ESSAYS ON THE PROCESSES OF ECONOMIC GROWTH

A Dissertation

Presented to

The Faculty of the Department

of Economics

University of Houston

In Partial Fulfillment

Of the Requirements for the Degree of

Doctor of Philosophy

By

Nadzeya Abramava

May 2015

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Abstract

This dissertation consists of three essays on the processes of economic growth. In the first chapter I show how growth behaves when protesting occurs. I continue with the topic of protests in the second chapter, where I consider the effect of political unrest on economic inequality. In the final chapter, I study the impact joining the WTO has on the composition of trade flows that may affect long term growth.

Protests occur regularly and at times involve millions of people, often disrupting economic activity. In Chapter 1 I examine the link between economic growth and protest events using the Global Database of Events, Language and Tone (GDELT). This dataset provides daily observations on protests and similar events for a panel of 150 countries over the past three decades. I show that protests have a significant negative relationship with short term growth. On average, protest activity is associated with a drop in growth of at most 1.5 percentage points of growth rate in the year of the protest event(s) with this effect persisting in subsequent years. Further, I reject the hypothesis that protesting can improve or damage GDP growth in the longer run. Protests also impact negatively other aggregate outcomes that may serve as channels through which protesting influences the growth rate. I establish that during the year of the protest gross capital formation declines, while unemployment goes up. The magnitudes of these effects are non-trivial even though the overall impact on economic growth is quantitatively small.

Protesting might affect the level of inequality in a country through post-protest redistributive policies. In Chapter 2 I study the relationship between protesting and inequality using a panel of 74 countries over 1979-2012. I find that across most of the specifications the effect of protesting on inequality, determined by the Gini Index, is

negative and statistically significant. On average, a 1% increase in protest activity decreases the Gini index immediately by 0.01 points. These results are robust to different ways of defining the protest variable itself such as number of protests or the intensity of protesting measured by the media coverage. A binary measure based on the intensity of protesting indicates that a large enough protest reduces inequality, lowering the Gini Index by 1.6 – 2.1 points.

When countries join the World Trade Organization (WTO), they gain mostly unhindered access to new markets allowing them to trade more. While it has been shown in the literature that after accession to the WTO volume of trade increases for the new members, it is unclear what effect, if any, the membership has on the composition of trade. Developing countries may be negatively affected through crowding-out of vital sectors due to foreign competition or positively — through strengthening of the sectors with comparative advantage. Using gravity equation estimation I show that while the volume of exports and imports increases after countries become WTO members, the resulting changes in the composition of trade differ depending on the sector and the income level. For example, in a developing country accession to the WTO increases the share of textile sector in total imports by 0.5%, while the same sector's share decreases by 33% when it comes to exports.

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to my dad

Chapter 1

Determinants of Growth: Should We Protest?

1.1 Introduction

What information do protests convey about future growth? In the World Bank Global Economic Prospects for 2012 it was shown that in many Middle Eastern countries GDP shrank by as much as 6 percent following the Arab Spring protests (World Bank, 2012). But does such a contraction apply to other events besides the Arab Spring? Does it depend on how large and violent the protests are?

In this paper I estimate the relationship between protests and GDP growth using a panel of 150 countries over 1979-2014. I define protests as non-military demonstrations, where participants are demanding a reform of political, economic, or religious nature (other causes constitute a small fraction of protests). Compared to the existing literature, which usually examines the link between general political unrest and growth (e.g. Barro, 1991; Alesina et al., 1996; Ades and Chua, 1997; Benhabib and Rustichini, 1996; Devereux and Wen, 1998), this paper considers protests of different sizes and excludes events which cannot be classified as pure protests (i.e. I exclude all armed conflicts but do not eliminate violent protests that are not military). This allows me to see whether the mere act of civic discontent has any impact on the economic well-being of the country. I estimate a range of specifications that differ by the definition of protest intensity, the set of control variables, and datasets to capture a consistent pattern of the relationship between growth and protesting.

I use thirteen proxies for protest intensity from two different data sets: five proxies from the Global Database of Events, Language and Tone (GDELT)[1] and eight proxies from the European Protest and Coercion Data (EPCD)[2]. The main differences between the two datasets are the scope and the quality of the data. GDELT covers the majority of existing countries from 1979–2014, while EPCD is limited to European countries from 1980–1995. Despite the narrow scope, EPCD is a richer data source as it contains information on the number of protesters on the streets, number of arrests and injuries and other details. While EPCD contains indepth data on the intensity of protest activity, GDELT provides only suggestive information on intensity, as it contains the absolute number of protests in a country as well as the amount of coverage in the media for any given protest (number of mentions). The idea behind this particular protest proxy is that the larger the given protest is, the

[1] Leetaru and Schrodt (2013)

[2] Francisco (2000)

more coverage it receives (the bias that may arise from this definition is discussed in Section 2.2). However, both data sets are retrieved from comparable media sources.

I find that on average there is a negative relationship between the intensity of protest activity and growth in the year of the conflict, controlling for other covariates (such as trade share in GDP and educational attainment). The magnitude of the effect reaches up to 1.5 percentage points of the growth rate. Using the number of mentions to define protest intensity, I find that the protest(s) during one year in country i have to receive at least 20 mentions in the media before I detect a statistically significant negative effect on growth. An example of such protest is country-wide demonstrations of thousands of people in Slovakia in 2012 following a so-called "Gorilla scandal" about government corruption ("Gorillas, Flowers", 2012). Naturally, as the number of mentions goes up, so does the magnitude of the effect. At the peak of protest activity, the magnitude of the coefficient goes up to 1.5 percentage points of growth rate (for a growth rate of 3 percent, for example, that amounts to a decline to 1.5 percent).

While the direct relationship between growth and protest activity appears to be negative, it does not have to be so. A protest can serve as a signal to the government and impact growth positively though government enacting reforms, rather than negatively through protesters not showing up for work or disrupting economic activity. However, I find that the year after the protest date the effect of protesting on growth largely disappears. In some cases, the relationship becomes weakly positive (albeit the coefficient is not statistically significant in most specifications), but overall protesting has a lasting impact on growth beyond the year of its occurrence.

Is the relation between protesting and economic growth a causal one? One runs into the issue of reverse causality as countries with low growth may see an increase in protest activity. On the one hand, acts of protest may affect growth through various channels such as disruption of production and transportation, and the destruction of property etc (Oneal, 1991; Jong-A-Pin, 2009). On the other hand, higher growth rates may cause a rise in urban unrest (Schwalbenberg, 1994) or they may dissuade potential protesters due to higher opportunity costs (Miguel et al., 2004; Bruckner and Ciccone, 2010; Arbatli et al., 2015). I test the impact of *growth* on protesting and find no evidence to support the claim that lower growth rates predict higher protest activity. This is in line with previous research (Oneal, 1991; Campos and Nugent, 2002; Jong-A-Pin, 2009) finding no link from growth to protest intensity.

While the effect of protests on growth rates may be quantitatively small, I establish the channels through which protest events may affect GDP growth. Due to their nature financial markets are prone to respond to protests almost instantly. Acemoglu et al. (2014) investigate the case of the Arab Spring and find that firms politically connected to the existing regime receive lower stock market returns as a result of protests. Black at al. (2005), however, do not find any statistically significant relationship between protests and market value of merging banks (authors restrict protests to those that can affect bank mergers). I investigate FDI, capital formation, trade, unemployment and inflation as the possible channels. There is a statistically significant link from protest activity to capital formation, unemployment in my estimates. A 1% increase in protesting, measured by the amount of media coverage, would cause a 0.12% drop in capital formation and a 0.09% increase in unemployment.[3]

Protesting is not the only political factor that can impact economic growth. More researchers have studied other political indicators which might affect economic growth. For example, when country leaders die during their term, growth can be affected if the leader's death was unexpected and accidental, rather than an assassination (Jones and Olken, 2005, 2009; Gilbert at al., 2011). Another set of papers deals with interrelationship between democracy and growth. The long standing result have been that democracy has no effect on growth (e.g. Przeworski, 2004). However, in Acemoglu et al. (2015) the authors show that democracy improves growth rates in the long run (30-year horizon). There is an extensive literature that studies various political determinants of growth, but the ones mentioned above are the most useful for this paper.

In the next section, I present data sources. Methodology is discussed in Section 2.3. Summary of the main results is described in Section 2.4. In Sections 1.5 and 1.6, I show estimates using EPCD and establish channels through which GDP might be affected, respectively. Section 2.5 concludes.

[3] Equivalent to an average increase of the number of mentions by 1.6.

1.2 Data

1.2.1 Protest Data

I collect protest data from two sources which are used in separate estimations. The main dataset is Global Database of Events, Language and Tone (GDELT), which pulls daily data about various events including protests from news sources across the world.[4] These sources are not limited to English-language-only newspapers, but cover broadcast, print and online media in over 100 languages. This almost universal inclusion eliminates some of the bias that could stem from newspapers' preferences towards coverage of disruptive events at the expense of other important events that might seem "boring" from the perspective of the media (for example, a foreign mass protest that has been going on for a while might not be news-worthy for a domestic newspaper). The events are coded according to the protest mode: demonstration or rally, hunger strike, obstruction of passage, strike or boycott, violent protest or riot, and unspecified political dissent. The latter includes protests that do not have a clear mode either because the information was not available or that multiple modes have been used. Each event lists participants on both sides as well as the country and the date of the occurrence. There is no information about the size of protest and its duration, the number of arrests (if any) and injuries incurred. To construct a variable that describes the intensity of a protest — whether it was a small protest of 5 disgruntled workers or an uprising of millions of people — I use the number of

[4]Some of the sources used are AfricaNews, Agence France Presse, Associated Press, BBC Monitoring, Christian Science Monitor, Foreign Broadcast Information Service, The New York Times, United Press International, and The Washington Post.

news source mentions provided in GDELT.

