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Maximilian Belschner BSc (WU)

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Abstract

The sudden appearance of SARS-Cov-2, a coronavirus which triggers the Covid-19 disease, in December 2019 led governments worldwide to implement drastic measures on a societal level to stop the spread of the virus and to contain outbreaks. The societal scale of these measures begs the question whether a variable like social trust is an important behavioural determinant for people's movement and amount of social interaction. In this thesis I will study the hypothesized connection between compliance to anti-covid-measurements and social trust. Using data on human mobility and social trust at the regional level in 70 countries from 7 continents I will examine how mobility reduction depends on the level of trust people in a society have to other members of that society. Using a difference-in-difference estimation and bootstrapped confidence intervals I find that social trust is not an important determinant for mobility reduction during the pandemic in 2020. I also tested whether the political institutions (dictatorship or democracy) have an effect on the importance of social trust for compliance, which is highly unlikely following my analysis. Additionally, I find regional and temporal variations in the importance of trust.

Kurzfassung

Das plötzliche Auftauchen des SARS-Cov-2 Coronavirus, welches die Covid-19 Krankheit auslöst, im Dezember 2019 führte dazu, dass Regierungen weltweit drastische Maßnahmen auf gesellschaftlicher Ebene einführten, welche zum Ziel hatten Ausbrüche einzudämmen und die Ausbreitung des Virus zu verhindern. Der gesellschaftliche Rahmen und die großen Freiheitseinschränkungen, die diese Maßnahmen nach sich zogen, werfen die Frage auf, ob eine Variable wie soziales Vertrauen ein wichtiger Faktor darin ist, ob Personen ihre Bewegung und Anzahl der sozialen Interaktionen reduzieren. In dieser Masterarbeit werde ich die mögliche Verbindung zwischen sozialem Vertrauen und Beachtung von Anti-Covid-Maßnahmen untersuchen. Ich verwende Daten zu Mobilität und sozialem Vertrauen auf regionaler Ebene für 70 Länder von 7 verschiedenen Kontinenten um herauszufinden, wie sehr Mobilitätsreduktion mit dem Level an sozialem Vertrauen in einer Region miteinander zusammenhängt. Für die Analyse verwende ich ein Difference-in-Difference Modell und Bootstrap Konfidenzintervall. Meine Ergebnisse zeigen, dass es keinen Zusammenhang zwischen sozialem Vertrauen und Mobilitätsreduktion im Beobachtungszeitraum 2020 gibt. Ein weiterer Test bestand darin, die politische Institutionen (Demokratie und Diktatur) zu untersuchen und ihre Rolle für soziales Vertrauen zu evaluieren, doch auch hier ließen sich keine Unterschiede feststellen. Meine Ergebnisse ergaben außerdem dass es zu großen regionalen und zeitlichen Unterschieden in der Bedeutung von sozialem Vertrauen kam.

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1 Introduction

On March 11th 2020 the World Health Organisation (WHO) declared Sars-Cov-2, a coronavirus first detected in Wuhan, China, and its resulting illness Covid-19 a worldwide pandemic. Sars-Cov-2 mainly spreads through aerosols, microscopically small particles containing the viruses, which come from infected persons breathing, sneezing, speaking or coughing. The infectiosity combined with a very high case-fatality rate for elderly people and people with underlying health conditions prompted national governments worldwide to implement countermeasures to reduce the spread of the virus. The Chinese government made headlines when it introduced a lockdown and stay-at-home order for Wuhan in the middle of January. Two months later, most governments introduced similar measures.

The sudden appearance of the virus, as well as the urgency of the pandemic prompted a wave of academic and policy interest in epidemiology, but also the social sciences. The drastic anti-Covid measures ranging from stay-at-home orders, workplace and school closures, cancellation of international flights and other movement restrictions sparked the interests of economists, sociologists, political theorists and other social scientists. One of their main concerns was to understand the key factors which played a decisive role in the compliance of individuals toward the imposed restrictions on mobility and recreation.

In this master thesis I am going to look at one of the determinants that is discussed in the literature to be of great importance: **social trust**. I first present the significance of the subject determinant and develop three key theoretical hypotheses relating to social trust and compliance. I then proceed to test these hypotheses using empirical data gathered from Facebook, Google and the World Value Survey.

The thesis is structured as follows. Section 2 introduces the current status of the literature on the topic of social trust and compliance. Section 3.1 discusses the methods used to evaluate the supposed relationship of social trust and compliance. Section 3.2 provides details on the various data sources I used. The main results of this thesis are presented in section 4. Finally, section 5 and section 6 ends with a discussion of the results and concluding remarks.

2 Literature Review

2.1 Social Trust

2.1.1 Importance of Social Trust

Trust as a philosophical concept has already been discussed by Aristotle in his treatise on how friendships are supposed to work ((Aristote et al., 2011)). Until the 20th century, literature focused primarily on the notion of trust within individual relationships between private individuals. In the mid-20th century philosophers, sociologists and psychologists started writing about more abstract forms of trust towards people that we do not know personally (Ho, 2021).

Luhmann (1973) is one of these first sociologists to discuss trust as a social construct and its importance. In the context of his theories of systems, which postulates that there is a multitude of social systems that all work according to their own inherent logic, trust is one of the key factors for individuals to deal with complexities. According to him, trust enables individuals to make decisions in a society, reducing "transaction costs" significantly. A person that does not trust her surrounding or the people she interacts with would thus face high costs in attaining a decision. Conclusively, trust is a mechanism to reduce complexities in decision making and its importance varies depending on the situation a person faces.

Siegrist & Cvetkovich (2000) summarise another crucial area where social trust is important which is more closely related to the management of pandemic policies: risk assessment. Most people do not have high knowledge of epidemiology, climate science, criminology or advanced technologies, whereas technical experts possess deeper understanding of such hazards. Consequently, experts are better able to assess the risks of these hazard and, according to Siegrist & Cvetkovich (2000) regular people are more likely to assess their social trust to these experts than the risk itself. The authors then conduct a quantitative survey and calculate correlation coefficients between perceptions of risk, perception of benefits, trust in authorities and their personal knowledge. They conclude

> No significant correlations between social trust and judged risks and benefits were found for hazards about which people were knowledgeable. Results suggest that the lay public relies on social trust when making judgments of risks and benefits when personal knowledge about a hazard is lacking (Siegrist & Cvetkovich (2000), p.719).

These two important factors that are deeply intertwined with each other, complexity reduction and a lack of information for risk assessment, determine the essential role of trust in the case of a pandemic. People often lack the information and the epidemiological knowledge to choose the optimal behaviour. Furthermore, pandemics are extraordinarily complex. In order to make decisions, regular individuals (everyone who is not an expert in that scientific field) must reduce the complexity that they are facing. While they are unable to accurately assess the risks and benefits of behaviours in a pandemic, they are able to assess the trust they have in experts that have the necessary expertise to judge benefits and risks.

Siegrist & Zingg (2014) provide a useful synopsis of trust theories in risk assessment and pandemic contexts. The first theory they present is the Trust, Confidence and Cooperation (TCC) model. In this model, the authors make a crucial distinction between trust and confidence. Trust is defined as "*the willingness to make oneself vulnerable to others based on an assessment of the similarity of intentions or values. The value similarity judged between one's salient values and the other ascribed values*" (Siegrist & Zingg (2014), p.25). Confidence on the other hand is more based on evidence that a certain event or situation that happened in the past might happen in the future. When people assess trust in an organization or institution, common intentions and values determine the level of trust, while performance-related information determines confidence. The authors do not build a hierarchy of trust, they do not claim that personal trust is more important than social trust or vice versa. Rather, they suggest that confidence is influenced by social trust.

Siegrist & Zingg (2014) also introduce the intuitive recognition theory model of trust, in which, the crucial role falls on the perception of hazard managers and their ability to distinguish safe and dangerous situations. There are four types of events: Hit (true positive), All Clear (true negative), False Alarm (false positive), Miss (false negative). Using the TCC modelling framework, we can see that the intuitive detection theorist model of trust describes confidence, and not trust. Siegrist & Zingg (2014) also point out that there is little empirical evidence to support this model, citing studies suggesting that even a false alarm can boost trust, since the accuracy of the information was not the determining factor, but the intention of the hazard manager.

In summary, trust is a relational concept. It is useful in situations where an individual lacks sufficient knowledge to correctly assess risks and benefits of a decision and thus, must rely on an expert's input. Trust is an instrument of complexity reduction. Instead of assessing the situation and its possible consequences by themselves, the person assesses how much they trust another person who may have greater knowledge on the subject. This placement of trust into another person need not stem from the expert's proven experience, competence, or qualifications; rather it is based on the foundation of shared values and intentions.

2.1.2 Determinants of Social Trust

Kwon (2019)provides two theories that describe the determinants of social trust: the individual-oriented theory and the societal-oriented theory. I focus on the latter due to the fact that my object of research are societal levels of social trust and their connection to compliance. The first and maybe most important determinant of social trust are historical institutions, which the economist Douglass C. North described in his classical paper as "[...]*humanly devised constraints that structure political, economic, and social interaction. They consist of both informal constraints (sanctions, taboos, customs, traditions, and codes of conduct), and formal rules (constitutions, laws, property rights)*"(North, 1991). Delhey & Newton (2003) uses historical examples of post-war Germany and post-colonial Korea to showcase how countrywide societal disruptions, such as foreign occupation, invasion or civil war, leads to a collapse of institutions and, consequently, to a collapse of social trust, too. Other examples of the importance of history and institutions would be the vast differences in social trust levels in Flanders and Wallonia in Belgium, Eastern and Western Germany or Southern and Northern Italy (see figure 2.1.

Culture plays an important role, too. For example, Putnam (1994) argues that the social trust differences between Northern and Southern Italy stem from cultural and historical differences. Kwon (2019) investigates differences between collectivism and individualism. Interestingly, he concludes that collectivist countries (Eastern Asian countries like Korea, Japan or China) have a lower level of social trust than more individualistic countries like the US or the Nordic countries. Hofstede (1991) argues that risk averse cultures demonstrate lower levels of social trust, because trusting strangers engulfs making oneself vulnerable and exposed to risks.

Formal institutions play an important role for social trust, too. Zak & Knack (2001) find that democracies have higher levels of social trust than authoritarian regimes or dictatorships. The authors explain that citizens of democratic nations can exercise greater social and political freedoms and are less exposed to political power gaps and oppressive regulatory structures. Rothstein & Stolle (2003) argue that legal institutions possess a key role in trust. They must be impartial, fair and efficient, such that punishment of non-compliance by citizens is perceived less injust or even upholds wider trust in formal institutions for compliant citizens. Additionally, people feel protected against fraud, violence and other crimes and misdemeanors if the institutions act accordingly. Fukuyama (1996) states that observance of rules and regulations rests on cultural roots which differ by country, thereby showcasing how culture, informal and formal institutions are intertwined.

Lastly, the economic development of a country is correlated with social trust and vice versa. Scholars have noted that during economic recessions, rent-seeking behaviour at the expense of others increases, which in turn decreases the level of social trust (Kwon, 2019). Conversely, economic growth is correlated with an increase in social trust Algan & Cahuc (2013). But since social trust and institutions are so deeply interrelated, the level of social trust a society has influences institutions, which in turn have a positive or negative effect on economic growth and other economic indicators. Nevertheless, there are more robust estimations of the relationship between inequality and social trust than

