work: Civic traditions in modern Italy*. Princeton university press.

Putterman, L. and Weil, D. N. (2010). Post-1500 population flows and the long-run determinants of economic growth and inequality. *The Quarterly journal of economics*, 125(4):1627–1682.

Ramachandran, S., Deshpande, O., Roseman, C. C., Rosenberg, N. A., Feldman, M. W., and Cavalli-Sforza, L. L. (2005). Support from the relationship of genetic and geographic distance in human populations for a serial founder effect originating in africa. *Proceedings of the National Academy of Sciences of the United States of America*, 102(44):15942–15947.

Rauch, J. E. and Trindade, V. (2002). Ethnic chinese networks in international trade. *Review of Economics and Statistics*, 84(1):116–130.

Razin, A., Sadka, E., and Swagel, P. (2002). Tax burden and migration: a political economy theory and evidence. *Journal of Public Economics*, 85(2):167–190.

Rege, M. and Telle, K. (2004). The impact of social approval and framing on cooperation in public good situations. *Journal of public Economics*, 88(7):1625–1644.

Reynal-Querol, M. (2002). Ethnicity, political systems, and civil wars. *Journal of Conflict Resolution*, 46(1):29–54.

Roberts, J. (1962). Sociocultural change and communication problems. *Study of the role of second languages in Asia, Africa, and Latin America*, pages 105–23.

Roeder, P. G. (2001). Ethnolinguistic fractionalization (elf) indices, 1961 and 1985.

Samuel, P. (1993). Huntington, the clash of civilizations. *Foreign affairs*, 72(3):22–49.

Santos, F. C., Santos, M. D., and Pacheco, J. M. (2008). Social diversity promotes the emergence of cooperation in public goods games. *Nature*, 454(7201):213–216.

Selmier, W. T. and Oh, C. H. (2013). The power of major trade languages in trade and foreign direct investment. *Review of International Political Economy*, 20(3):486–514.

Shleifer, A. and Vishny, R. W. (1993). Corruption. *The quarterly journal of economics*, 108(3):599–617.

Smaldino, P. E. (2015). The evolution of the social self: Multidimensionality of social identity solves the coordination problems of a society.

Speciale, B. (2012). Does immigration affect public education expenditures? quasi-experimental evidence. *Journal of public economics*, 96(9):773–783.

Spolaore, E. and Wacziarg, R. (2009). The diffusion of development. *Quarterly Journal of Economics*, 124(2):469–529.

Spolaore, E. and Wacziarg, R. (2015). Ancestry, language and culture. Technical report, National Bureau of Economic Research.

Stiglitz, J. (2012). *The price of inequality*. Penguin UK.

Taylor, C. L. and Hudson, M. C. (1972). World handbook of social and political indicators. *Ann Arbor, MI: ICSPR.*

Trax, M., Brunow, S., and Suedekum, J. (2012). Cultural diversity and plant-level productivity. *IZA Discussion Paper Series*, 6845.

Turner, B. (2008). Goods non gods: New spiritualities, consumerism and religious markets. *Consumption and Generational Change: The Rise of Consumer Lifestyles.*

USSR (1992). *Gosudarstvennyi komitet SSSR po statistike. Itogi vsesoiuznoi perepisi naseleniia 1989 goda.* Minneapolis: East View Publications.

Van Praag, C. and Hoogendoorn, S. (2012). Ethnic diversity and team performance: A field experiment. *IZA Discussion Paper Series*, 6731.

Vandenbussche, J., Aghion, P., and Meghir, C. (2006). Growth, distance to frontier and composition of human capital. *Journal of economic growth*, 11(2):97–127.

Weidmann, N. B. and Schutte, S. (2017). Using night light emissions for the prediction of local wealth. *Journal of Peace Research*, 54(2):125–140.

Yu, S., Beugelsdijk, S., and de Haan, J. (2015). Trade, trust and the rule of law. *European Journal of Political Economy*, 37:102–115.