For instance, one newspaper talking about the Arab Spring for a week would accumulate 7 mentions for the protest. If another source picks up on the story, the number of mentions goes up depending on how many newspapers start carrying the story. The idea is that the larger the protest is, the more talked about it is. For instance, in Figure 1.1 I present two graphs for Tunisia based on the number of mentions the protests there received over time. The left panel shows protest activity in Tunisia before the Arab Spring. The peak in 2000–2001 corresponds to an increase in protesting due to general unhappiness with the political regime ("Freedom in the World", 2001). The panel on the right captures protest intensity before, during and after Tunisian Revolution of 2010–2011 (also known as part of the Arab Spring protests). In Figure 1.2, I compare four European countries by adjusting the scale to see how the protest activity in one country relates to another. The largest protests occurred around the time of the financial crisis of 2008. France appears to have more protests than other countries, while Germany has the least. Note that a small peak in 1989 in Germany corresponds to the fall of the Berlin Wall and a similar peak in 1995 in France is due to country-wide general strikes that disrupted transportation systems across the country. From this information it could be concluded that the Berlin Wall protests were smaller in magnitude than those attributed to the Great Recession of 2008.

Of course, there is a caveat to this thinking as newspapers are known to be biased in most cases. For example, a large protest in Nigeria might not get as much coverage as a similar-sized (or smaller) protest in US. In addition, in some countries newspapers are de jure or de facto controlled by the government, which might wish to suppress coverage of anti-government protests. I am addressing these issues through the use of country fixed effects and a secondary dataset.

The secondary protest dataset is European Protest and Coercion Data (henceforth, EPCD) which contains information on protest activity in Europe between 1980-1995.[5] The obvious handicap of the dataset is its geographical and time limitations. GDELT allows me to study protests that occur in 150 countries during 1979-2014 period, which is more representative. However, EPCD contains information that GDELT is lacking, namely number of protest participants, number of deaths on both sides, number of arrests and injuries as well as the main reason for the protest (political, economic, nuclear power related or other). The data in this set also comes from news sources, but it has been compiled manually rather than by a computer which has allowed for more information about every protest to be pulled out. Arguably, this richer data allows me to construct a superior measure of protest intensity.

Due to its limited span EPCD is used mostly as a robustness check to support the findings from GDELT data. If the findings for the same period and countries match up across the datasets then it can be argued that all findings from GDELT dataset are valid even though the constructed protest intensity measure is not perfect.

Using these two datasets, I construct a number of different measures for the intensity of the protest activity in country i in year t. Five measures come from the

[5] Countries in the sample: Albania, Austria, Belgium, Bulgaria, Cyprus, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Iceland, Italy, Luxembourg, Netherlands, Norway, Poland, Portugal, Romania, Spain, Sweden, Switzerland and United Kingdom.

GDELT and eight — from the EPCD. The simplest way to define protest activity is to count the number of protests that occur in a certain country during a designated time period. This method does not account for the magnitude of the protest, thereby lumping small and large protest events together. A second measure counts the number of times a certain protest was mentioned in the media, and gives me a proxy for intensity of the protest event. A third measure is similar, but I weigh the number of newspaper mentions by the number of news sources to account for larger protests being picked up by multiple media outlets. In the fourth measure I find a cut-off point for a large protest and make the variable binary rather than continuous. This allows me to interpret the results more easily, although some of the information is lost due to this simplification. The fifth measure is based on the mode of the protest. I construct a set of dummy variables based on how the protest occurred. When its effect on growth is considered, a protest that was a peaceful march could have different implications compared to a riot with excessive violence.

From EPCD, I get protest intensity proxies based on the number of protesters during the event, the number of protesters arrested, injured and killed (all of these are separate measures) as well as the number of state forces that counteract the protesters, and number of those injured or killed. All of these measures are continuous and consist of the number of people in each of those categories. Lastly, I consider a proxy that is a set of dummy variables for the cause of the protest. An expressly economic protest is likely to be more closely connected with the economic growth and is also likely to be caused by unsatisfactory economic conditions. On the other hand, a protest that has its roots in religious issues or anti-war sentiments is not immediately caused by poor growth. Using protests that do not have economic reasons is one of the ways to get rid of the underlying endogeneity in the relationship between growth and protesting.

Both datasets are described in more detail in Tables 2.2, 3.1, and 3.4. In Table 2.2, I present the sources of all variables used. Tables 3.1 and 3.4 provide descriptive statistics for GDELT and EPCD samples respectively. I summarize explanatory variables in both of these tables because the samples are different, and the countries in EPCD are not randomly selected. For example, trade share in GDP is on average 84% in GDELT sample, but only 71% in the EPCD one. On average, 24 protests occur per year in any country, but this does not take into account the size of the protest. As far as the intensity of protests is concerned protests are mentioned about 160 times per year in any country. That could translate into 160 newspapers writing about a protest for 1 day or 1 newspaper writing about a protest for 160 days, and anything in between these extremes.

Based on the summary statistics from Table 3.4, roughly 3 million protesters took to the streets in Europe between 1980–1995 every year in every country. Out of those 500 would be arrested, 150 injured and 4 killed, on average. To quell or at least manage the protests around thirty thousand members of police and military would go out every year. Almost half of them would be injured, and on average 82 would die annually per country. There are two possible reasons for such a high injury rate among state forces compared to protesters. Firstly, protesters might not be reporting their injuries, especially if they are minor, thereby driving down the number of those injured, or the government is not reporting these numbers out of the fear of international sanctions. That would also mean that all those protesters who are considered injured have likely sustained serious injuries. Secondly, relative to 3 million protesters, thirty thousand state forces are outmatched, and protesters are likely to express their anger against the government by attacking members of police and military. In the second case there is no bias, but if the first idea is true, then the dataset underestimates the number of the injured and, possibly, deceased protesters. However, if such underestimation is common across countries, the results will not be impacted.

1.2.2 Other variables

The rest of the variables are described in Tables 2.2, 3.1 and 3.4. Notably, the dependent variable is GDP growth per capita which I calculate from GDP per capita in 2005 constant dollars in the World Bank Development Indicators database (World Bank, 2012). The control variables come from various sources all of which can be found in Table 2.2. They have been selected based on the existing research (Sala-i-Martin, 1997; Acemoglu et al., 2015) and the possible channels for protests to affect growth have been taken into account as well.

The "Polity" variable comes from the Polity IV dataset (Marshall and Jaggers, 2002), and it is a proxy for country's regime. It gets a value of 10 if country is a democracy and a value of -10 if it is an autocracy. The values in between offer various degrees between these two extremes. This variable belongs in my estimation because it may determine whether people protest or not. In addition Acemoglu et al. (2015) show that being a democracy positively impacts economic growth.

The war dummy is a variable for armed conflicts that took place on the territory of a country. "War intensity" takes a value of 0, 1 or 2 depending on the severity of the conflict (an event gets a value of 2 when at least 1,000 deaths have occurred).

1.3 Methodology

The estimation equation is similar to those used in the literature on democracy and growth (e.g. in Acemoglu et al., 2015). My main specification is:

$$\Delta lnY_{it} = \alpha_0 + \sum_{m=1}^{M} \alpha_1 \Delta lnY_{i,t-m} + \sum_{k=0}^{N} \alpha_2 Protest_{i,t-k} + \alpha_3 X_{it} + \delta_t + \gamma_i + \epsilon_{it}, \quad (1.1)$$

where ΔlnY_{it} is first difference of the log of real GDP per capita, $Protest_{i,t-k}$ denotes the protest intensity variable which is defined as the log of the number of protests in country i during previous year, X_{it} is a vector of standard explanatory variables such as level of education, life expectancy and trade share in GDP (see Table 2.2 for the full list). Another variable included in vector X_{it} is an interaction between "Polity" and protest variables. This allows a more democratic country is likely to see different levels of protesting activity then a more autocratic one, which could impact the estimation of the coefficient for protest variable if this interaction variable is not included. I also account for country and year fixed effects. The baseline specification uses a count measure of protest intensity. The remaining measures used are described in the preceding section.

I estimate this equation using OLS.[6] One issue regarding this estimation is serial correlation due to GDP growth being persistent over time and the use of its lagged value in the right hand side of the estimating equation. Acemoglu et al. (2015) shows that adding more lags of GDP growth solves the issue of autocorrelation. In Table 1.15 I show the baseline estimation with a different number of lags of GDP growth to select the optimal number of lags for this dataset. I also use robust standard errors, clustered at country level, which alleviates serial correlation and heteroskedasticity.

I use logarithms of all the protest variables (with the exception of binary ones) because the protest measures used here have a skewed distribution, which might affect the coefficients. Instead I use a transformation of the form $log(Protest + 1)$. I add a value of 1 to every observation in order to preserve information about the control group (countries that had no protests in a given year). Another way to alleviate non-normality of the data is to use a dummy variable constructed from the original measure, which I discuss in Section 2.4.2.

I cannot say with certainty using my estimates that the relationship between growth and protesting is indeed causal. On the other hand, there is no evidence in this paper (see Table 1.16) or in the related literature (e.g. Campos and Nugent, 2002) that growth significantly forecasts protest activity. Lastly, I have used a range of different sensitivity checks with a variety of control variables and found that the relationship between growth and protesting is robust, while there is still a possibility that an omitted variable (or variables) drives the results.

[6] The fixed effects estimation of dynamic panels carries a potential bias of order $\frac{1}{T}$ for panels with small T. However, in this case $T = 36$, which eliminates the issue.