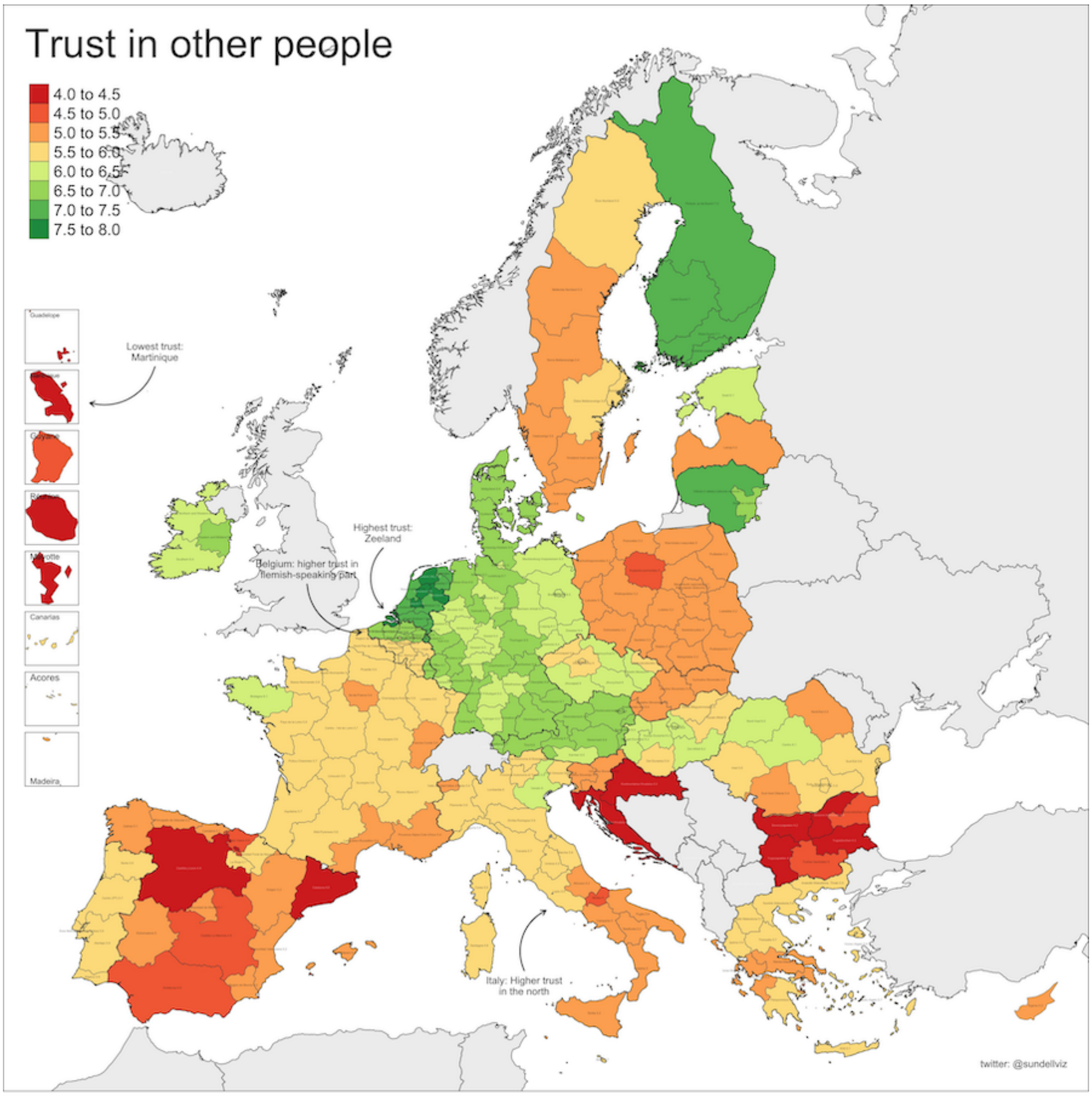

Figure 2.1: Social Trust in European Regions, Jacobs (2022)

economic growth and social trust, which gives us an indication that the former might be of greater importance. For example Bjørnskov (2007) make a cross country comparison and find that two variables have significant impacts on a general level of social trust: income inequality and ethnic diversity (both of which have negative impacts). Welch et al. (2005) summarize how social trust and social capital are related. The higher the social capital of a person is, the more he/she trusts other people (friends, family, but also strangers). Hake & Belabed (2018) find a significant relationship between income inequality and distrust into government in Southeastern and Eastern Europe. Interestingly, they do not consider aggregate, national levels of income inequality and trust, but look at it at a regional level.

2.2 Compliance

There is a significant volume of literature on the relationship of various forms of trust and compliance to public health measures in pandemics. This section is divided in two subsections 2.2.1 covers the literature of trust and compliance for previous pandemics (importantly, the H1N1 pandemic); subsection 2.2.2 deals with the recent literature on the Covid-19 pandemic.

2.2.1 Evidence in previous pandemics

Prati et al. (2011) provide great insight into the compliance to measures of the H1N1 pandemic in Italy (increased hygiene, some forms of social distancing, vaccination) and how this compliance relates to levels of trust, risk perception, worry or control. They also control for several socioeconomic factors and psychological factors which can explain some variation. They find no significant correlation between socioeconomic factors (gender, age, economic hardship, parental status, work status) and compliance to social distancing and vaccine acceptance. Some "softer" recommended measures (like washing hands, cleaning objects and using tissues when sneezing) are more likely to be adopted by women, parents, and people facing greater economic hardship (Prati et al., 2011). The correlation between trust and compliance, however, is significant. Trust in media, the Italian Ministry of Health and medical science are all positively correlated with compliance to the measures. "Trust in the institutional response to the outbreak", which is "confidence" in the TCC model, is only weakly positively related to compliance. Perception of risk (worry, severity of illness, likelihood of infection) is positively correlated with compliance, too.

Gilles et al. (2011) present a similar survey with respondents from French-speaking Switzerland (also covering the H1N1 pandemic). The difference to Prati et al. (2011) is, that Gilles et al. take 2 longitudinal surveys and gather data on the actual take up of vaccines in the sample as well as the individuals willingness to do so. They find common traits in the socioeconomic factors which improve compliance e.g., level of education and gender; as well as similar importance of risk perceptions as a predictor. But when it comes to predictors of vaccination behaviour, only trust in medical organizations (they did not test for trust in government or media) have significant predictive power of vaccination behaviour. The more the respondents trust in medical organization, the more likely they were to take the H1N1 vaccination (Gilles et al., 2011).

van der Weerd et al. (2011) take a closer look at trust in government and risk perception during the H1N1 pandemic in the Netherlands. Here, the authors test the TCC model by taking several telephone surves in a 6 month period and observe the dynamics of trust and perception. Initially, trust in government is remarkably high, but it decreases over time. Trust of governmental information is high (77,1% in the beginning) but decreases as well (to 61% in period three). The main reason to distrust government information is that it appears to be incomplete, kept secret or withheld.
In the beginning of the pandemic, all factors (fear/worry, government trust, perceived

vulnerability) are highly correlated with adopting protective measures. In period 3, the only significant factor is fear/worry, while government trust and perceived vulnerability lose their significance. Interestingly, after controlling for demographics, all three factors are always significant for the intention to accept a vaccination (van der Weerd et al., 2011).
Overall, their study seems to suggest some parts of the TCC model. It shows the importance of trust and risk perception with respect to vaccination acceptance. It also emphasizes the importance of accuracy in public crisis communications and overall transparency of governments. The respondents acknowledge that there are huge knowledge gaps about the H1N1 influenza, but this has no effect on their trust in government. However, once they have the feeling that the government intentionally withholds information, mistrust increases, which would be another indication for the TCC model. It is not the fact that the government mishandles interventions or is not able to publish information, but that the system of values (transparency vs. control of information flow) is completely different.

2.2.2 Evidence for the Covid-19 pandemic

The Covid-19 pandemic differs significantly from the H1N1 pandemic, which is why not all insights from the previous section are valid for the current outbreak. Most importantly, during the H1N1 pandemic, the governmental measures were rather "soft" with a focus on hygienic measures like sneezing-etiquette, frequent handwashing and disinfections. Moreover, governments communicated recommendations rather than imposing strict regulations for citizens to comply with. Finally, the outbreak of H1N1 was less severe outside of Mexico (the country of origin) (Murphy, 2011). Contrastingly, governments imposed strict lockdown measures to prevent the spread of Covid-19. Non-compliance was tackled through monetary fines and tougher policing. In the early stages of the Covid-19 pandemic, almost every country introduced some kind of lockdown/stay-at-home order and used non-pharmaceutical interventions to stop the spread of the virus. In the latter stages of the pandemic, tough restrictions were only applied to people that are not vaccinated against the virus. Nevertheless, it is safe to say that the stringency of measures to stop the spread of the virus was a lot higher during the Covid-19 pandemic.

Plohl & Musil (2021) outline how compliance and trust interact in the context of Covid-19 prevention. They create a model (which they also tested using an online survey) that aims to explain the compliance with Covid-19 guidelines. Compliance to Covid-19 guidelines is largely determined by the perception of Covid-19 as a risk and trust in science, which are themselves linked (the more people trust in science, the more they perceive Covid-19 as a risk). They then look at four more factors that are explaining trust in science: Political conservatism, religious orthodoxy, conspiracy ideation and intellectual curiosity (with the education level being a determinant of these four factors). Plohl & Musil (2021) find that people that are more conservative, more religious, less intellectually curious and more prone to believe conspiracies typically have a low trust in science, perceive Covid-19 less as a risk and are therefore less compliant with Covid-19 guidelines.

A problematic aspect of the H1N1 literature is that it is largely based on survey data which captures an individual's self reported intentions over actual actions. However, Bargain & Aminjonov (2020) address this problem well by combining regional level survey data on trust in governments with a stringency index to account for the variation.[1]. To measure the compliance of citizens the authors use data from Google, which collects mobility data by using the GPS signal almost all smartphones nowadays have. Using Google data is a good way to measure actual compliance for two reasons: Firstly, Google constantly observes the movement of their customers, so we do not expect any huge data gaps. Secondly, we can almost definitely expect that the Hawthorne effect, the observation in psychological experiments that people behave differently because they know that they are being observed, is not an issue. Mobile phone users are likely aware that Google collects their data, but they don't move around differently due to that fact.
Bargain & Aminjonov (2020) find that there is a significant statistical correlation . Furthermore, panel 4 in figure 2.2 shows how much the citizens in the countries stayed at home, respectively, and this observation confirms the trend of the other three panels: citizens from regions that trust their government stayed at home more likely than citizens that are more distrustful of their government. Furthermore, they find that citizens from high-political trust regions were less likely to visit transit stations, grocery stores or leisure activity spots. Although, the study only looks at trust into government in European countries, so it is questionable whether findings from that study can easily be translated to other regions of the world or other forms of trust. Nevertheless, the paper is a huge inspiration for this master thesis due to its convincing conceptual approach by using mobility data to operationalize compliance to Covid-19 measures.

My focus on social trust and compliance also derives from an observation of Wong & Jensen (2020) called the "paradox of trust". As mentioned, in the literature it is generally argued that a person with greater governmental trust (or other important societal institutions) is more likely comply with public health policies and recommendations. The paradox of trust describes the situation where the population displays a high level of trust into their political leadership such that they become complacent in following recommended personal safety precautions. Wong & Jensen (2020) observe this behaviour in Singapore, which is one of the countries with the highest levels of trust into government and an authoritarian government that has a strict enforcement of their laws. Singaporeans trust their government and the authorities so much that they became careless, felt extremely safe and did not take the individual precautions that were recommended.

Wu (2021) provides a useful summary of the literature on social capital and compliance. Social capital is a sociological umbrella term for phenomenons of social organisations that have formal and informal norms. Social capital is often described as the density

[1] The countries included in their sample were Germany, Finland, Norway, Sweden, Netherlands, Belgium, UK, Ireland, France, Italy, Spain, Portugal, Poland, Hungary, Estonia, Slovenia, and the Czech Republic

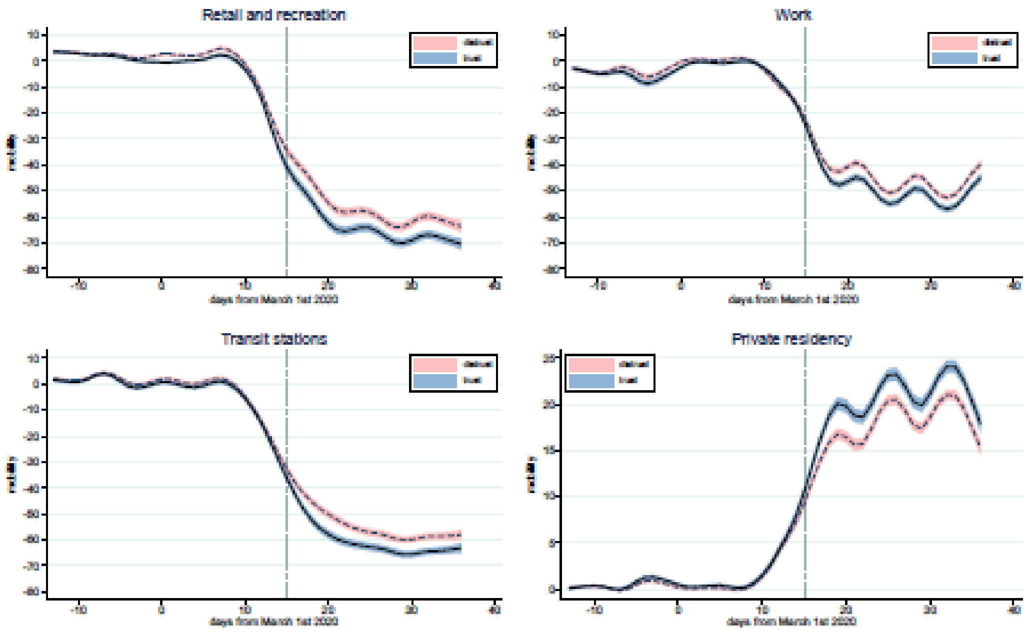

Figure 2.2: Mobility Change in various types of places, Bargain & Aminjonov (2020)

of a social network and the amount of connections a person has to other people, but social trust is, according to Wu (2021) part of this conception as well. She remarks that the relationship between social capital and compliance to public health measures is complex and contradictory at times. On the one hand, places with high social capital are better prepared for pandemics and are more likely to adapt strict and necessary policies (like stay-at-home orders, increases in testing capacity and hygiene rules) than places with lower social capital (and less dense social networks) On the other hand, there are empirical estimations that social capital increases the risks of infections due to denser social networks. Fraser et al. (2020) estimate that Japanese prefactures that have high social capital saw a faster increase in infections. This could, in turn, lead to the perception of Covid-19 as being more risky and lead to more compliance to public health measures.