1.4 Effects of Protesting on Economic Growth

1.4.1 Main Results

Baseline specification estimates for number of protests and intensity of protests are presented in Tables 2.4 and 2.5, respectively. In column (1), I regress the GDP growth on its lag and the protest variable including country and year fixed effects as controls. In subsequent columns I add more control variables to capture more of the variation in GDP growth. In column (2), I add lagged values of the protest variable to see if there is any persistence with respect to GDP growth. Column (3) includes Polity variable and its 2 lags (corresponding to the number of lags used for the protest variable). In column (4), I include explanatory variables (life expectancy, trade share, gross capital formation, primary and secondary school enrollment, population, war dummy and interaction variable with Polity). Columns (5) includes further lags of GDP growth (2 lags)[7]. In column (6), I partially replicate Acemoglu et al. (2015) by using the explanatory variables they use (note: instead of using an index for democracy as the authors use, I include my protest variables).

Across these different specifications the estimated of effect of protests remains stable. In Table 2.4, the log of the number of protests is consistently negative and statistically significant at 1%, which supports the idea that the immediate effect of protesting on GDP growth is negative. A similar picture appears in Table 2.5, where the number of newspaper mentions are used, but in this case the effect is weaker in terms of the significance level. I would attribute it to the additional information that

[7]Choice of GDP growth and protest variable lags is discussed in Section 1.4.2.

a number of mentions presents over a simple count of protest events as the data is finer. A similar picture is seen in Table 1.6 where I weight the number of mentions proxy by the number of media sources used. Again there is an immediate negative effect of protesting on economic growth.

The lagged values of protests do not show consistent statistically significant long-run negative persistence in Tables 2.4 or 2.5. First and second lags appear to show coefficients turn positive rather than negative, which would support either the hypothesis that reforms take time to be passed and the effect on GDP growth is delayed by at least a year, or that the GDP growth rebounds quickly after the initial post-protest drop. However, this effect is not statistically significant with the exception of the first lag in columns (4) and (5) of Table 2.5 and 1.6, which is why I cannot make a conclusive statement about these based on Tables 2.4, 2.5 and 1.6. Consequently, there is no definitive evidence that growth bounces back after the protest has ended, which means GDP is permanently lower afterwards.

1.4.2 Lag Selection

In Tables 2.9 and 1.15 I provide estimates based on which I selected the lag length for protest variables and GDP growth. These tables are based on the log of number of newspaper mentions only, but I have performed the same estimations on the other specifications of the protest variables and came to the identical conclusions.

In Table 2.9 I deal with the lag length selection for the protest variable. I settle on 2 lags in column (3), even though it does not appear to be superior to 1 or more lags.

Regardless of the number of lags considered, the estimate of the effect of protesting on growth in Table 2.5 remains negative and the magnitude is not affected.

GDP growth is highly persistent. Therefore, adding just one lag as a control might not be sufficient. In Table 1.15 I show the coefficients for the variable of interest with a different number of growth lags. Following the same rule of thumb as I did with deciding on the lag length for protest variable, I use the adjusted R-squared. However, it appears to be the same across all columns. In this case I choose to add 4 lags of GDP growth to all specifications that include more than a single lag following Acemoglu et al. (2015). The number of GDP lags used does not impact the coefficient of the protest variable to a large extent. The magnitudes fluctuate slightly, but neither the sign nor the statistical significance are impacted. Protesting still has an immediate negative impact on growth.

1.4.3 Binary Estimates

From Tables 2.4 and 2.5 the variable that includes the number of newspaper mentions rather than a raw count of protest events yields more information about the intensity of protest activity in country i in year t. However, with more information more noise is added to the data. In Table 2.8 I estimate the impact of protest activity using a binary form. The protest variable of interest now takes a value of 1 if the number of newspaper mentions exceeds a certain threshold and 0 otherwise. The thresholds that I chose are 0 (any positive number of mentions), 20 (more than 20 mentions), 50, 100, 250 and 500. From Table 2.8 it appears that the protest(s) should be large enough to garner at least 20 mentions during a calendar year to have an impact on growth. The largest effect comes from larger protests that amass at least 100 newspaper mentions. The negative effect on growth ranges from 0.6 to 1.5 percentage points per year depending on the threshold.

As in Tables 2.4 and 2.5 the coefficients for the first lag of the binary variable seem to become positive, but none are statistically significant.

1.4.4 Other Estimates using GDELT

Tables 1.8 and 1.9 show the differential effect of different modes of protest on growth and the long run effect, respectively.

GDELT divides protests into the following categories: demonstration, riot, strike, hunger strike, obstruction of passage and unspecified political dissent. In Table 1.8, I construct binary variables based on the most prevalent mode of protest in country i in year t as long as there are at least 20 newspaper mentions based on the findings from Table 2.8. For example, a dummy for riots takes on a value of 1 if rioting was the most common mode of protest in a particular year in a particular country and 0 otherwise. Each country only gets a value of 1 in one of the dummy variables per year (there is no overlap). One could imagine that more violent modes of protest would have a more profound effect on GDP growth. Demonstrations and rallies tend to have a negative effect on growth, while most of the other modes of protest do not have a statistically significant impact. However, it appears that violent protesting influences growth positively. This unusual finding could be due to a limited number of cases where violent protests were the prevalent mode: there were only 12 country-year observations where this dummy variable took a value of 1.

In Table 1.9 I show the estimates over 3- and 5-year periods using the number of mentions specification of the protest intensity variable. The first three columns show estimates of 3-year intervals with three different specifications and the last three columns show the same but for a 5-year horizon. The coefficient for the protest variable is mostly in line with the previous results being negative and statistically significant (if small). In columns (3) and (6) when all the control variables are added to the estimation it appears that there is no impact of protesting on long run growth as the coefficients are not statistically significant. But given that in previous tables the effect of protesting on growth was only present in the year of the event and not afterwards, these results are not out of the ordinary. The effect on long term GDP level stems from the persistence of the immediate growth effect.

1.5 Robustness check: European Data

GDELT is a rich dataset that covers a long span of years and many countries, but the quality of the data is lacking in some respects as it does not provide enough information about the protests. I use EPCD as a robustness check to see whether the pattern of the relationship between growth and protesting holds for a limited subsample of European countries from 1980-1995.

Table 1.10 shows the same specifications as in Tables 2.4 and 2.5 but this time the protest variable is a log of the total number of protesters participating in various events over the course of 1 year in country i. All the covariates remain the same as in the GDELT estimations, only the protest variable has been changed. The coefficients for the year of protest show a negative and statistically significant effect on growth. According to specification in column (5) each additional percent increase in the number of protesters decreases growth by 0.005%.

In Table 1.11 I compare GDELT estimates to those from EPCD. In order to do that I limit GDELT dataset only to those countries and years that are covered in EPCD. The resulting estimates using the simple count measure and the number of mentions measure (columns (1) and (2) respectively) are considerably larger than those in Tables 2.4 and 2.5 and there also appears to be a similar effect of protesting in two subsequent years after the protest occurs. Knowing the mean of the protests for this sample is only 5 (compared to 24 in the entire sample) the estimate becomes less alarming. After adjusting for this difference, the estimates in the limited sample are comparable. The persistence across years can be attributed to the specifics of the sample. One hypothesis is that protesting in developed countries in that period did more harm to growth than it does on average for the entire sample. Developed nations have more to lose when every aspect of economic activity halts to accommodate a mass protest than their developing neighbours.

Across columns (3)–(9) in Table 1.11 the coefficients of interest are negative and statistically significant (with the exception of column (8)). While the magnitude of coefficients in GDELT and EPCD are not directly comparable due to the different nature of the variables, the general pattern holds: protesting has an immediate small negative effect on growth which does not carry over to subsequent periods.

Another aspect of EPCD that makes it a superior dataset from the standpoint of the data quality is the fact that I am able to code the protests according to their underlying cause: economic, political, and other. As with the modes of protest, these three dummy variables do not overlap with each other for country i in year t. If the largest protest has been identified as having political causes then the entire year for that country would take on the value of 1 for political cause dummy and 0 otherwise. I present the results in Table 1.12. There does not seem to be any consistent results based on the cause of the protest. It is comforting, however, that protests with explicitly economic causes (which could be inversely related to growth) do not have a statistically significant impacts, as it removes some of the concerns about reverse causality.

1.6 Effect on Other Economic Variables

In two previous sections I have established that protesting seemingly causes a decline in the growth rate albeit a small one. In this section I briefly explore the channels through which this decline can be realized. Protesting in itself can have a direct effect on growth when people shirk work and do not produce anything, but the impact of protesting on other economic variables provides a stronger link to changes in growth.

In Table 1.13 I run regressions similar to equation 2.2 but use different dependent variables. For example, the regression for even columns looks as follows:

$$DependentVariable_{it} = \beta_0 + \beta_1 DependentVariable_{i,t-1} + \sum_{k=0}^{N} \beta_2 Protest_{i,t-k} + \sum_{k=0}^{N} \beta_3 Y_{i,t-k} + \beta_4 Z_{it} + \delta_t + \gamma_i + \eta_{it} \tag{1.2}$$

where the dependent variable is the trade share in GDP, gross capital formation, FDI, inflation or unemployment. Vector Z_{it} includes the same control variables as its counterpart in equation 2.2 with the exception of the dependent variable itself. The regressions in the rest of Table 1.13 are based on similar equations. I run two regressions for each economic variable where the first one is only controlling for the lagged value of the dependent variable, protest variable and its lags and country and year fixed effects. In addition to these the second regression includes all the control variables that are in equation 2.2 as well as the growth rate and it's first lag.