Wu (2021) outlines an important factor which inspired my second hypothesis to test in this master thesis: The regime type has important implications for the relevance of social capital and social trust for compliance. Social trust and social capital are only important for democracies, where the potential punishment for non-compliance is no more than a monetary fine in most cases. Under dictatorships there are more severe modes of control and coercion available. Wu (2021) notes how during the first lockdown in Wuhan in 2020 the Chinese military patrolled the streets with soldiers and tanks and enforced rigorous controls on anyone who left their homes. Potential punishment was not just of monetary nature but also linked to the Chinese system of social credit scores, where a low social credit score can prevent a Chinese citizen from riding high-speed trains, getting access to bank accounts and similar restrictions.

3 Methods and Data Sources

3.1 Methods

3.1.1 Hypotheses

Following the theoretical introduction to the relationship of trust and compliance in the context of the H1N1 and Covid-19 pandemic, I will now present the main hypotheses that I am going to test in this master thesis. The aim is to falsify the following hypotheses.

There is no significant relationship between the level of social trust in a region and compliance to non-pharmaceutical Covid-19 measures.

This hypothesis is the main hypothesis that I want to refute in this master thesis.

If there is a relationship between social trust and compliance to non-pharmaceutical Covid-19 measures, it remains stable over time.

Following the theoretical contributions from Siegrist & Zingg (2014) I suppose that social trust (and trust in general) is a very important factor for compliance throughout a pandemic.

There is no difference in the importance of social trust for compliance between democracies and dictatorships.

This hypothesis directly follows from Wu (2021) argumentation that social trust is not a relevant factor for compliance in dictatorships since a dictatorial government has more forceful means to achieve citizen's compliance and is also more willing to use these means.

3.1.2 Regression Framework

I will estimate compliance to non-pharmaceutical Covid-19 measures in a **Difference-in-Difference** (DiD) framework, following the equation below. Compliance to Covid-19 measures is operationalized by a mobility variable, thus I assess citizen's changes in mobility due to Covid-19 and the measures against its spread.
An important feature of a DiD framework are the two dummy variables and the interaction term, which in my case are called $Trust_i$ for the treatment variable (the treatment in this case is whether a region has high social trust or not) and $Post_{i,t}$ which denotes the period after the treatment. In my estimation, the $Post_{i,t}$ variable denotes the presence of a lockdown, the post-intervention period. The most important coefficient to look at in this estimation is β_1 which captures the group differences after treatment.

$$Mobility_{i,t} = \beta_0 + \beta_1 * Trust_i * Post_{i,t} + Trust_i + Post_{i,t} + Deaths_t + Deaths_{t-1} + X_i + Day\ FE_t + Country\ FE + \varepsilon \quad (3.1)$$

In the following paragraph I summarise key facts about the various variables that are in the main regression framework. Note that a subscript i indicates that each region has a value for this variable, while the subscript t denotes that variable has different temporal expressions, it changes from day to day.

1. $Mobility_{i,t}$ Continuous variable that denotes the change of mobility in a region i at a given day t compared to the reference period.
2. $Trust_i$: Social trust variable. In this case it is a dummy variable.
3. $Post_{i,t}$: Post-Intervention dummy variable, which indicates the presence of a lockdown or not.
4. $Deaths_t$: 3–day moving average of Covid deaths in a country on day t
5. $Deaths_{t-1}$: Lag of 3–day moving average of Covid deaths, used as an instrumental variable in this case.
6. X_i: Is a vector containing region-specific control variables, including share of employed people, share of people aged 65 and older, population density, GDP per capita, religiosity and people valuing obedience.
7. $Day\ FE_t$: These are the day dummies which capture common time trends (for example information available to all citizens on the pandemic situation
8. $Country\ FE$ These are country dummies which account among other things for different national healthcare systems or underlying long-term trends that affect mobility or cultural differences that cannot be captured by other variables.

To exclude the possibility that any significant relationship appears just because of the way the social trust variable is measured, I am also going to include two more estimations, both in a **Fixed Effects** framework. The first one, following equation 3.2 replaces the social trust dummy variable with a continuous variable of social trust shares, i.e. the share of people that have high social trust in a region. This way it is a fixed effects regression with the $Post_{i,t}$ variable functioning as a time-dependent control variable.

$$Mobility_{i,t} = \beta_0 + \beta_1 * Trust_{i,continuous} + Post_{i,t} + Deaths_t + Deaths_{t-1} + X_{i,t} + Day\ FE_t + Country\ FE + \varepsilon \quad (3.2)$$

In the next estimation the $Post_{i,t}$ variable is replaced by a continuous $Stringency_{i,t}$ variable. In this case, the variable indicating lockdown measures is replaced by a stringency index which encapsulates additional Covid-related policies like testing regimes, school closures, workplace closures and income support.

$$Mobility_{i,t} = \beta_0 + \beta_1 * Trust_{i,continuous} + Stringency_{i,t} + Deaths_t + Deaths_{t-1} + X_{i,t} + Day\ FE_t + Country\ FE + \varepsilon \quad (3.3)$$

Finally, I consider the regression for the dictatorship estimation. This estimation is very similar to equation 3.1. $Post_{i,t}$ does not denote pre-and-post treatment periods, but it acts as a time-dependent control variable like in equation 3.2. What is new is the interaction term of $Trust_i * Dictatorship$. While the term $Trust_i$ captures the mobility differences for regions with high social trust while the term $Dictatorship$ captures the country-wide mobility differences for regions that are dictatorships. Therefore this interaction term shows the additional effect that a high trust region in a dictatorship shows. The hypothesis is that this term is **not** statistically significant.

$$Mobility_{i,t} = \beta_0 + \beta_1 * Trust_i * Dictatorship + Trust_i + Dictatorship + Post_{i,t} + Deaths_t + Deaths_{t-1} + X_{i,t} + Day\ FE_t + Country\ FE + \varepsilon \quad (3.4)$$

3.2 Data Sources

3.2.1 Mobility Data

For the mobility data I use both the Google Mobility Reports and the Facebook Movement Data, with the latter being the more important data source. Facebook calculates mobility with "movement tiles", 600m x 600m big tiles where people move in and out of. The movement is captured using GPS and mobile internet data from smartphone users, and it is calculated in how many different tiles each user is [1]. Finally, for each subnational region (mostly admin-1 regions like states in Austria and Germany) the sum of visited tiles is calculated and the relative difference to a reference period[2] is computed (Facebook, 2020).
The following countries are present in the World Value Survey but do not have any mobility data, neither from Google nor from Facebook: Azerbaijan, Armenia, Andorra, Montenegro and Cyprus. For countries that are not included in the Facebook dataset (Russia, Ukraine, Pakistan and Myanmar) or only have very broad subnational categories

[1] The data was clipped at 200 tiles to prevent extreme movers to bias the data. Additionally, they add some statistical noise to each individual observation to make it impossible to identify an individual in the dataset.

[2] February 2020

(United Kingdom)[3]. I use the Google dataset, which is calculated in a slightly different way. Instead of counting the tiles an individual passed through each day, Google uses its database of places that people visit from Google Maps and classifies all of these places in one of five categories: "leisure and shopping", "groceries", "parks", "train stations and transit stations", "workplaces", "home". Like Facebook, they use a reference period[4] to calculate the relative difference of people visiting these places (Google, 2021).

Since it is not possible to simply average the results from Google and translate it into the Facebook format for the mobility index, I use a random forest algorithm to make the data comparable. A random forest is a collection of bootstrapped and randomly generated classification trees (or regression trees in my case with a continuous dependent variable). A regression tree looks something like this:

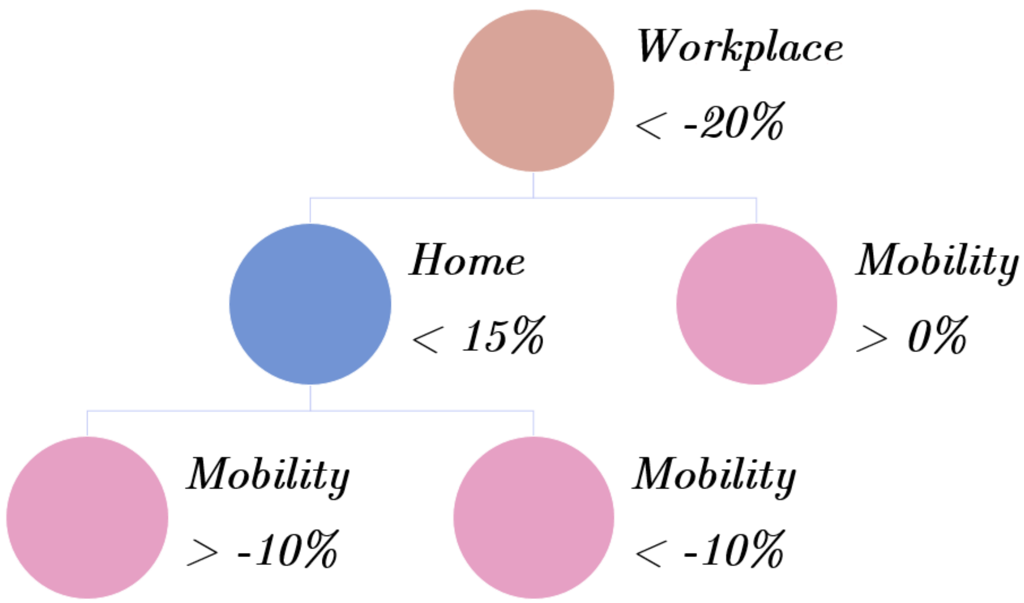

Figure 3.1: Regression Tree Example, own graphic

Every observation starts the regression process at the top. In my example, if an observation has a "visited workplace" reduction of less than 20%, I would go down the tree the left side and use the next indicator, "visited home", as a predictor. The pink circles are the so-called end-nodes which then predict the dependent variable. For example, if

[3] I ran all my regressions with two different samples. The first sample was all countries, regardless of the source of the mobility data. The second sample did not contain the above countries that did not have Facebook mobility data. There were no significant differences between the samples.

[4] First 2 weeks in February 2020

my observation has a visited workplace reduction of less than 20% and a visited home increase with more than 15%, the regression tree would predict overall mobility reduction of less than 10%.

In the case of random forests, the algorithm creates hundreds of these trees by randomly choosing independent variables and randomly choosing a sample (with replacement) from the data. The order of the independent variables is chosen by their respective predictive power, using indicators like reduction in root mean squared error (RMSE) or reduction in mean absolute error (MAE). For the final predictions, a random forests uses the average of all predictions from the individual trees (Irizarry, 2020).

Additionally I also use the so-called "gradient boost" method, where instead of a multitude of regression trees only one regression tree is built with a weighting factor for each independent variable (See Singh (2018) for more details). For my final predictions of the mobility index I use the average of two random forests[5] and a gradient boosted regression tree. Figure 3.2 compares the different models with the actual values[6] on the x-axis and the predicted values on the y-axis. The graph shows the clear correlation between the Facebook and Google mobility data, allowing us to use the Google mobility data in the regressions.

3.2.2 Trust Data

Social Trust and Dummy Variable

Trust data comes from the World Value Survey wave 7 (2017-2021). For the social trust variable, Q57 was used (Haerpfer et al., 2021):

> Q57
> Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?"
> 1 – most people can be trusted
> 2 – need to be very careful.

For each region I calculate the share of people that answered with 1 for this question. Depending on the type of estimation - continuous or dummy - I then either use the share of people answering with 1 or construct a dummy variable. As it is typical for dummy variables, it can either have the value of 0 or 1. In my case, the variable was 1 if the region has an above average share of respondents with high social trust compared to the remaining regions in a country. In the case of a region having a below average share of respondents with high social trust the dummy variable has the value 0.

[5] The random forests vary in which R packages where used calculating them. One was used with the "randomforest" package, the other one with the "caret" package.