Out of the five economic variables I test two respond to protesting. Inflation, trade share in GDP and FDI inflows do not change with respect to fluctuation in protest activity. I find that gross capital formation (measured in percent) decreases and unemployment goes up following protest events. Quantitatively, a 1% increase in protesting, measured by the amount of media coverage (about a 1.6 increase of the number of mentions on average), would cause a 0.12% drop in capital formation and a 0.09% increase in unemployment. Inflation appears to increase after protest events as well, but the relationship is not statistically significant.

As with the growth rate, protesting has an effect on these economic variables but the scale of this impact is small. Not surprisingly, when a small effect on gross capital formation and unemployment feeds back into the growth rate, the resulting change in growth rate of GDP is also small.

1.7 Conclusion

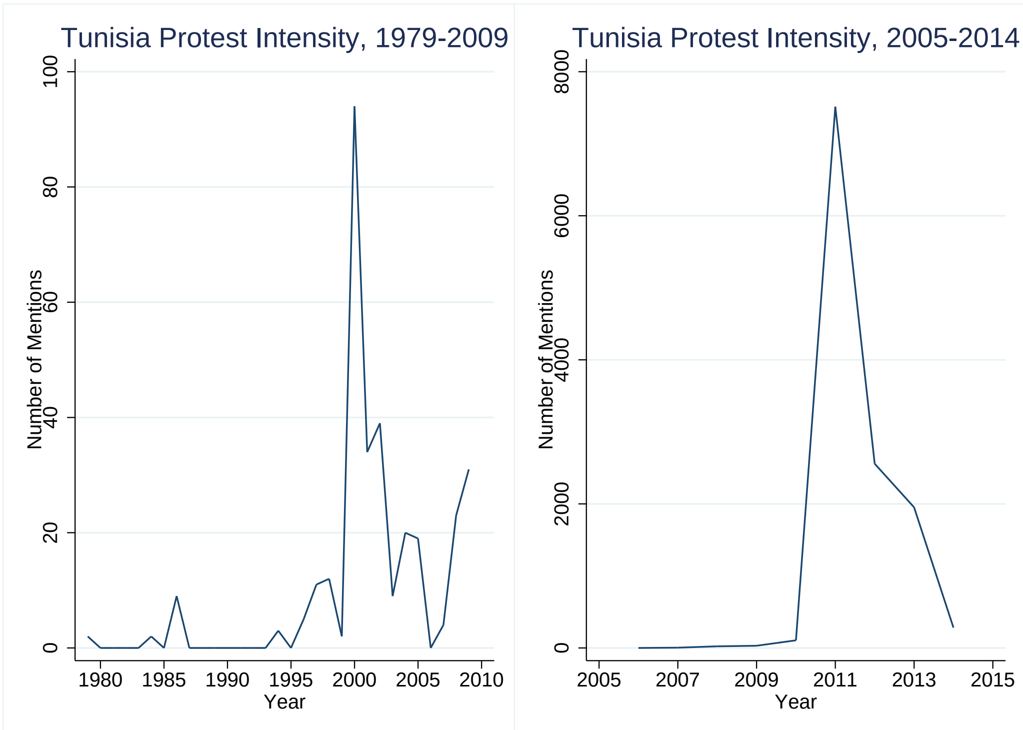
I find that there is an immediate negative impact on the growth rate in the year when the protest occurs. Namely, an increase of 1% in the number of protests in one year would result in a roughly 0.005% decrease in GDP growth. Given that the mean number of protests is 24, one more protest would cause a 0.02% decline in growth. When I consider the same coefficient for a measure of the intensity of protest activity, I find that the GDP growth drops by 0.002% per 1% increase in newspaper mentions of a protest.

The difference in these results comes from the fact that the variable based on the sheer number of protests includes both small and large protests without being able to distinguish between them. Naturally, such protests would have very different effects on GDP. The results obtained from estimating the impact of protest activity by its intensity via the number of newspaper mentions is a more reliable measure.

There is some weak evidence that 1–2 years after the protest event the effect on GDP becomes positive, but it is not consistent across different specifications. The idea behind this change is that whatever reforms are passed as a result of the protest do not affect the economy until several years after. However, there is no conclusive result on this front.

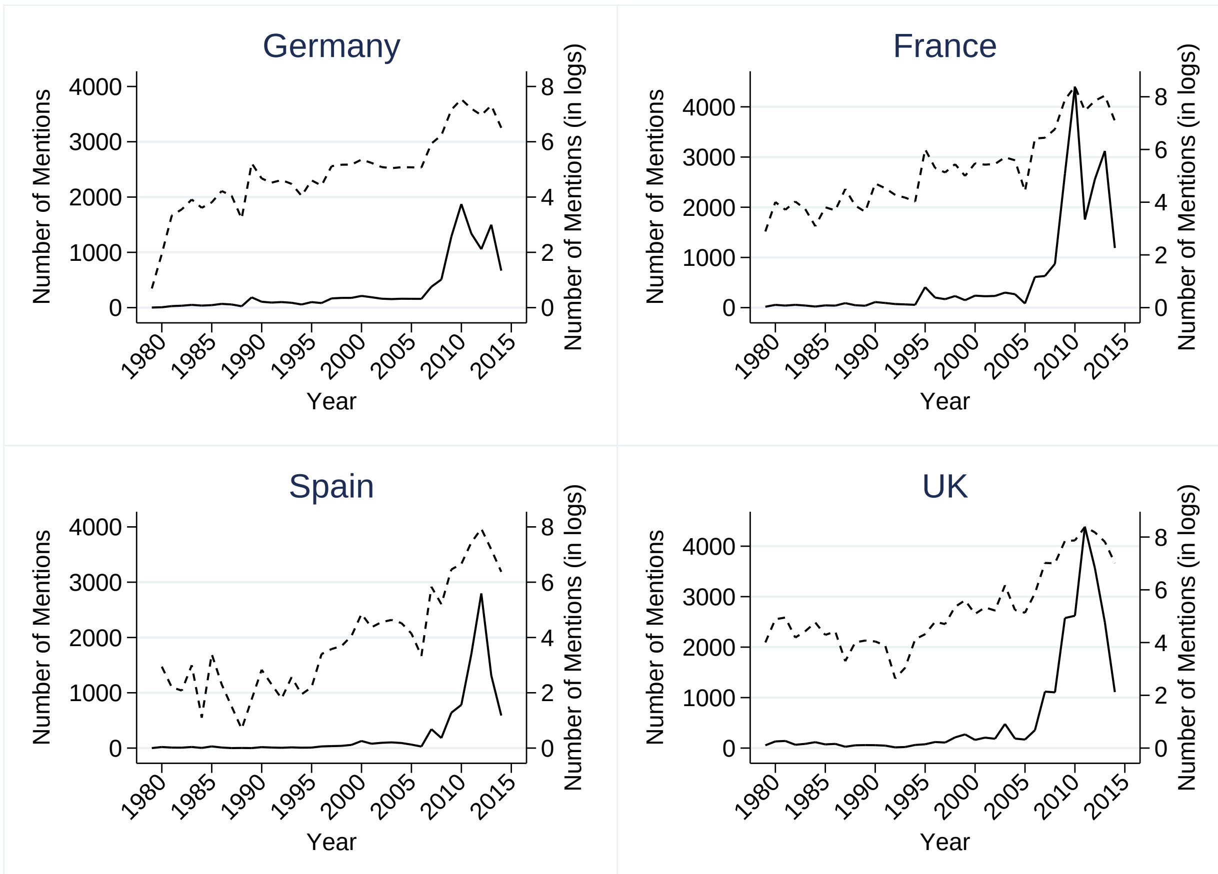
I uncover two of the potential indirect channels though which protesting may affect growth: gross capita formation and unemployment. One of the options for the future research would be to see what other economic variables beyond those considered here could be affected by protesting and serve as a channel to economic growth. Another avenue for future research would be to see whether protesting affects the likelihood of the reforms being passed as a form of appeasement from the government.

Figure 1.1: Tunisia: Before and After the Arab Spring



Notes: The graph on the left shows protest activity in Tunisia before the Arab Spring. The peak corresponds to an increase in protesting in 2000 due to general unhappiness with the political regime. The graph on the right captures protest intensity before, during and after Tunisian Revolution of 2010-2011 (also known as part of the Arab Spring protests).

Figure 1.2: Protest Intensity across time in Europe



Notes: The graphs show protest activity in four European countries during the entire time period considered in both unit (solid line) and log form (dashed line). The largest protests occurred around the time of the financial crisis of 2008. The scale used is the same in all graphs. Note that a small peak in 1989 in Germany corresponds to the fall of the Berlin Wall and a similar peak in 1995 in France is due to country-wide general strikes that disrupted transportation.

Table 1.1: Description of variables

Variables	Description	Source
GDP per capita	Output-side real GDP per capita at chained PPPs (in mil. USD 2005)	WDI
Protest:		
- count	Number of protests occuring in country i in yeat t	GDELT
- number of mentions	Number of newspaper mentions of protests occuring in country i in year t	GDELT
- Europe	Protest measures constructed from number of protesters, number of injuries, etc	EPCD
Polity	Variable indicates if a country is democratic or autocratic,range -10,10	Polity IV
Life expectancy	Life expectancy	WDI
School enrollment	Primary and secondary enrollment rates, separated in two variables	WDI
Gross capital formation	Gross capital formation, % of GDP	WDI
Trade share	Share of trade in GDP	WDI
War dummy	Indicator that shows if there was a war in country i in year t	PRIO
Population	Size of total population	WDI
Inflation	Inflation, consumer prices (annual %)	WDI
Unemployment	ILO estimate of Unemployment (% of total labor force)	WDI
FDI	Foreign direct investment, net inflows (% of GDP)	WDI

Notes: WDI - World Bank Development Indicators, GDELT - Global Database of Events, Language and Tone, EPCD - European Protest and Coercion Data, PRIO - UCDP/PRIO Armed Conflict Dataset, Version 4-2015.

Table 1.2: Descriptive Statistics: Full Dataset

Variables	(1) N	(2) Mean	(3) St. Dev.	(4) Min	(5) Max
GDP Growth p.c.	6980	0.017	0.063	-1.050	0.884
Polity IV	4668	2.1	7.1	-10	10
Life expectancy	7067	66.1	10.3	20.7	83.8
Primary school enrollment	5461	98.4	20.8	15.7	211.9
Secondary school enrollment	4660	67.3	32.8	2.0	165.5
Gross capital formation	5860	23.7	10.8	-5.7	219.1
Trade share	6070	84.3	52.6	0.3	531.7
War dummy	7918	0.54	0.65	0	2
Population (mln)	7660	27.2	111	0.01	1360
Inflation	5840	29.6	393.2	-18.1	23773
Unemployment	4002	8.8	6.2	0	39.3
FDI	6207	3.5	10.6	-82.8	466.5
Protest Variables:					
Count	7918	23.9	140.4	0	6002
Number of Mentions	7918	158.5	1338.3	0	69067

Notes: Contains WDI data in 1978-2014 and GDELT protest variables.

Table 1.3: Descriptive Statistics: European Sample

Variables	(1) N	(2) Mean	(3) St. Dev.	(4) Min	(5) Max
Growth p.c.	429	0.020	0.036	-0.344	0.192
Primary school enrollment	359	99.4	8.5	70.4	127.2
Secondary school enrollment	353	93.0	14.7	53.8	146.1
Trade share	353	71.8	34.4	30.5	201.8
Population (mln)	384	19.1	22.1	0.23	81.7
Life expectancy	384	74.5	2.5	68.9	79.2
Gross capital formation	355	24.2	4.9	5.1	37.9
Polity IV	342	7.1	6.0	-9	10
War dummy	384	0.125	0.331	0	1
Protest Variables:					
Number of Protesters (thousands)	384	3,319	8,756	0	80,700
Number of Protesters Arrested	384	536.2	2,556.8	0	31,739
Number of Protesters Injured	384	150.0	857.2	0	15,221
Number of Protesters Killed	384	4.0	42.8	0	834
Number of State Forces (thousands)	384	29.6	218.1	0	3,496
Number of State Forces Injured (thousands)	384	13.1	255.1	0	5,000
Number of State Forces Killed	384	82.6	1,530.8	0	30,001

Notes: Contains WDI data in 1975-1995 for select European countries and EPCD protest variables.

Table 1.4: Number of Protests: Baseline Specification

Dependent Variable: First Difference of the Log of real GDP per capita

	(1)	(2)	(3)	(4)	(5)	(6)
First Lag of GDP Growth	0.356	0.357	0.358	0.330	0.313	0.299
	(8.06)***	(8.05)***	(8.14)***	(6.96)***	(6.47)***	(6.26)***
Log of Number of Protests	-0.0040	-0.0047	-0.0050	-0.0048	-0.0050	-0.0048
	(3.29)***	(3.27)***	(3.19)***	(3.06)***	(3.19)***	(3.43)***
Number of Protest Lags:						
First Lag		0.0009	0.0017	0.0019	0.0018	0.0007
		(0.71)	(1.21)	(1.34)	(1.26)	(0.56)
Second Lag		0.0007	0.0003	0.0003	0.0006	0.0011
		(0.67)	(0.22)	(0.26)	(0.52)	(1.12)
Polity and its Lags	No	No	Yes	Yes	Yes	No
Explanatory Variables	No	No	No	Yes	Yes	No
Further Lags of GDP	No	No	No	No	Yes	No
Acemoglu et. al (2015)	No	No	No	No	No	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.23	0.23	0.23	0.25	0.25	0.24
Observations	2,989	2,989	2,989	2,989	2,989	2,989

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Standard Explanatory Variables: life expectancy, school enrollment (primary and secondary), gross capital formation, trade share, war dummy, population. Control variables included in Acemoglu et al. (2015): log of infant mortality, school enrollment (primary and secondary), investment share, trade share, tax revenue, TFP, financial flows and 4 lags of GDP. Mean of number of protests - 23.93, Median - 1. Lags used: 4 lags of GDP growth, 2 lags of Polity and Interaction with Polity.

Table 1.5: Intensity of Protests: Baseline Specification

Dependent Variable: First Difference of the Log of real GDP per capita

	(1)	(2)	(3)	(4)	(5)	(6)
First Lag of GDP Growth	0.357	0.358	0.356	0.327	0.311	0.300
	(8.13)***	(8.17)***	(8.01)***	(6.95)***	(6.47)***	(6.34)***
Log of Intensity of Protests	-0.0021	-0.0024	-0.0020	-0.0018	-0.0019	-0.0025
	(2.65)***	(2.69)***	(2.33)**	(1.81)*	(1.91)*	(2.86)***
Log of Intensity of Protests Lags:						
First Lag		0.0010	0.0012	0.0018	0.0017	0.0009
		(1.35)	(1.52)	(2.00)**	(1.95)*	(1.15)
Second Lag		-0.0003	-0.0003	-0.0004	-0.0003	-0.0001
		(0.47)	(0.47)	(0.55)	(0.37)	(0.22)
Polity and its lags	No	No	Yes	Yes	Yes	No
Control Variables	No	No	No	Yes	Yes	No
Further Lags of GDP	No	No	No	No	Yes	No
Acemoglu et al. (2015)	No	No	No	No	No	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.23	0.23	0.23	0.25	0.25	0.24
Observations	2,989	2,989	2,989	2,989	2,989	2,989

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Standard Explanatory Variables: life expectancy, school enrollment (primary and secondary), gross capital formation, trade share, war dummy, population. Control variables included in Acemoglu et al. (2015): log of infant mortality, school enrollment (primary and secondary), investment share, trade share, tax revenue, TFP, financial flows and 4 lags of GDP. Mean of number of protests - 158.56, Median - 5. Lags used: 4 lags of GDP growth, 2 lags of Polity and Interaction with Polity.

Table 1.6: Intensity of Protests: Number of Media Sources

Dependent Variable: First Difference of the Log of real GDP per capita

	(1)	(2)	(3)	(4)	(5)	(6)
First Lag of GDP Growth	0.356	0.357	0.355	0.326	0.310	0.299
	(8.09)***	(8.10)***	(7.96)***	(6.93)***	(6.45)***	(6.30)***
Log of Intensity of Protests	-0.0015	-0.0017	-0.0015	-0.0014	-0.0015	-0.0017
(weighted by media sources)	(3.11)***	(3.12)***	(2.76)***	(2.25)**	(2.35)**	(3.29)***
Log of Intensity of Protests Lags:						
First Lag		0.0005	0.0006	0.0010	0.0009	0.0004
		(0.97)	(1.16)	(1.76)*	(1.68)*	(0.84)
Second Lag		0.0001	0.0001	0.0001	0.0002	0.0002
		(0.25)	(0.23)	(0.15)	(0.35)	(0.54)
Polity and its lags	No	No	Yes	Yes	Yes	No
Control Variables	No	No	No	Yes	Yes	No
Further Lags of GDP	No	No	No	No	Yes	No
Acemoglu et al. (2015)	No	No	No	No	No	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.23	0.23	0.23	0.25	0.25	0.24
Observations	2,989	2,989	2,989	2,989	2,989	2,989

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Standard Explanatory Variables: life expectancy, school enrollment (primary and secondary), gross capital formation, trade share, war dummy, population. Control variables included in Acemoglu et al. (2015): log of infant mortality, school enrollment (primary and secondary), investment share, trade share, tax revenue, TFP, financial flows and 4 lags of GDP. Mean of number of protests - 158.56, Median - 5. Lags used: 4 lags of GDP growth, 2 lags of Polity and Interaction with Polity.

Table 1.7: Intensity of Protests: Binary Specification

Dependent Variable: First Difference of the Log of real GDP per capita

Number of Mentions	(1) >0	(2) >20	(3) >50	(4) >100	(5) >250	(6) >500
Binary (cutoff as shown)	0.000	-0.006	-0.009	-0.015	-0.010	-0.010
	(0.08)	(2.53)**	(3.34)***	(3.71)***	(2.55)**	(2.41)**
Lags:						
First Lag	0.004	0.002	0.003	0.002	0.005	0.004
	(1.60)	(0.81)	(1.13)	(0.50)	(1.06)	(1.07)
Second Lag	-0.002	0.001	0.004	0.005	0.000	-0.003
	(0.86)	(0.50)	(1.42)	(1.62)	(0.02)	(0.93)
Polity and its Lags	Yes	Yes	Yes	Yes	Yes	Yes
Explanatory Variables	Yes	Yes	Yes	Yes	Yes	Yes
Lags of GDP Growth	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.25	0.25	0.25	0.25	0.25	0.25
Observations	2,989	2,989	2,989	2,989	2,989	2,989

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Standard Explanatory Variables: life expectancy, school enrollment (primary and secondary), gross capital formation, trade share, war dummy, population. Lags used: 4 lags of GDP growth, 2 lags of Polity and Interaction with Polity. Binary variable is based on the number of mentions and takes on the value of 1 if the number of mentions is as specified in the column headers (e.g. in column 2 number of mentions is above 20) and 0 otherwise.