[6] The training dataset consisted of mobility data for Austria

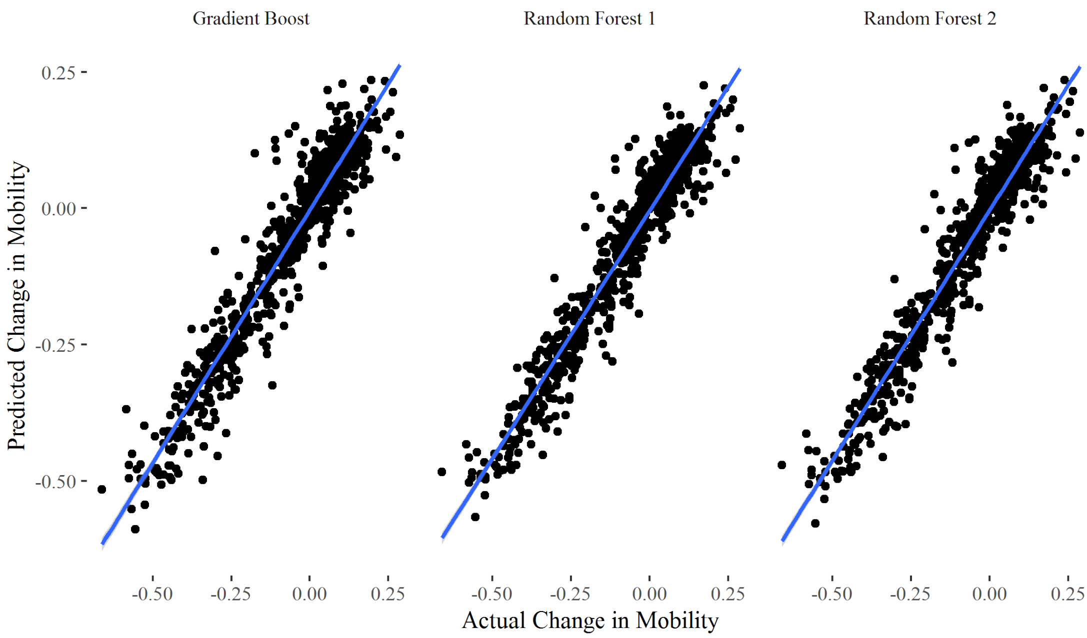

Figure 3.2: Model Comparison

Other Trust and Confidence Variables

One step of my analysis includes an examination of trust and confidence variables other than social trust which were also in the World Value Survey. Particularly, I look at these forms of trust and confidence:

1. **Family Trust:** This question is phrased in the following way: "I would like to ask you how much you trust people from various groups. Could you tell me for each whether you trust people from this group completely, somewhat, not very much or not at all? - Your Family"
   The share of people trusting their family (answering with either $1 = Trust\ completely$ or $2 = Trust\ somewhat$) is calculated in a similar fashion like the social trust variable.

2. **Neighborhood Trust:** Same phrasing like family trust, just with "People in your neighborhood" instead.

3. **Personal Trust:** Trust in people the respondents knows personally. Same phrasing like family trust and neighborhood trust.

4. **Confidence in Parliament:** "Please look at this card and tell me, for each item listed, how much confidence you have in them, is it a great deal, quite a lot, not very much or none at all? - Parliament"

This variable measures confidence instead of trust, but the values 1 and 2 are the same in the sense that they represent agreement or great trust/confidence in said entity.

5. **Confidence in Government:** Like the previous variable, just with confidence in government instead of parliament.

3.2.3 Control Variables

Covid Data

The data for Covid deaths and cases comes from the Johns Hopkins University (Dong et al., 2020). Due to some countries not having data for subnational units I use the national numbers. For Puerto Rico, Hong Kong and Macao there was no data available, so I use the numbers from the US and China respectively.

Lockdown and Stringency Index

Lockdown variable and stringency index come from the Oxford Covid-19 Government Response tracker. The lockdown variable measures whether countries had a nationwide stay-at-home order or curfew mandated, not just recommended. It has the values 1 to 3, with 1 being a stay-at-home recommendation for vulnerable people, 2 being a mandated curfew for several hours and 3 a mandated curfew for the whole day. I transformed it into a dummy variable which is equal to one if the underlying variable is either 2 or 3. The stringency index is the mean of 20 indicators which Hale et al. (2021) summarise in their database, containing policy measures from banning public events, mandatory tests, school closures, income support or health system policy. The index ranges from 0 to 100, which 100 being the strictest policies possible.

Age

The age variable (share of people aged 65 and older) is calculated using age-specific populations from worldpop.org (World Pop, 2021), which provides raster-based population data. To get the population headcounts from the raster format to the subnational format I cropped shapefiles and summed up the values inside each shapefile. Afterwards I made consistency checks [7] to be sure the numbers are accurate.

GDP

Similar to the age variable, GDP (or rather, GDP per capita) is calculated using raster data from **?**, but instead of summing up the values inside a shapefile I calculated the mean. The GDP values are the 2015 levels of GDP with purchasing power parity applied.

[7] The consistency check was rather simple, I just went to a small subset of national statistics offices and compared their population estimates to mine.

Population Density

Population density is provided in a raster format by Center For International Earth Science Information Network-CIESIN-Columbia University (2017). Again, I calculated the mean over the various raster data points inside a shapefile to get the population density of the respective region. In a similar fashion to the age variable, here I conducted consistency checks for robustness and better accuracy.

WVS control variables

The following variables are all control variables coming directly from the World Value Survey[8].

1. **Education:** Share of people with post-secondary or higher formal education (ISCED classification 4 to 8). Item Q275 in the World Value Survey.
2. **Obedience:** Item Q248 in the World Value Survey which asks whether obedience is an essential feature of democracy. Takes the values 0 to 10 with 10 meaning that it is an essential feature of democracy and 0 meaning that it is not important at all. Dummy variable was created with values of one for all people that score higher than 6 on this scale.
3. **Employment:** Whether the respondent was employed (full- and part-time) or self-employed at the time of the interview. Dummy variable created with value of 1 for employed and 0 for not employed people or people out of labour force.
4. **Religiosity:** Self assessment of one's own religiosity, corresponding to Q173 in the survey. "Independently of whether you go to church or not, would you say you are ..." 1 - religious person, 2 - not religious person, 3 - convinced atheist. Dummy variable created with value of 1 for all persons answering that question with 1.

Democracy Index

The data for the democracy-dictatorship variable comes from the Economist Intelligence Unit (Economist Intelligence Unit, 2021) which releases an annual report on the state of democracy worldwide. Here I follow the classification of the Economist Intelligence Unit and classify every country with an index higher than 6 to be a democracy (which includes so called "flawed democracies" like Indonesia and Mexico and full democracies like Austria or Japan). Consequently, every country with a value below 6 is classified as dictatorship.

[8] Missing values for WVS variables were replaced by the median value of that variable in each country.

4 Results

4.1 Summary Statistics

To get an overview of the dataset, I present a summary table (4.1) of the numerical variables that are included in the regressions. Some variables, like the dummies for lockdowns, social trust or dictatorships, are of course also included in the regressions but not mentioned in this table. Table 4.1 provides the sample size, mean and standard deviations. We can see that the sample size is 287,100 for all variables except new deaths. This is because new deaths was calculated with $New\,Deaths_{i,t} = Deaths_{i,t} - Deaths_{i,t-1}$, therefore the missing 609 samples were all in $t = 0$.

Crucially, the mean for mobility was negative while the mean share of people having high social trust was 0.249, both variables have a very high standard deviation. Another important variable, the stringency index which captures the rigidity of anti-Covid-19 measures, has a mean of 61.844. All independent variables have rather high standard deviations, which is good for the upcoming regressions.

Statistic	N	Mean	St. Dev.
Mobility	287,100	−0.105	0.185
New Deaths, daily	286,491	0.182	0.402
Stringency Index	287,100	61.844	21.268
Perc. of People with high Social Trust	287,110	0.249	0.205
Perc. of religious People	287,110	0.615	0.264
Share of people with Tertiary Education	287,110	0.293	0.194
Perc. of Employed People	287,110	0.591	0.159
Perc. of People valuing obedience	287,110	0.452	0.228
Perc. of People aged 65 and older	287,110	0.135	0.074
GDP/Gapita	287,110	11,768.440	35,820.690
Population Densitry	287,110	994.836	4,374.408

Table 4.1: Summary Statistics

4.2 Summary of Mobility Trends

This section provides some general insights and graphical summaries to the mobility trends. Firstly I will look at the distribution of the mobility changes. In figure 4.1 we can see that the distribution is skewed to the left, with the mean value being -10.5%. The majority of values are unsurprisingly negative and indicate a lower mobility level throughout the year 2020. The lowest value was -86.27% for the Peruvian region of El Callao on April 10th, while the highest value was the Iraqi Region of Dhi Qar on September 23rd with +63.64%.

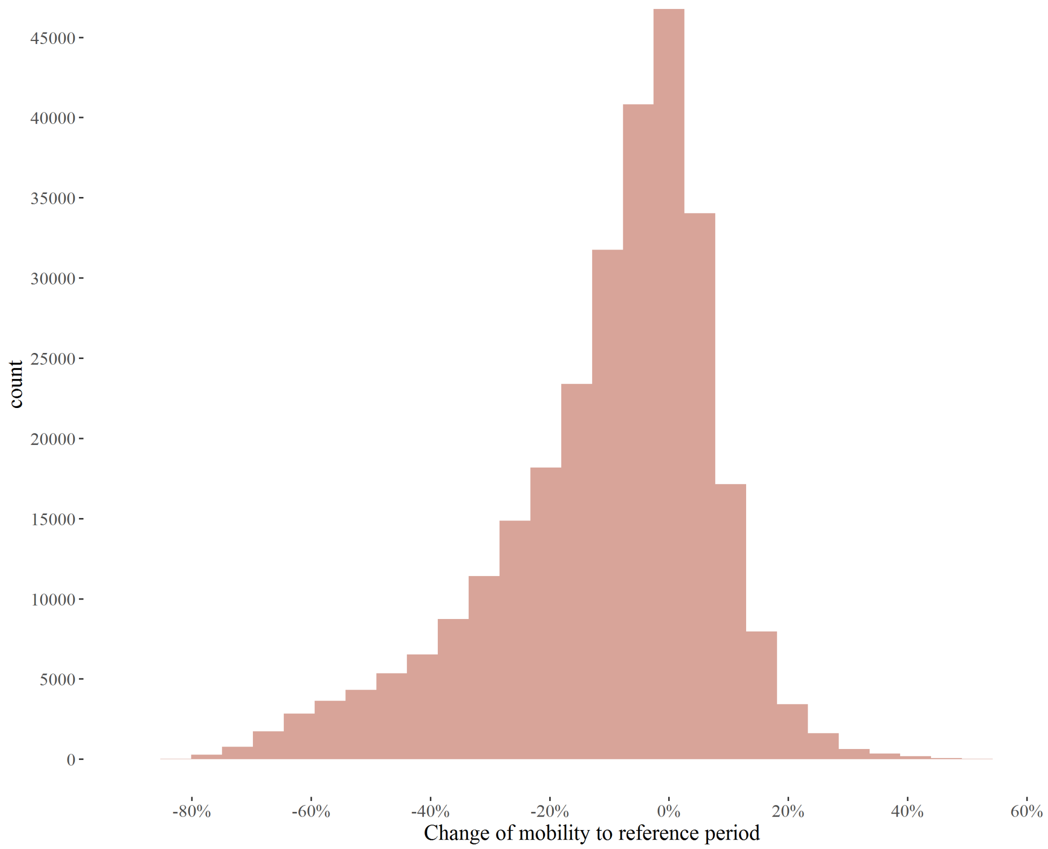

Figure 4.1: Histogram for Mobility Change, own graphic

Figure 4.2 plots the average mobility change over time for all regions, based on its classification for social trust. In this case, the dummy variable is used, so a region that has a higher social trust value than the average of the respective country is = 1. We can see how mobility drastically dropped in March and April, where most of the countries went into lockdowns or introduced other kinds of measures. Starting in May, mobility increased again, leveling off in August. At the end of the year, mobility decreased again due to the holiday season in Christian countries. We can observe that regions with lower social trust generally have slightly more mobility than higher social trust regions, but the difference is minimal and disappears after October.

The average mobility across all regions hides important heterogeneous mobility trends

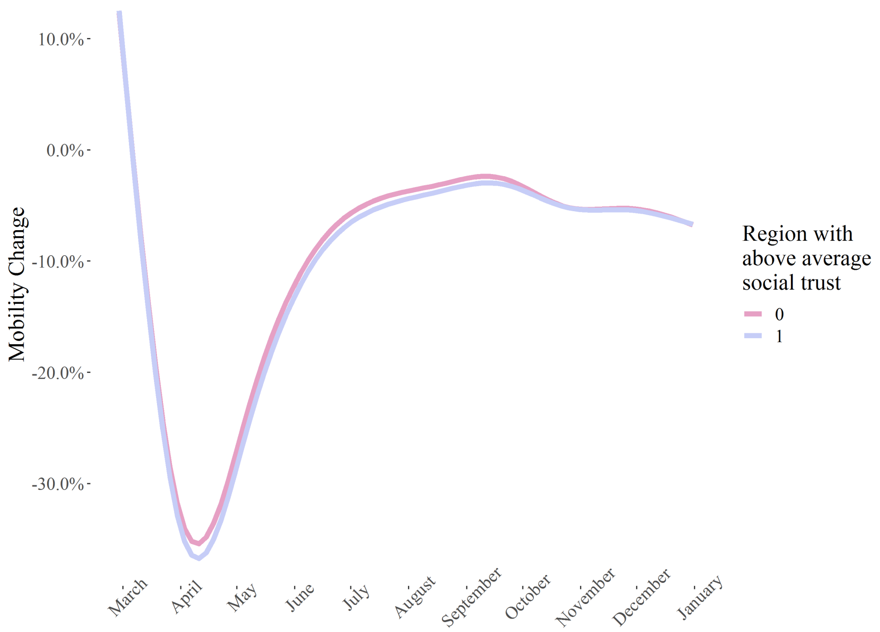

Figure 4.2: Average Mobility Change over all Regions, grouped by Social Trust, own graphic

in various countries, a selection of countries therefore gets its individual graphs in figure 4.3. Noticeable is the plunge in mobility across all countries in March and April 2020, which is noticeable and reconfirms results from the previous graph. Italy, with a mobility decrease of more than 75% is especially remarkable, while the mobility change in the other countries, like Vietnam, Nigeria or Iraq was at a maximum of -25%. The mobility change at the end of the year only occurs in majority Christian countries like Portugal, Austria or Italy, which is why I infer that this decrease comes from the holiday season and several non-pharmaceutic interventions at the end of the year (e.g. Austria went into a second nationwide lockdown in November).