Table 1.8: Binary Protest Variable: Modes of Protest

Dependent Variable: First Difference of the Log of real GDP per capita

	(1)	(2)	(3)	(4)	(5)	(6)
Unspecified Political Dissent	-0.007					
	(0.56)					
Demonstration/Rally		-0.006				
		(2.87)***				
Hunger Strike			0.002			
			(0.46)			
Strike or Boycott				-0.003		
				(0.60)		
Obstruction of Passage					-0.009	
					(1.21)	
Violent Protest/Riot						0.044
						(2.26)**
Polity and its lags	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Further Lags of GDP	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.25	0.25	0.25	0.25	0.25	0.25
Observations	2,989	2,989	2,989	2,989	2,989	2,989

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Modes of protests are coded as binary variables taking on a value of 1 if such a protest took place in country i in year t. The protest intensity has to be at least 20 media mentions to be included here. Standard Control Variables: life expectancy, school enrollment (primary and secondary), gross capital formation, trade share, war dummy, population. Lags used: 2 lags of Polity, 2 lags of GDP growth.

Table 1.9: Intensity of Protests: 3 and 5 Year Estimates

Dependent Variable: 3-year or 5-year Difference of the Log of real GDP per capita

	3-Year Estimates			5-Year Estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
Third Lag of Log of GDP	0.468	0.455	0.385			
	(6.51)***	(5.95)***	(4.57)***			
Third Lag of Number of Mentions	-0.0057	-0.0044	-0.0002			
	(1.88)*	(1.57)	(0.02)			
Fifth Lag of Log of GDP				0.383	0.382	0.329
				(2.96)***	(2.92)***	(2.52)**
Fifth Lag of Number of Mentions				-0.0189	-0.0153	0.0140
				(1.93)*	(1.61)	(0.49)
Polity and its lags	No	Yes	Yes	No	Yes	Yes
Control Variables	No	No	Yes	No	No	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.16	0.18	0.25	0.13	0.14	0.23
Observations	2,670	2,670	2,670	2,670	2,670	2,670

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Standard Control Variables: life expectancy, school enrollment (primary and secondary), gross capital formation, trade share, war dummy, log of population.

Table 1.10: European Data: Baseline Specification

Dependent Variable: First Difference of the Log of real GDP per capita

	(1)	(2)	(3)	(4)	(5)	(6)
Lag of GDP Growth	0.367	0.389	0.290	0.312	0.358	0.337
	(7.43)***	(9.16)***	(4.58)***	(3.51)***	(3.47)***	(2.61)**
Log of Number of Protesters	-0.0033	-0.0048	-0.0035	-0.0050	-0.0047	-0.0038
	(4.36)***	(2.52)**	(2.59)**	(5.80)***	(5.58)***	(2.84)**
Lags of Number of Protesters:						
First Lag		0.0000	-0.0010	0.0000	0.0008	-0.0010
		(0.01)	(1.09)	(0.00)	(0.31)	(0.99)
Second Lag		0.0035	-0.0003	-0.0002	-0.0011	-0.0002
		(1.70)	(0.24)	(0.10)	(0.66)	(0.23)
Polity and its lags	No	No	Yes	Yes	Yes	No
Control Variables	No	No	No	Yes	Yes	No
Further Lags of GDP Growth	No	No	No	No	Yes	No
Acemoglu et al. (2015)	No	No	No	No	No	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.34	0.37	0.47	0.56	0.59	0.62
Observations	256	256	256	256	256	256

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Standard Control Variables: life expectancy, school enrollment (primary and secondary), gross capital formation, trade share, war dummy, population. Control variables included in Acemoglu et al. (2015): log of infant mortality, school enrollment (primary and secondary), investment share, trade share, tax revenue, TFP, financial flows and 4 lags of GDP. Mean of number of protesters - 3,319,499, Median - 356,801.5. Lags used: 4 lags of GDP growth, 2 lags of Polity and Interaction with Polity.

Table 1.11: Comparison across all Protest Measures for 1980-1995 in a sample of European Countries from EPCD

Dependent Variable: First Difference of the Log of real GDP per capita

	GDELT Dataset		European Dataset						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Protests	Intensity	Protesters	Arrested	Injured	Killed	State Forces	SF Injured	SF Killed
Lag of GDP Growth	0.300	0.276	0.358	0.381	0.492	0.338	0.375	0.343	0.287
	(2.74)**	(2.60)**	(3.46)***	(4.79)***	(4.96)***	(3.50)***	(4.52)***	(3.26)***	(2.76)**
Protest variable	-0.0099	-0.0030	-0.0047	-0.0045	-0.0108	-0.0104	-0.0049	-0.0063	-0.0621
	(1.24)*	(0.56)*	(5.49)***	(5.12)***	(5.28)***	(3.96)***	(2.64)**	(2.49)**	(1.81)*
Lags of Protest variable:									
First Lag	-0.0158	-0.0127	0.0008	-0.0026	0.0088	0.0027	-0.0006	0.0070	0.0177
	(2.40)**	(2.64)**	(0.32)	(1.55)	(1.44)	(0.64)	(0.33)	(1.01)	(1.45)
Second Lag	-0.0205	-0.0167	-0.0011	0.0030	0.0049	-0.0060	0.0006	-0.0056	-0.0053
	(5.03)**	(4.66)**	(0.64)	(0.71)	(0.53)	(1.65)	(0.31)	(2.33)**	(1.11)
Polity and its lags	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Further Lags of GDP	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.60	0.61	0.59	0.59	0.66	0.59	0.60	0.59	0.62
Observations	256	256	256	256	256	256	256	256	256

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Columns 1-2: GDELT data, but the sample is limited to correspond to that from EPCD covering 1980-1995 in a subset of European countries. Columns 3-9: EPCD data. Standard Control Variables: life expectancy, school enrollment (primary and secondary), gross capital formation, trade share, war dummy, population. Lags used: 4 lags of GDP growth, 2 lags of Polity and Interaction with Polity.

Table 1.12: European Data: Protest Causes

Dependent Variable: First Difference of the Log of real GDP per capita

	(1)	(2)	(3)	(4)
Lag of Growth	0.328	0.324	0.321	0.321
	(3.21)***	(3.20)***	(3.11)***	(3.14)***
Protest Causes:				
Economic	-0.0057			
	(1.32)			
Political		0.0022		
		(0.46)		
Nuclear Power Related			0.0046	
			(1.64)	
Other				0.0033
				(0.69)
Polity	No	Yes	Yes	Yes
Control Variables	No	No	Yes	Yes
Further Lags of GDP	No	No	No	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R-squared	0.57	0.57	0.57	0.57
Observations	256	256	256	256

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Standard Control Variables: life expectancy, school enrollment (primary and secondary), gross capital formation, trade share, war dummy, population. Lags used: 2 lags of GDP growth. Other causes: includes religious protests, immigration-related protests, nuclear power and ecological protests etc.

Table 1.13: Impact of Protests on Other Economic Variables

	(1) Trade Share	(2) Trade Share	(3) Capital Formation	(4) Capital Formation	(5) FDI Inflows	(6) FDI Inflows	(7) Unemp.	(8) Unemp.	(9) Infl.	(10) Infl.
Log of Protest Int.	-0.058	0.184	-0.168	-0.119	-0.013	0.032	0.091	0.086	6.499	8.280
	(0.27)	(0.86)	(2.39)**	(1.97)*	(0.18)	(0.39)	(2.62)***	(2.70)***	(0.73)	(0.69)
Lags of Protests:										
First Lag	0.222	0.155	-0.043	-0.043	-0.025	-0.024	0.033	0.024	5.601	3.182
	(1.04)	(0.61)	(0.56)	(0.54)	(0.30)	(0.29)	(1.16)	(0.97)	(0.85)	(0.50)
Second Lag	0.243	0.152	0.090	0.043	-0.133	-0.211	0.035	0.013	-9.304	-9.448
	(1.49)	(0.73)	(1.21)	(0.53)	(1.51)	(2.17)**	(1.29)	(0.51)	(1.02)	(1.03)
Lag of Dep. Var.	0.781	0.769	0.758	0.720	0.531	0.518	0.785	0.778	0.093	0.069
	(29.88)***	(28.63)***	(27.58)***	(24.96)***	(10.92)***	(10.47)***	(21.78)***	(22.07)***	(1.80)*	(1.32)
Growth		-5.323		20.080		2.640		-4.262		-862.9
		(0.88)		(5.24)***		(1.76)*		(3.34)***		(2.37)**
Lag of Growth		-17.020		2.806		-0.662		-0.987		-1,596.3
		(2.26)**		(0.87)		(0.37)		(1.05)		(1.49)
Polity and its lags	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Control Variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.72	0.73	0.60	0.63	0.32	0.33	0.59	0.61	0.02	0.04
Observations	3,001	3,001	2,998	2,998	2,917	2,917	2,036	2,036	2,670	2,670

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Dependent variable “Unemp.” stands for “Unemployment.” “Capital Formation” stands for “Gross Capital Formation.” “Lag of Dep. Var.” stands for “Lag of Dependent Variable.” “Infl” stands for “Inflation.” Standard Control Variables: life expectancy, school enrollment (primary and secondary), gross capital formation, trade share, war dummy, log of population. Lags used: 2 lags of Polity, 1 lag of dependent variable.

Table 1.14: Intensity of Protests: Lag Selection

Dependent Variable: First Difference of the Log of real GDP per capita

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log of Protest Intensity	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
	(1.97)*	(1.16)	(1.30)	(1.30)	(1.33)	(1.45)	(1.41)
Number of Protests Lags:							
First Lag		0.0005	-0.0004	-0.0006	-0.0008	-0.0009	-0.0011
		(0.20)	(0.17)	(0.24)	(0.32)	(0.35)	(0.46)
Second Lag			0.0027	0.0022	0.0019	0.0018	0.0020
			(1.53)	(1.24)	(1.05)	(0.99)	(1.09)
Third Lag				0.0020	0.0015	0.0013	0.0013
				(1.42)	(1.04)	(0.92)	(0.91)
Fourth Lag					0.0015	0.0012	0.0011
					(1.15)	(0.92)	(0.84)
Fifth Lag						0.0007	0.0006
						(0.51)	(0.36)
Sixth Lag							0.0010
							(0.66)
Polity and its Lags	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Explanatory Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lags of GDP Growth	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.33	0.33	0.33	0.33	0.33	0.33	0.33
Observations	1,202	1,202	1,202	1,202	1,202	1,202	1,202

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Standard Explanatory Variables: life expectancy, school enrollment (primary and secondary), gross capital formation, trade share, war dummy, population. Mean of number of protests - 23.98, Median - 1. Lags used: 4 lags of GDP growth.

Table 1.15: Intensity of Protests: GDP Lag Selection

Dependent Variable: First Difference of the Log of real GDP per capita

Lags of Growth included	(1) 1 Lag	(2) 2 Lags	(3) 3 Lags	(4) 4 Lags	(5) 5 Lags
Log of Number of Protests	-0.003	-0.003	-0.003	-0.003	-0.003
	(1.85)*	(1.84)*	(1.82)*	(1.91)*	(1.91)*
First Lag	0.0007	0.0007	0.0007	0.0007	0.0007
	(0.43)	(0.49)	(0.47)	(0.47)	(0.48)
Second Lag	0.0010	0.0010	0.0010	0.0011	0.0011
	(0.70)	(0.72)	(0.70)	(0.80)	(0.80)
Polity and its Lags	Yes	Yes	Yes	Yes	Yes
Explanatory Variables	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.23	0.23	0.23	0.23	0.23
Observations	2,905	2,905	2,905	2,905	2,905

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Standard Explanatory Variables: life expectancy, school enrollment (primary and secondary), gross capital formation, trade share, war dummy, population. Mean of number of mentions - 23.98, Median - 1. Lags used: 2 lags of Polity and Interaction with Polity.

Table 1.16: Impact of Growth on Protesting Activity

Dependent variables are different in each column.

	(1) Number	(2) Intensity	(3) Protesters	(4) Prot. Injured	(5) Prot. Arrested	(6) Prot. Killed
GDP Growth	-1.107	-1.235	-10.310	-12.933	-2.703	-3.351
	(2.59)*	(2.09)	(1.78)*	(2.42)	(0.64)	(1.50)
First Lag of GDP Growth	-0.048	-0.097	7.862	6.041	9.350	-0.129
	(0.13)	(0.19)	(1.43)	(1.53)	(1.87)*	(0.09)
Polity and its lags	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.58	0.54	0.48	0.11	0.13	0.12
Observations	3,006	3,006	288	288	288	288

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Standard Control Variables: life expectancy, school enrollment (primary and secondary), gross capital formation, trade share, war dummy, population. Lags used: 2 lags of Polity.

Chapter 2

Protesting and Inequality: Is there a Link?

2.1 Introduction

A seemingly minor event can spur people into action. On a society-level this action could be a protest, a strike, even a revolution. A small or random occurrences can spark a wide response like an increase in the price of bus tickets in Brazil in 2013 or a self-immolation by a street vendor in Tunisia in 2010. When it is over, people go back to their lives, but the ripple effect of the protest runs through the economy for years to come if the event was significant enough.

If the protest is successful, the government might be induced to change certain policies. Some reforms may be of a redistributive nature either because of the direct demand by protestors or as an unintended consequence. Therefore, a protest might affect the level of inequality in the country rather than its economic growth, which I addressed in the previous chapter.

In this work I study the link between protesting and inequality using a novel panel of 74 countries over 1979–2012. I find that across most of the specifications the effect of protesting on inequality, measured by the Gini index, is negative and statistically significant.

The existing literature linking unrest and inequality describes inequality as one of the drivers of unrest, thereby reversing the direction of causality relative to what I estimate in this paper. However, there are mixed results, with some of them indicating that more unequal societies are prone to civil strife (Alesina and Perotti, 1996; Acemoglu and Robinson, 2000) and others finding more compelling causes for unrest than income inequality (Tadjoeddin et al., 2001; Deininger, 2003). Notably, the first branch of literature consists of aggregate studies and the second is based on individual country cases. Contrary to the first strand of literature, when I estimate the effect of inequality on protests to check for reverse causality I do not find the same effect in this panel study. Rather it appears that inequality reduces unrest, albeit the coefficient is only statistically significant at 10%. This seeming disparity is likely to stem from the difference in data sources, as aggregate studies generally use constructed indices or only include the largest cases of unrest in their estimations, both of which introduce bias. In contrast, I use highly disaggregated protest data, which alleviates these concerns. While I find no effect of inequality on protests, the main contribution of this paper to the existing research is the estimation of the link from protesting to inequality, which has not been examined previously.

Data on protesting comes from the Global Database of Events, Language and Tone (GDELT)[1], which contains daily information on protest events across the globe. I specify the protest variable in three different ways: a simple count measure of protests in country i in year t, a number of times protests that originated in country i have been mentioned in the media during the year, and a binary measure based on a threshold number of newspaper mentions. The number of mentions serves as a proxy for the intensity of protest activity in the country as one can expect larger and longer protests to be covered more heavily in the media.

I examine a range of specifications and find a robust relationship of protest activity with future changes in inequality. On average, a 1% increase in protest activity decreases the Gini index immediately by 0.01 points. The binary measure based on the intensity of protesting indicates that a large enough protest reduces inequality, lowering the Gini index by 1.6 – 2.1 points. To impact inequality the protest activity in a country has to garner at least 250 media mentions per year. One of such protest events was the anti-austerity protests in Ireland in 2008 which involved over 25,000 people (Anderson, 2008).

One of the possible channels of this relationship is through post-protest reforms. However, reforms usually take longer to implement and, therefore, are not a reasonable explanation of the immediate drop in inequality. Consequently, when lags of protest activity measures are used, the effect of protesting on income inequality disappears. Although most coefficients in these tables indicate that protesting increases

[1]Leetaru and Schrodt (2013)

inequality, the relationship is not statistically significant. It appears that protests do not seriously impact inequality though redistributive policies.

In the next section, I present data sources in more detail. Methodology is discussed in Section 2.3. Summary of the main results is described in Section 2.4. Section 2.5 concludes.

2.2 Data

Data used in this paper comes from 4 distinct sources. The variable-by-variable description is available in Table 2.2. The main dataset that contains the protest variables is the Global Database of Events, Language and Tone (GDELT). Daily data on protest events is available, but I aggregate it to the annual level due to the restrictions from the availability of the other variables. I use two measures of protesting activity from the GDELT: the number of protests and the number of newspaper mentions of those protests. The latter is a superior proxy of the intensity of protest activity as it gives information on the scope of every protest rather than lumping small and large protests together. More detailed information on this dataset is available in Section 2 of the previous chapter.

Inequality is measured by the Gini index (or, coefficient) which indicates how unequal the income is across the population. It ranges from 1 to 100 with the more unequal countries receiving a higher value. I obtain the data from the World Bank database (Milanovic, 2014), but it contains standardized data series from multiple sources. This includes Luxembourg Income Study (LIS), Socio-Economic Database for Latin America (SEDLAC), Eurostat's Survey of Living Conditions (SILC), World Income Distribution, World Bank Europe and Central Asia dataset, World Institute for Development Research (WIDER), World Bank Povcal, and individual inequality studies. Therefore, this dataset allows me to use the richest panel of Gini index data available. It spans 1979-2012 (the lower bound is fixed by the availability of the protest data) and includes 74 countries with at least 10 years of information on inequality levels. I omit countries which only have sporadic observations, thereby eliminating most of LDCs (Least developed countries). However, both developed and developing countries are equally well represented. The full list of countries is available in Table 2.1.

Remaining variables which are used to control for other sources of fluctuations in inequality are described in Tables 2.2 and 3.1. Most come from the World Bank Indicators database with the exception of the "Polity" variable and the War dummy. "Polity" receives a value of 10 for a democratic country and -10 for an autocratic one (Marshall and Jaggers, 2002). The war dummy is taken from the PRIO dataset (Gleditsch et al., 2002) and indicates whether a war has occurred in year t in country i.

I present the descriptive statistics of my sample in Table 3.1. The Gini index takes a value of 38.1 on average, which is roughly equivalent to the level of inequality in Venezuela in 2011. The maximum of 67.6 corresponds to Jamaica in 1996 (possibly due to the elimination of favorable trade conditions with the European Union and agricultural subsidies and the recession of 1996-1997)[2] and the minimum of 16.6 —

[2] "Jamaica must stabilize its economy and diversify its exports" (1998).

to Luxembourg in 1986.

During the period described in this paper roughly 28 protests occurred per year in an average country i. Those protests were mentioned in the media about 147 times. The maximum number of mentions corresponds to the USA in 2011 which is a combination of the Occupy Wall Street movement and public employees protests related to labor union legislation changes [3].

From the simple correlation between protesting and inequality data presented in Figure 2.1 it is clear that there is a slight negative relationship as the fitted line that represents how protesting and inequality data relate to each other has a negative slope. From this information I expect that more protesting would reduce inequality.