No clear trend can be deduced for social trust regions. For Nigeria, Italy or Austria no clear trend is visible, while Iraq, Portugal and the United Kingdom show a trend that goes into the expected direction: region with a comparatively high social trust saw a greater decrease in mobility than the lower social trust regions. Lithuania on the other hand shows a trend that is the exact opposite: lower social trust regions do not see a big enough reduction in mobility. Generally speaking, the mobility trends and the relationship to social trust appear to be very heterogenous judging from these eight countries.

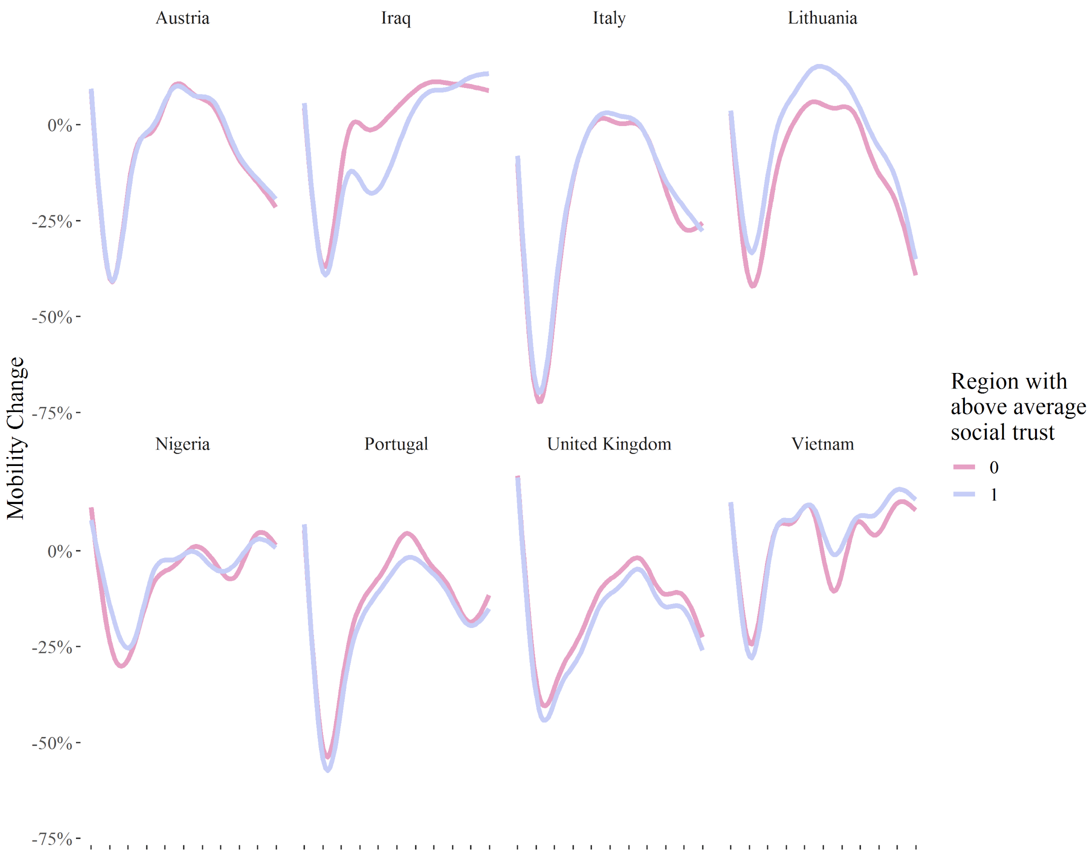

Figure 4.3: Mobility Change across 8 selected countries, own graphic

4.3 Two Dummy Variables, Lockdown and Social Trust

As mentioned in the methods chapter, the first regression I conduct is the one with both social trust and the lockdown variables being dummy variables, the Difference-in-Difference estimation. Table 4.2 provides the results for this regression, with the three columns including or excluding the control variables for day and country.

What is striking is that most coefficients are highly significant, regardless of day or country controls. Social trust consistently has a negative coefficient, albeit a very small one in the regressions without region controls. In the case with all controls, its coefficient is -0.005 which translates to a mobility reduction of 0.5% in regions with comparatively more social trust. In the other two regressions this coefficient is -0.004, which indicates a difference in mobility of less than one percent. This mobility reduction is observable regardless of a lockdown or other variables, it is simply the mobility difference between high and low social trust regions. The high significance for almost all coefficient very likely comes from the vast amount of observations ($N = 271.759$). The R^2 is relatively high if day and country controls are included with a value higher than 65%, which means that only 35% of mobility variations are not explained by the included variables.

One variable which also deserves special attention is the lockdown variable. The presence of a nationally-mandated lockdown decreases mobility by around 8.7%. This is the average effect in all regions, regardless of high or low social trust. The very small standard errors also hint that the lockdown variable is not just statistically significant because of its large sample size, but because it is a determinant for mobility.

The most important term nonetheless is the interaction term of **Social Trust x Lockdown** in which all three regression is highly statistically significant. The coefficients vary from -0.003 to -0.007, the latter suggesting a mobility reduction of 0.7% in regions with high trust as long as a lockdown was in place. But since the R^2 is very low for this regression (only 22%) I adhere to the main results from the one including both day and country dummies. A coefficient of -0.003 would translate into a mobility reduction of 0.3%. Note what this interaction term means: There is an additional mobility reduction in regions with high social trust that are in a nationally mandated lockdown. A region with high social trust will see a mobility reduction (all other variables being equal) of 9.5%, while a region with low social trust will see a mobility reduction of 8.7%. The 0.8% difference come from the generally lower mobility in high social trust regions (which was 0.5%) and the interaction term with 0.3%. But this very small effect size of just 0.3% raises questions of whether social trust is actually a relevant variable, despite the statistical significance.

Looking at the other control variables we can see some coefficients are negative, while others have a positive contribution towards mobility. Religiosity and the share of people older than 65 both have a positive influence on mobility with 4.9% and 24.9% mobility increase respectively. The share of people with at least tertiary education (bachelor's degree or higher) is negatively correlated with mobility. When interpreting these shares one must consider that the mobility change happens on hypothetical regions with share = 0 or share = 1. So the coefficient for religiosity for example denotes a 5% mobility increase from a region with no religious person to a region with only religious persons.

The time-dependent control variables new deaths per 100.000 and the 1st lag of new deaths per 100.000 are both negatively correlated, the non-lagging variable with a bigger effect. An increase of deaths per 100.000 by one[1] leads to a mobility reduction of 4.8%.

[1] At the time of writing this, the 7-day average of people/100.000 dying from Covid was 0.19 in Austria, with the peak death rate at around 1.4 in December 2020**?**

Table 4.2: Main Regression Results

	Mobility Change		
	(1)	(2)	(3)
Social Trust (High = 1)	−0.005***	−0.004***	−0.004***
	(0.001)	(0.001)	(0.001)
Lockdown (Lockdown present = 1)	−0.087***	−0.106***	−0.161***
	(0.001)	(0.001)	(0.001)
New Deaths/100.000	−0.048***	−0.061***	−0.040***
	(0.001)	(0.002)	(0.002)
1st Lag of New Deaths	−0.006***	−0.009***	−0.0004
	(0.001)	(0.002)	(0.002)
Religiosity	0.049***	−0.027***	0.011***
	(0.002)	(0.001)	(0.001)
Share of People w. tertiary education	−0.043***	−0.026***	−0.022***
	(0.002)	(0.001)	(0.002)
Share of People >65	0.249***	0.103***	0.058***
	(0.010)	(0.004)	(0.006)
Share of Employed People	0.002	0.021***	0.026***
	(0.002)	(0.002)	(0.002)
GDP/Capita	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Population Density	−0.00000***	0.00000***	0.00000***
	(0.00000)	(0.00000)	(0.00000)
Perc. of People valuing obedience	0.006***	0.035***	0.041***
	(0.001)	(0.001)	(0.002)
Social Trust x Lockdown	−0.003***	−0.007***	−0.006***
	(0.001)	(0.001)	(0.001)
Constant	−0.145***	−0.053***	−0.067***
	(0.008)	(0.005)	(0.002)
Day Controls	Yes	Yes	No
Country Controls	Yes	No	No
N	286,185	286,185	286,185
R^2	0.658	0.491	0.221
Adjusted R^2	0.657	0.491	0.221

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

In the second step, I will look at three different intervals and whether the coefficient and statistical significance of the social trust variable varies over time. In figure 4.2 we could see that the effect of social trust decreases over time, which I will check in the following intervals:

1. Interval 1: March 1st 2020 until May 31st 2020
2. Interval 2: June 1st 2020 until August 31st 2020
3. Interval 3: September 1st 2020 until December 31st 2020

In the first two intervals, the regression model performs even better than over the whole period, indicated by an R^2 of more than 74% in interval 1 and an R^2 of 68% in interval 2. Its overall predictive power diminishes drastically in the third period, though. Interestingly, the coefficient for social trust itself remains rather stable, as does the coefficient for deaths per 100.000 or other control variables. The coefficient changing the most is the one for the lockdown dummy, at around -14.5% in the first period and diminishing towards -1% and -0.5% in the second and third period, respectively

The coefficient for the interaction term is very small over all periods, in the last period it even loses its statistical significance. This is not surprising since the effectiveness of lockdowns generally diminished greatly. Thus, we also expect the effectiveness of social trust during lockdowns to decline. Nevertheless, these results give us an indication that social trust might not be relevant as far as compliance to anti-Covid-19 measures is concerned.

Table 4.3: Results over various intervals

	Mobility Change		
	(01/03 to 31/05)	(01/06 to 31/08)	(01/09 to 31/12)
Social Trust (High = 1)	−0.007***	−0.005***	−0.004***
	(0.001)	(0.001)	(0.001)
Lockdown (Lockdown present = 1)	−0.145***	−0.010***	−0.053***
	(0.001)	(0.001)	(0.001)
New Deaths/100.000	−0.048***	−0.031***	−0.037***
	(0.004)	(0.003)	(0.002)
1st Lag of New Deaths	−0.010**	0.007***	0.00004
	(0.004)	(0.002)	(0.002)
Religiosity	0.046***	0.064***	0.040***
	(0.003)	(0.002)	(0.002)
Share of People w. tertiary education	−0.052***	−0.032***	−0.041***
	(0.003)	(0.002)	(0.002)
Share of People >65	0.216***	0.293***	0.240***
	(0.018)	(0.014)	(0.013)
Share of Employed People	−0.007**	0.007***	0.001
	(0.003)	(0.003)	(0.002)
GDP/Capita	0.00000**	0.00000**	−0.00000***
	(0.00000)	(0.000)	(0.000)
Population Density	−0.00000***	−0.00000***	−0.00000***
	(0.00000)	(0.00000)	(0.00000)
Perc. of People valuing obedience	−0.003	−0.001	0.018***
	(0.003)	(0.002)	(0.002)
Social Trust x Lockdown	−0.004***	−0.004***	0.001
	(0.001)	(0.001)	(0.001)
Constant	−0.108***	−0.396***	−0.166***
	(0.009)	(0.005)	(0.005)
Day Dummies	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
N	87,396	85,058	112,600
R^2	0.738	0.681	0.487
Adjusted R^2	0.737	0.680	0.486
Residual Std. Error	0.109 (df = 87225)	0.085 (df = 84889)	0.091 (df = 112401)
F Statistic	1,444.255*** (df = 170; 87225)	1,076.964*** (df = 168; 84889)	539.154*** (df = 198; 112401)

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

4.4 Continuous Social Trust, Dummy Lockdown Variable

Changing the measurement of the social trust variable from a dummy variable to a continuous one and the whole regression framework from a difference-in-difference one to a fixed effects framework nonetheless yields similar results. (see table 4.4. Important note to these regressions: I do not evaluate an interaction since including such a term would change the regression results in an implausible way, especially regarding the stringency/-lockdown variables. If the interaction term $Social\ Trust_{Continuous}\ x\ Lockdown$ is present in the regressions, the lockdown variable itself becomes positive. This would mean that the presence of a lockdown **increases** mobility, which is implausible and not consistent with the empirical facts as shown in graphs 4.2 or 4.3. Instead, the variation is then attributed to the interaction term which becomes statistically significant and highly negative.

Leaving aside the interaction term, we can see that the results of regressions with continuous social trust variables are similar to the ones with dummy variables. The dummy lockdown variable has a coefficient of -8.9%, which is almost indistinguishable from the coefficient size in the DiD estimation. The coefficients for the other static control variables, like religiosity, share of people with tertiary education or GDP/capita are close to their DiD counterparts. The R^2 behaves similarly to the DiD estimations: Without fixed effects for countries or days, it collapsed towards 22.2%, while it is slightly below 66% if the fixed effects are included.

The most important variable in these regressions is of course the continuous social trust variable. Its effect size is rather small, at -0.5%. It is essential to stress out that these -0.5% do not occur for every percentage point of social trust, but describes the difference of hypothetical extreme regions, where one region has 100% social trust and the other one has 0% high trust. To observe the coefficient changes to percentage point change, we simply have to divide it by 100. So a 1 percentage point increase in social trust would lead to a 0.005% reduction in mobility, an almost negligible effect.

Table 4.4: Continuous Social Trust Variable, Dummy Lockdown, Regression Results

	Mobility Change	
	(1)	(2)
Social Trust (in %)	-0.005^{***}	0.043^{***}
	(0.002)	(0.002)
New Deaths/100.000	-0.047^{***}	-0.038^{***}
	(0.001)	(0.002)
1st Lag of New Deaths	-0.006^{***}	-0.002
	(0.001)	(0.002)
Religiosity	0.049^{***}	0.020^{***}
	(0.002)	(0.002)
Share of People w. tertiary education	-0.044^{***}	-0.027^{***}
	(0.002)	(0.002)
Share of People >65	0.248^{***}	0.017^{***}
	(0.010)	(0.006)
Share of Employed People	0.002	0.023^{***}
	(0.002)	(0.002)
GDP/Capita	0.000	-0.00000^{*}
	(0.000)	(0.000)
Population Density	-0.00000^{***}	0.00000^{***}
	(0.00000)	(0.00000)
Perc. of People valuing obedience	0.007^{***}	0.039^{***}
	(0.001)	(0.002)
Lockdown (Lockdown present = 1)	-0.089^{***}	-0.163^{***}
	(0.001)	(0.001)
Constant	-0.149^{***}	-0.076^{***}
	(0.008)	(0.002)
Day Controls	Yes	No
Country Controls	Yes	No
N	286,491	286,491
R^2	0.658	0.222
Adjusted R^2	0.657	0.222

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

4.5 Continuous Social Trust, Stringency Index

Similar to the regression in table 4.4, the regression for table 4.5 also does not contain an interaction term to avoid huge changes for the coefficients.

Comparing the results from table 4.5 with the results from table 4.4 we can see some important changes. First of all, the R^2 is considerably larger in the case of no fixed effects (almost 10 percentage points) with the stringency variable in comparison to the lockdown-dummy variable, and it is slightly bigger with fixed effects added (70.3% compared to 65.8%). The coefficients for the static control variables remain similar. Religiosity, the share of old people and the share of people with tertiary education remain positive, too. The stringency index has a negative effect on mobility, which is plausible and statistically significant.

The effect size of social trust is almost unchanged, regardless of how the stringency of non-pharmaceutical Covid-19 policies is measured. In the case of lockdown-dummies, the continuous social trust variable had a coefficient of -0.5%, in this regression it has a coefficient of -0.6%, thus the difference is insignificant. Regardless of the way social trust is measured, its influence on mobility is small.

Table 4.5: Continuous social trust and stringency index regression

	Mobility Change	
	(1)	(2)
Social Trust (in %)	0.051***	−0.006***
	(0.002)	(0.002)
New Deaths/100.000	−0.035***	−0.040***
	(0.002)	(0.001)
1st Lag of New Deaths	0.006***	−0.003*
	(0.002)	(0.001)
Religiosity	0.018***	0.049***
	(0.001)	(0.002)
Share of People w. tertiary education	−0.034***	−0.044***
	(0.002)	(0.002)
Share of People >65	−0.019***	0.249***
	(0.005)	(0.009)
Share of Employed People	0.049***	0.002
	(0.002)	(0.002)
GDP/Capita	0.00000***	0.000
	(0.000)	(0.000)
Population Density	0.00000***	−0.00000***
	(0.00000)	(0.00000)
Perc. of People valuing obedience	0.031***	0.007***
	(0.001)	(0.001)
Stringency Index	−0.005***	−0.004***
	(0.00001)	(0.00002)
Constant	0.131***	−0.062***
	(0.002)	(0.007)
Day Controls	No	Yes
Country Controls	No	Yes
N	286,491	286,491
R^2	0.317	0.703
Adjusted R^2	0.317	0.702

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

4.6 Bootstrap Confidence Intervals

A big issue that I encountered is the fact that my sample size is very large. While this is usually good, since it gives consistent estimators, it makes inference very tough. As we could see in table 4.2, the standard errors for all variables are extremely small and except for one coefficient, all of them are highly statistically significant. The p-values for some of these coefficient are as low as $1 * 10^{-16}$. With such large sample sizes, even the slightest of variations in the data can be interpreted as a statistically significant effect. There exists a growing body of literature on the complications arising from large sample sizes and p-values, one of the most illuminating articles came from Demidenko (2016). In his 2016 article he argued:

> "The little-known fact among nonstatisticians is that, with a large enough sample, n, the null hypothesis will always be rejected. This fact stems from the consistency of the test: With the sample size increasing to infinity, the power of the test approaches 1 even for alternatives very close to the null. In other words, with a large enough sample, the null hypothesis will always be rejected regardless of the Type I error α"(Demidenko, 2016).

There are methods to counter the issue of inference with big sample sizes, one of them are bootstrap confidence intervals. The main idea of bootstrap confidence intervals is repeated sampling with replacement, for example 2.000 times. Interstingly, through this repetitive process the distribution of the coefficients is asymptotically normal, which means we can calculate confidence intervals to the coefficients. The inference testing is then pretty straightforward: if 0 is not included in the confidence interval, we have a significant effect.

I did the bootstrap confidence interval with a sample size of $n = 1000$ (meaning the random sample that I drew was 1.000 each time, repeating the process $B = 2000$ times. Figure 4.4 shows the distribution of the coefficients for the difference-in-difference estimator, the $Social\ Trust\ x\ Lockdown$ variable.

We can see in the below figure that the mean of the coefficients is slightly lower than 0 and that the minimum value of the coefficient is approx. -0.04, while the maximum value is 0.03. This confirms the coefficients from the regression, which were all very small (except for the coefficients with regional dummies), indicating an only limited role that social trust plays in mobility reduction.

Looking at the actual numbers we can see that the mean is -0.0034, with the 95% confidence interval being {-0.025,0.0197}. This means that we cannot say that social trust has a significant and relevant effect on compliance during lockdowns, because "0" is part of the confidence interval. We cannot reject the null hypothesis based on this evidence.

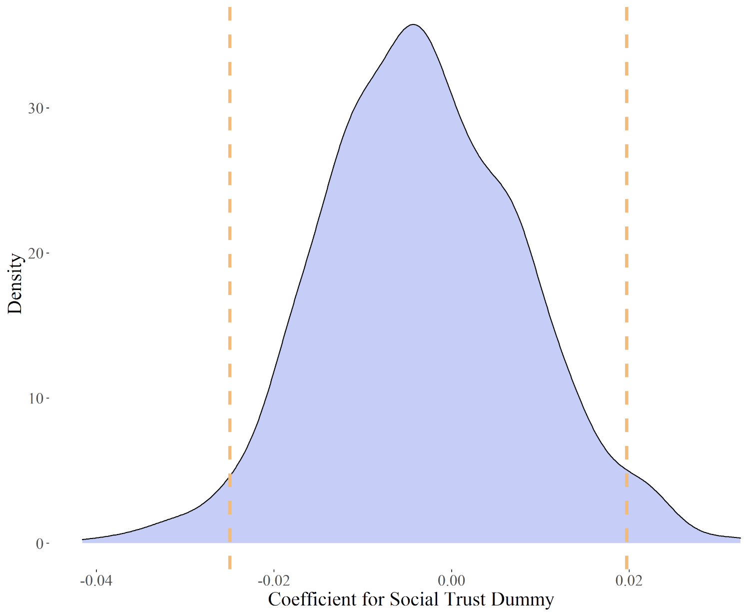

Figure 4.4: Distribution of bootstrapped coefficients, DiD estimator

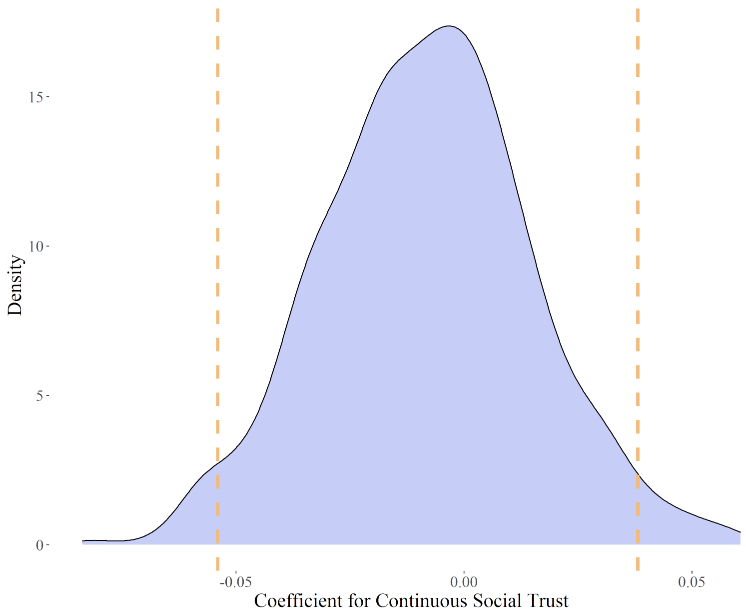

Figure 4.5: Distribution of bootstrapped coefficients, continuous

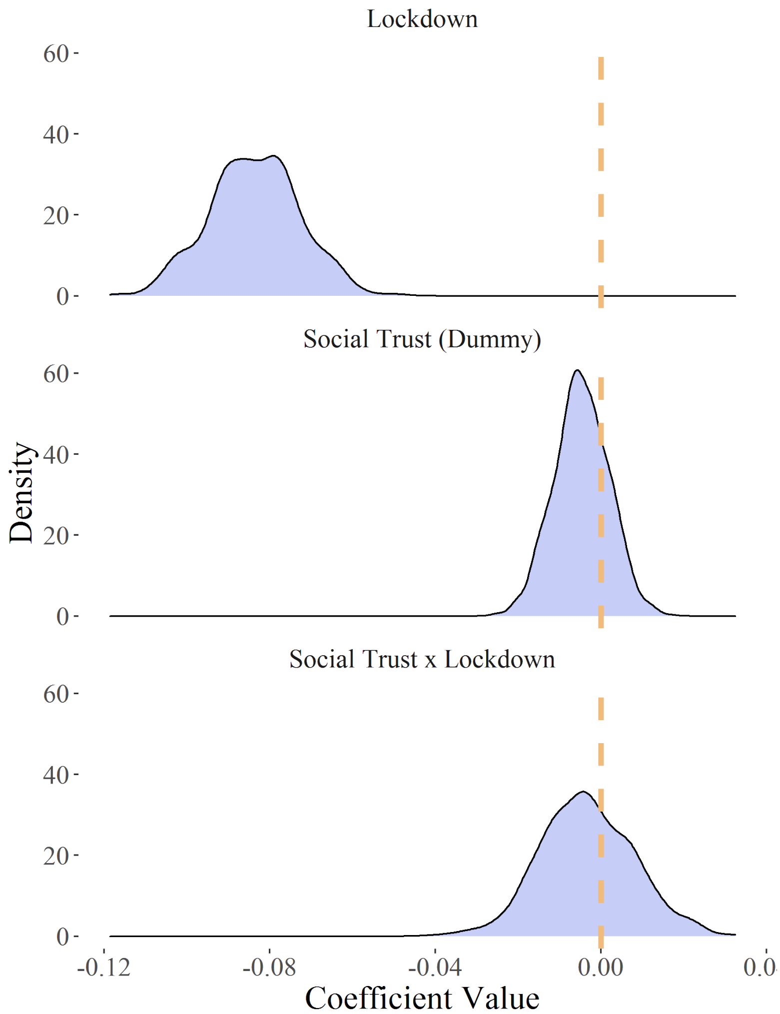

Figure 4.6: Distribution of bootstrapped coefficients

Figure 4.5 shows the same graph for the continuous social trust variable, again with a dummy lockdown variable and fixed effects dummies for day and country. Like in the bootstrapped coefficient regression for the DiD estimator, the mean is very close to zero and the confidence interval spans from negative values (-0.054) to positive values (0.0381). Here it becomes quite clear that we cannot reject the null hypothesis that social trust does not have a significant influence on compliance to Covid-19 measures.

Lastly I will look at the distribution of coefficients for the social trust dummy and the lockdown variable and compare it with the interaction term. Figure 4.6 displays the distribution for said coefficients. What is clearly visible is that the lockdown variable is indeed statistically significant, since its curve is far from 0. Both the social trust dummy and the difference-in-difference estimator have a mean coefficient value that is slightly below 1. The fact that their confidence interval spans from negative to positive values indicates that these coefficients are not statistically significant.

4.7 Social Trust and Dictatorship

In this section I will look at my second hypothesis, which was whether social trust is an important factor in democracies while it is irrelevant in dictatorships. The results are in table 4.6. Answering this question now becomes a little bit redundant, since I already concluded that social trust very likely is not an important factor for compliance to anti-Covid measures. Nevertheless I will examine whether there are mobility differences for dictatorships and democracies and whether social trust plays a role in that.

The coefficients for the social trust dummy variable are not different, they have the value of -0.006 and -0.005. The lockdown variable is slightly bigger in the dictatorship regression, increasing from -8.7% to -8.3%. The control variables stay the same, as does the R^2. The only variable that changes after the inclusion of a dictatorship variable is the intercept, which increases from -14.5% to -6.4%. The dictatorship variable itself has a value of 7.9% which is a little bit surprising. Mobility in dictatorships did not decrease as much as in democracies, in fact in dictatorships mobility across the year 2020 was around 8% higher than in democracies, a sizeable difference.

Looking at the interaction terms we can see some confirmation to the hypothesis that social trust is irrelevant in dictatorships. The interaction term for social trust and dictatorship is not statistically significant, which is remarkable with a sample size of 286.185. The more important interaction term is $Social\ Trust\ x\ Dictatorship\ x\ Lockdown$, which would denote the additional mobility change within a region that has high social trust, is in lockdown and whose national government is a dictatorship. The coefficient for that is statistically significant, but the effect size is just 0.5% with a higher standard error than the simple social trust dummy variable, and we know from the bootstrapping exercise that this coefficient was not statistically significant after accounting for the massive sample size.

Can I conclude that social trust is less important in dictatorships as far as compliance to non-pharmaceutical measures is concerned? Probably not, since I have already discussed the non-importance of social trust for compliance in general. But the various interaction terms I observe do not point at any significant difference of the importance of social trust in dictatorships or democracies. We can even see that, in general, mobility was significantly higher in dictatorships than in democracies.

Table 4.6: Regression Results for Dictatorship Estimation

	Mobility Change	
	(1)	(2)
Social Trust (High = 1)	−0.006***	−0.005***
	(0.001)	(0.001)
Dictatorship (Dictatorship = 1)	0.079***	
	(0.007)	
Lockdown (Lockdown present = 1)	−0.083***	−0.087***
	(0.001)	(0.001)
New Deaths/100.000	−0.047***	−0.048***
	(0.001)	(0.001)
1st Lag of New Deaths	−0.006***	−0.006***
	(0.001)	(0.001)
Religiosity	0.049***	0.049***
	(0.002)	(0.002)
Share of People w. tertiary education	−0.043***	−0.043***
	(0.002)	(0.002)
Share of People >65	0.250***	0.249***
	(0.010)	(0.010)
Share of Employed People	0.002	0.002
	(0.002)	(0.002)
GDP/Capita	0.000	0.000
	(0.000)	(0.000)
Population Density	−0.00000***	−0.00000***
	(0.00000)	(0.00000)
Share of People valuing Obedience	0.006***	0.006***
	(0.001)	(0.001)
Social Trust = 1 x Dictatorship = 1	−0.002	
	(0.001)	
Dictatorship = 1 x Lockdown = 1	0.006***	
	(0.002)	
Social Trust = 1 x Lockdown = 1	0.0003	−0.003***
	(0.002)	(0.001)
Social Trust = 1 x Dictatorship = 1 x Lockdown = 1	0.005***	
	(0.002)	
Constant	−0.064***	−0.145***
	(0.005)	(0.008)
Day Controls	Yes	Yes
Country Controls	Yes	Yes
N	286,185	286,185
R^2	0.658	0.658
Adjusted R^2	0.658	0.657

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

4.8 Additional Regression on Confidence

Since I can not reject the null hypothesis that social trust does not have an influence on mobility, I decided to do some additional analysis on which factors could be important for mobility. Firstly, I look at a correlation plot of social trust to see which other variables that are related to trust could have an influence on mobility. All of these variables measure some kind of trust or confidence either in people or political institutions. The plot (figure 4.9 is presenting simple Pearson correlation coefficients.

Unfortunately, no variable has a significant influence on mobility in this rather simple regression setting. Religiosity and obedience have negative coefficients, but they are not statistically significant. What is interesting are some cross correlations of social trust, for example towards religiosity and obedience or other forms of trust. Unsurprisingly, social trust has a positive correlation with trust to family members, people that are known personally or people from one's own neighborhood. It has a negative relationship with religiosity and obedience. Confidence in two different political institutions, the parliament and government, are closely positively correlated, which also aligns with expectations.

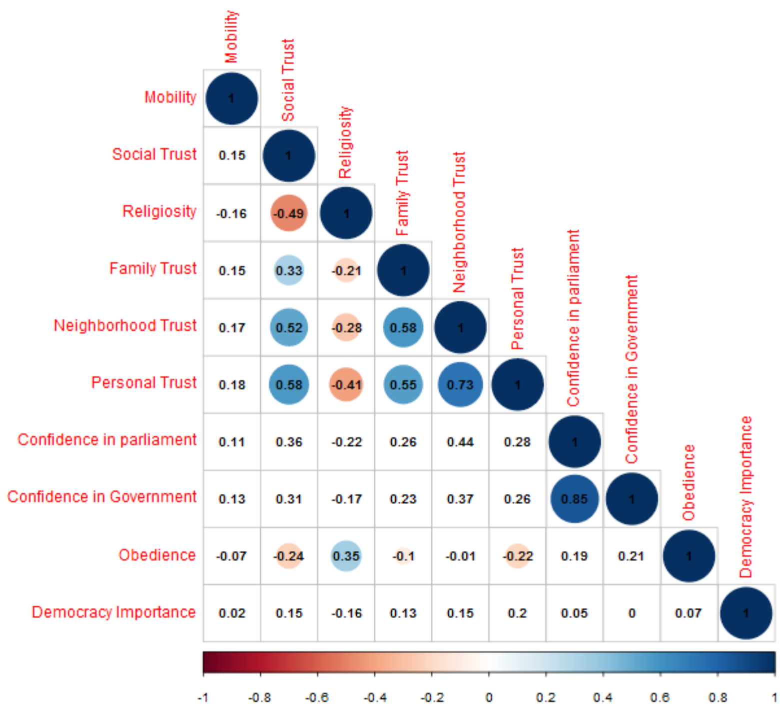

Figure 4.7: Correlation plot for trust and confidence related variables

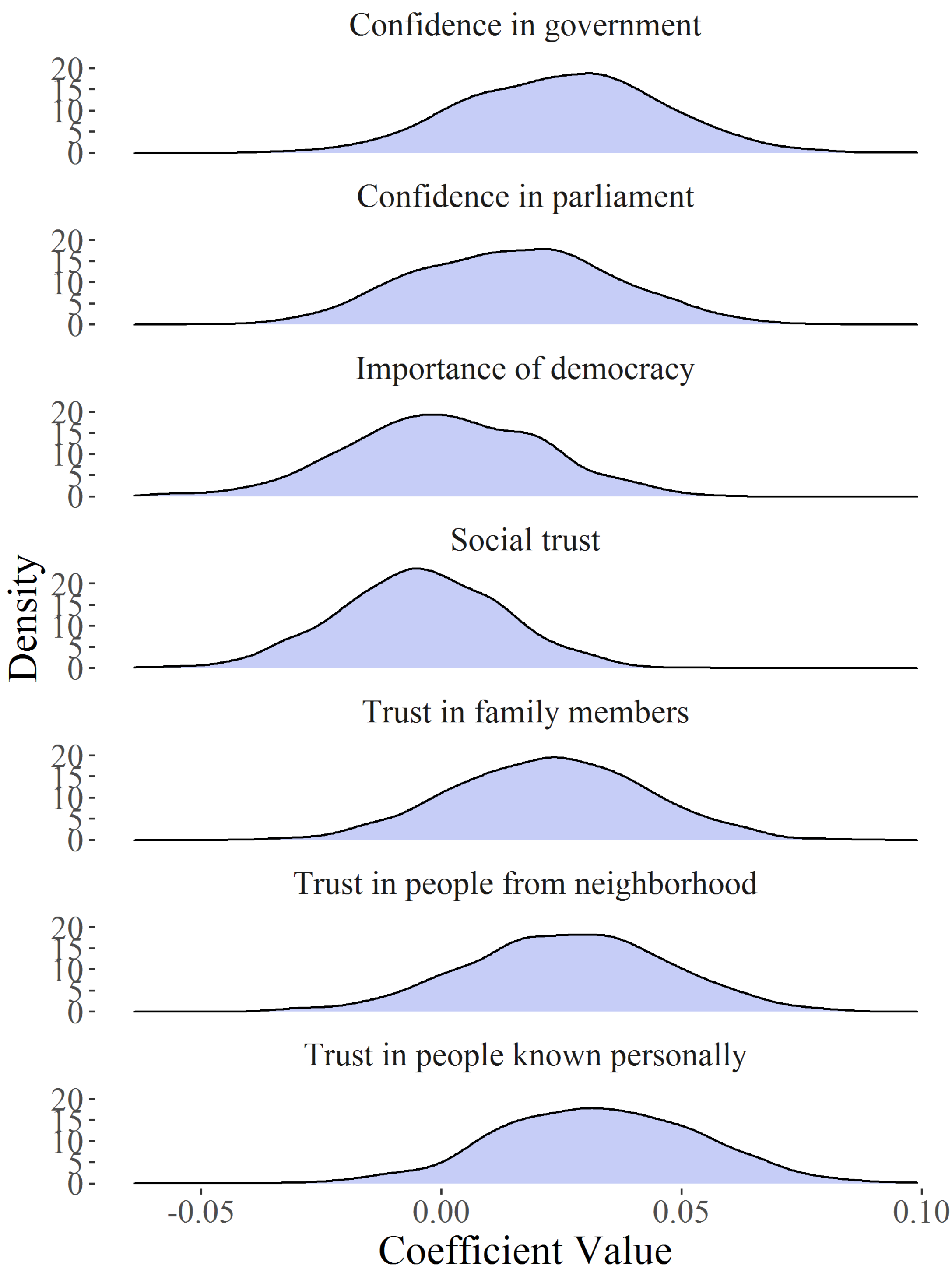

Figure 4.8: Distribution of Difference-in-Difference estimators

Secondly, I run bootstrapped confidence intervals for seven different variables that are related to social trust which could potentially influence mobility: Confidence in government, confidence in parliament, the extent to which people think democracy is an important value, trust in family members, trust in people from one's neighbourhood and trust in people known personally. All of the estimations follow the below formula:

$$\begin{split} Mobility_{i,t} = \beta_0 + \beta_1 * Variable_{Trust,Confidence} * Lockdown_{i,t} + Variable_{Trust,Confidence} + \\ Deaths_{i,t} + Deaths_{i,t-1} + Share\ Old_i + Employment\ Rate_i + GDP_i + \\ Pop\ Density_i + Lockdown_{i,t} + Day\ FE_t + Country\ FEi + \varepsilon \end{split} \tag{4.1}$$

Notice that in this equation I do not have a variable for obedience, religiosity or regional fixed effects, since the fixed effects would create weird coefficients and the other two variables are potentially endogenous to some of the variables I am using in my estimation.

Figure 4.8 shows none of the coefficients is statistically significant. The coefficients for personal trust, trust in family members, or confidence in government, appear to be more often positive than negative. The DiD estimator for personal trust is almost statistically significant on a 95% level. Only the coefficients from social trust and importance of democracy have a mean value that is negative, indicating that the other factors are either not relevant or have a positive contribution to compliance, meaning that they increase mobility (and consequently lower compliance).

4.9 Region Specific Regressions

Lastly I will take a look at some regional differences for the social trust DiD estimator. For this I only look at the first interval from beginning of March until the end of May, since that was a time when lockdowns and stay-at-home orders were implemented in most countries.

We can observe great variation for the DiD estimator in the various regions. While the mean coefficient is around 0 for Latin America & Caribbean and South Asia, it is slightly negative for Europe, East Asia Pacific, North America and the Middle East North Africa. Surprisingly we even have statistically significant coefficients at the 90% level for the former USSR states (like Russia, Belarus, Kazakhstan, Kyrgyzstan) and the Sub-Saharan African countries (including Ethiopia, Nigeria and Zimbabwe). While the former USSR states have a negative coefficient, confirming the expectations that I had from the theory that social trust indeed increases compliance, the Sub-Saharan countries have a positive one, implying that regions with high social trust had **increased** mobility and **decreased** compliance during the 1st lockdown. In the next chapter I discuss the possible aspects which have resulted in these outcomes.

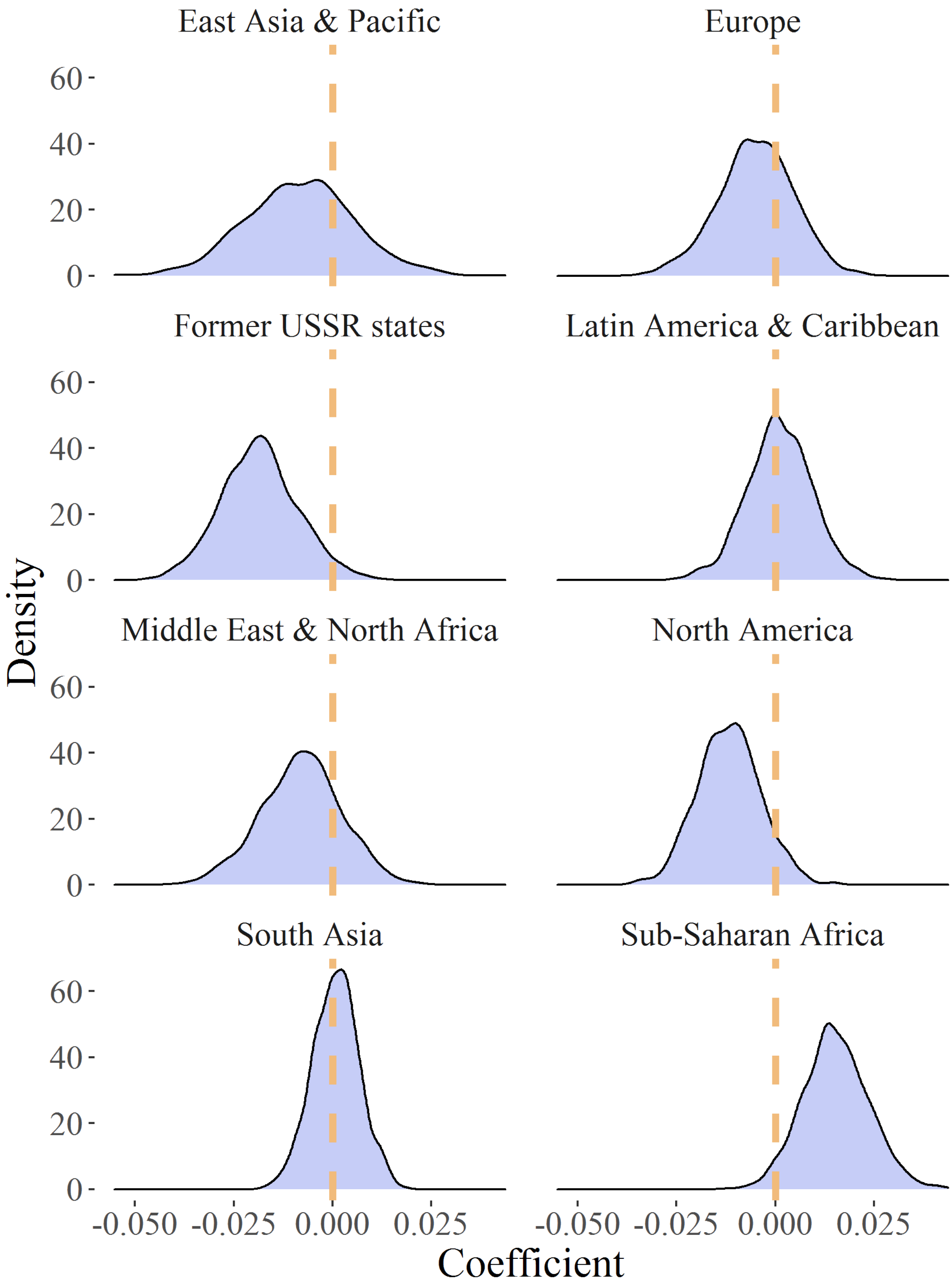

Figure 4.9: Distribution of DiD estimators for 8 regions

5 Discussion

In this chapter I am going to discuss the validity of my results as far as my methodological approach is concerned, as well as discussing the insights that my research has generated.

Following my results, I can conclude with a high degree of certainty that social trust does not play an important role for compliance during the Covid-19 pandemic. Looking at the whole time period, the coefficients remain statistically significant, regardless of whether the lockdown or social trust variables are dummy variables or continuous variables. Previously, I argued that this significance comes from the fact that the sample size is very big. After controlling for the sample size, the statistical significance disappears, confirming that the statistical significance was only achieved by the sample size. But even in the regression framework the very small effect size is noticeable. Even in the event that social trust actually has a statistically significant effect on mobility, its effect is very likely to be small. None of my estimations yield a coefficient (in absolute terms) bigger than 0.5%.

The lack of statistical significance in the first estimations complicates the conclusions to be drawn from the estimations for dictatorships. My hypothesis was that social trust is an important variable for compliance, but only in democracies since dictatorships have more severe forms of control and coercion available. The regressions in this topic show a similar trend like the regressions without dictatorship variables, that social trust is irrelevant in both contexts, regardless of whether the country is classified as a dictatorship or not. The only surprising result came from the general mobility trends, which show that mobility in democracies was a lot lower level than in dictatorships.

Whilst the main hypothesis about the relevance of social trust for compliance cannot be refuted, the hypothesis about the stability of that relationship can. As table 4.3 shows, the coefficient for the interaction term changes over time. Though it is negative for the first two intervals (which lasted from March 1st until May 3st and June 1st until August 31st respectively), it is slightly positive and no longer statistically significant in the third interval, which spanned the period from September 1st until December 31st. Additionally, the huge drop for the R^2 from 73.8% to 48.6% is another sign that social trust became less relevant over the course of the year, with other, unobserved variables becoming more relevant.

Why did social trust become even less relevant over the course of the pandemic? One relevant factor can be the availability of information regarding SARS-Cov-2. In the early stages of the pandemic, knowledge about the virus was scarce. It was not clear how it was transmitted, what its origin was and how deadly it could be. Given the many unknowns about it, trusting other people to abide by the Covid rules is an important mechanism.

With increasing duration of the pandemic, more information was available and people updated their risk perception of Covid-19, with especially younger people perceiving it as less risky.

Another factor can be the increasing presence of disinformation and Covid-19 conspiracies. While the theories vary in plausibility and their overarching narratives, most of them exhibit distrust towards "mainstream media", politicians, government authorities and general "mainstream narratives", as Lebernegg & Eberl (2021) analyze as part of the Coronapanel project by the University of Vienna. What is also visible in the Coronapanel data is that conspiracy theories and disinformation about Covid-19 become more prominent and popular over time.

The last factor I want to mention is connected to the TCC model by Siegrist & Zingg (2014). They specify that trust arises in situations where there is a similarity of values and intentions, while confidence arises in situations where people perceive the other as competent and knowledgeable enough to handle said situation. The relevance of social trust could have also declined because people updated their beliefs about the values and intentions of the other people. While in the beginning there was a largely unified sense of solidarity with the risk-persons and vulnerable and which encouraged compliance to the very drastic rules, these perceptions changed overtime due to a sense of fragmentation in solidarity, overload of restrictions, and exposures to conspiracy theories. This is how the second factor, the conspiracy theories and disinformation, and trust might interact with each other to decrease the importance of the latter for compliance. Since more and more people were following these theories and chose not to follow the Covid regulations, it is likely that the people that did not believe the conspiracy theories and still trusted authorities and science could not trust other members of their society anymore.

Another interesting result is the huge regional variety for the coefficient of the interaction term. Figure 2.1 showed that in post-USSR countries, the relationship of social trust and compliance was actually statistically significant and negative, while it was significant and positive in Sub-Saharan-African countries. Figure 4.3 demonstrates differences between countries, where some countries (like Nigeria or the US) have no clear correlation between social trust and mobility and other countries (like Portugal and Lithuania) had a visible difference between high and low social trust regions, sometimes with a negative relationship of social trust and mobility, other times a positive one.

I can only speculate about the reasons for this varying importance of social trust. One possible explanation could be institutional settings that differ more from each other than a simple dictatorship/democracy dichotomy. The fact that in former USSR countries there is a statistically significant relationship could be explained by a specific set of institutions that these countries inherited from the Soviet Union. Similarly, Sub-Saharan African countries could have inherited colonial institutions that diminish the importance of trust or the huge variety of different ethnic groups can be a decisive factor. Trust into people from one's own ethnicity could then be a more important factor than social trust in general. Additionally, varying regional poverty rates could be the real driver of mobility reduction (or the lack thereof).

There are some possible limitations to my analysis. Firstly, there is a possibility that there are variables that are essential for compliance but are left out in my regression framework. Following the compliance model from Plohl & Musil (2021), it is very likely that risk perception and trust in science are essential variables to describe the relationship of trust and compliance, but they were not asked in the World Value Survey. Figure 4.9 shows that there exist correlations between social trust and other forms of trust and confidence, with trust in science or trust in government[1](which were both described in the literature as being essential) not being available.

Risk perception is another key variable that I can not observe. I operationalize it by using Covid deaths per 100.000 as a proxy variable, but of course there exists the possibility that people do not see the deaths of others as a threat to them (considering the vast differences in case-fatality rates according to age, this is a very likely possibility). Furthermore, the paradox of trust by Wong & Jensen (2020) could also apply regarding social trust. If enough people assume that everyone else is complying to the rules, complacency might arise and will paradoxically lead to less people being compliant. This effect could totally offset any mobility reduction associated with social trust.

One possible argument to the validity of my results is that there exists a selection bias for regions with high social trust and the lockdown. Regions that have a high degree of social trust are more likely to implement lockdowns and stay-at-home orders more probably than regions with low social trust. The counterargument to that is that the lockdown variable expresses lockdowns on a national level, not regional ones. The selection argument is therefore wrong, since the regions cannot choose to have a lockdown, the federal government (in the case of Austria f.ex.) chooses to implement a lockdown. This is true for most countries except for Australia and the US, where federal states like Victoria, New South Wales or Michigan implemented stay-at-home-orders independently.

Another kind of selection bias can occur considering how the mobility variable is measured. The movement was captured using GPS and mobile internet data from smartphone users, and it was calculated in how many different tiles each user was. A person that moves around without a smartphone is not accounted for in this mobility index. This would not pose a problem if smartphone ownership followed a random pattern, i.e. would not be influenced by demographic or socioeconomic circumstances. However, this is highly unlikely. Smartphone ownership varies greatly between countries (Newzoo, 2022), with the United States having a rate of 82.2% and Nigeria having one of 19.7%. Smartphone penetration

[1]Confidence in government was an available indicator, but following the TCC framework from Siegrist & Zingg (2014) we know that confidence and trust are two vastly different concepts with different origins.

rate also varies within countries, depending on the degree of urbanisation, age and income levels of a region. In the United Kingdom, the smartphone penetration rate is 100% among under-24 year olds, while it is only 40% for the 65+ year olds (cybercrew.uk, 2021). In my estimations I try to accommodate the fact that old people are less mobile or are less likely to have a smartphone by including control variables, yet there remains some possibility of selection bias. Additionally, I account for the different smartphone penetration rates by using the country-fixed effects, which can fix some of the omitted variable bias, but not all.

6 Conclusion

In this master thesis, I explore the relationship of social trust and compliance to non-pharmaceutical Covid-19 measurement, specifically movement restrictions and stay-at-home orders. On the one hand, my findings refute previous literature on the connection of trust and compliance: regardless of the type of regression that I run or how the variables were coded (continuous or dummy variables) the result is the same: there is either no significant relationship at all (after choosing a method that was more appropriate for large sample sizes) or the effect size is so small as to doubt whether the effect is relevant. Since the general regressions do not yield results which refute my main hypothesis of "*There is no significant relationship between the level of social trust in a region and compliance to non-pharmaceutical Covid-19 measures.*", I cannot refute one of the other hypotheses, namely the one about the importance of social trust in dictatorships and democracies. Social trust is a rather irrelevant factor regardless of the political system. Nevertheless, the fact that mobility in democracies is on average 8% lower than in dictatorships is surprising, given the variety of forceful instruments a dictatorship can deploy to make people comply to their rules.

The refutability of the second hypothesis, that the relationship of social trust and compliance remains rather constant over time, does not depend on the main hypothesis being false. The results of my estimations suggest that the relationship indeed does change, with the limited importance of social trust disappearing altogether in the third interval, which spanned from September 1st to December 31st of 2020. I have already discussed the possible reasons for this fading importance (change of values, conspiracy theories, risk perception) in section 5.

This thesis provides new insights on the relationship of trust and compliance in a pandemic. The previous literature is focused on political trust, with a geographic emphasis on wealthy nations in Europe, North America and the Asian-Pacific region. The thesis bridges such research gaps by extending the geographic focus to countries in Southern Asia, South America, Central Asia, Sub-Saharan Africa and the Middle-Eastern North Africa regions, while the thematic focus is on a broader category of trust. The greater geographic coverage also takes into account the different political contexts, with crucial insights into differences in mobility patterns between democracies and dictatorships.

Nevertheless, the results of this thesis create new questions useful for further study. The most intriguing of these is the regional variety of the importance of social trust and the different coefficients for the regions. While I discussed some methodological issues that could have created this variety (most notable an omitted variable bias), there is the possibility that there exist factors that influence the importance of social trust that vary across the regions, like institutions or poverty rates. Similarly intriguing is the question of why the importance of social trust declines over time. Those are all worthwhile endeavours for future research on this topic.

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