2.3 Methodology

In this section I describe the estimation methodology. The main equation is similar to those used in the literature on the determinants of inequality (e.g. Breen and Garcia-Peñalosa, 2005; Muinelo-Gallo and Roca-Sagalés, 2013). The baseline specification is:

$$G_{it} = \alpha_0 + \alpha_1 G_{i,t-1} + \sum_{k=0}^{N} \alpha_{2k} Protest_{i,t-k} + \alpha_3 X_{it} + \delta_t + \gamma_i + \epsilon_{it}, \qquad (2.1)$$

where G_{it} is the Gini index measured from 0 to 100, $Protest_{i,t-k}$ denotes the protest variable, X_{it} is a vector of explanatory variables used in the inequality literature

[3] "US union protests intensify as thousands rally" (2001)

such as levels of primary and secondary education, GDP per capita, trade share in the GDP, investment etc (see Table 2.2 for the full list). Another variable included in vector X_{it} is the "Polity" measure of country's regime. I include it to allow a differential effect based on how democratic or autocratic a country is. The different specifications use count measure of protest intensity, number of newspaper mentions proxy and the binary measure based on the various thresholds of media mentions number.

This equation is estimated using Ordinary Least Squares (OLS) with country and year fixed effects.[4] Certain years see protests across multiple countries due to an underlying even such as the financial crisis of 2007-2008. Similarly on the country level some countries see more protests than the other for a variety of reasons, and not all of them might be captured by the control variables. For instance, a protest in a developed country might be covered more by the media than a protest of the same size in a less developed country. Year and country fixed effects take care of such issues.

Lastly, there is a concern regarding reverse causality, as some of the existing literature has found that inequality makes political unrest more likely (Alesina and Perotti, 1996; Acemoglu and Robinson, 2000). However, competing research finds no such relationship (Tadjoeddin et al., 2001; Deininger, 2003). I find suggestive evidence that inequality reduces protesting, thereby establishing a weak link from inequality to protesting (see Table 2.1). It appears that endogeneity might be an issue. To alleviate it I estimate 3–Stage Least Squares, which addresses situations

[4] The fixed effects estimation of dynamic panels carries a potential bias of order $\frac{1}{T}$ for panels with small T. However, in this case $T = 34$, which eliminates the issue.

when two or more estimating equations are determined simultaneously. In this model Equation (1) and (2) are estimated together.

$$Protest_{it} = \beta_0 + \beta_1 Protest_{i,t-1} + \sum_{k=0}^{N} \beta_{2k} G_{i,t-k} + \beta_3 X_{it} + \theta_t + \lambda_i + \upsilon_{it}, \qquad (2.2)$$

where the variables are defined the same as in Equation (1).[5]

2.4 Effects of Protesting on Inequality

2.4.1 Main Estimates

In Table 2.4 I estimate 4 versions of Equation (1) by using different combinations of explanatory variables. In column (1) I only account for a lagged value of Gini index, a contemporaneous value of log of number of protests and country and year fixed effects. I add 5 lags of the protest variable in the next column[6]. In column (3) I include the Polity variable with its lags and in the last column — other explanatory variables such as school enrollment, GDP, investment and more (see Table 2.2). I find that when most right-hand side variables are included in the estimation, protesting lowers the Gini coefficient by 0.009 points at 5% statistical significance. However, remaining lags do not show any effect from protests in the previous years. Most of the coefficients are positive, indicating an increase in inequality following an increase

[5]Results from 3SLS do no differ from my baseline estimates presented in this paper and are available upon request.

[6]Lag choice is based on the estimates in Table 2.9, which indicate that 4 or 5 lags of the protest variable would be the most appropriate.

in protesting, but this is not statistically significant. This suggests that the effect of protesting on inequality measured by the Gini index is permanent.

I also include F-tests to see whether all the coefficients for the protest variable in a given regression are jointly equal to 0. In columns (3) and (4) I reject the null hypothesis and conclude that at least one of the coefficients is non-zero, which supports the estimates discussed above.

A different proxy for protest activity is used in Table 2.5 — a log of the number of newspaper mentions. The results here are very similar to those from Table 2.4, but predictably the point estimates are slightly lower to account for the difference in the protest variable. I find that a 1% increase in the number of media mentions results in a 0.0086 point drop in the Gini index at a 1% significance level.

In Table 2.6 I test whether separate lags of the protest variable could explain the fluctuations in inequality better than a block of lags. I find that only the contemporaneous protests have an effect on inequality, while none of the lagged values do.

Another way to check for long-term effects is to look at averages over time. I estimate 3-year averages in Table 2.7 and find that none of the coefficient are statistically significant but appear to show that protesting increases inequality.

2.4.2 Binary Estimates

The last proxy for protesting intensity that I consider is a binary measure constructed from the number of media mentions. I choose a range of varying threshold levels based on the number of mentions and create a dummy variable which takes on a value of 1 if at least a certain number of mentions has been reached during the year and 0 otherwise. In Table 2.8 the thresholds are at 0, 20, 50, 100, 250 and 500 mentions. I find that only in the case of larger protests there is an effect on inequality. Namely, if a protest of at least 250 mentions occurs, the Gini index declines by 1.6 points out of the possible 100. An even larger protest of 500 mentions at least would decrease the Gini by 2.1 points.

Again as with the previous tables the impact on inequality follows immediately after the protest occurs. There are some statistically significant coefficients for the remaining 5 lags of the binary variable, but none are consistent across different thresholds. Therefore, I cannot say with certainty whether there is a delayed effect on inequality from protesting.

2.4.3 Reverse Causality

Lastly, I consider the possible issue of reverse causality, meaning that just as protesting can affect inequality, inequality can impact protesting. I estimate Equation (2) using OLS in Table 2.10. While there are two significant coefficients in columns (2) and (4), F-tests performed indicate that jointly all Gini coefficients are zero in all four columns as I fail to reject the null hypothesis.

In addition, I estimate Equations (1) and (2) using 3-stage Least Squares estimation (3SLS), which allows me to determine the relationships between protesting and inequality simultaneously thereby accounting for the possibility of reverse causality.

I find similar results as those presented in Tables 2.5 and 2.10.[7] I conclude that there is no link from inequality to protesting in the panel data set used in this paper.

2.5 Conclusion

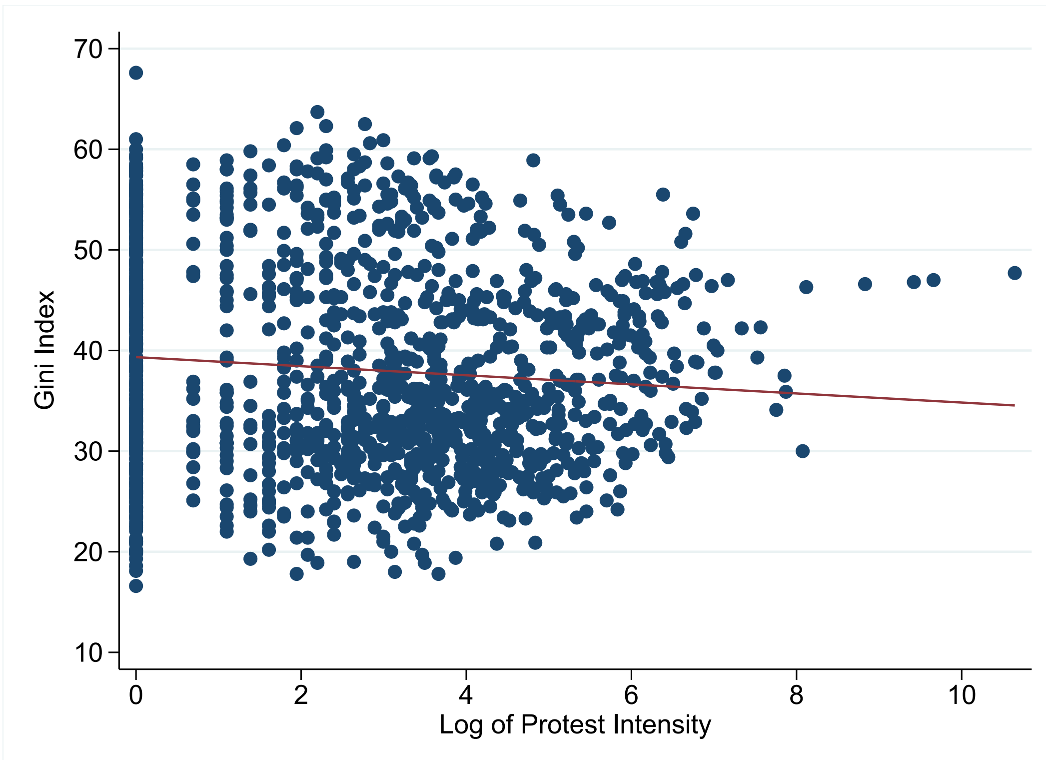
In this paper I study the link between economic inequality and protesting on a panel of 74 countries during 1979–2012. I find that protesting does not have a consistent impact on inequality. The effect is only statistically and economically significant when large enough protests are considered (at least 250 newspaper mentions).

During an average year a 1% increase in protests decreases Gini index by 0.009–0.01 points. When really large protests are considered, this effect causes up to 2.1 point change in Gini index. This means that protesting lowers inequality especially in the cases of more significant protest events.

However, the change in inequality appears to come immediately after the protest occurs, which is contrary to my initial assumption that post-protest reforms are the reason inequality might be affected. It appears that a different channel is the culprit, finding which would be a good avenue for future research.

[7] Not in this paper.

Figure 2.1: Inequality and Protests, 1979-2012



Notes: Gini Index is on the vertical axis and log transformation of the number of newspaper mentions is displayed on the horizontal axis. The fitted line suggest a slight decline of inequality as the protest activity picks up..

Table 2.1: List of Countries

Developed Countries	Developing Countries	Least Developed Countries
Australia	Argentina	Bangladesh
Austria	Armenia	Uganda
Belgium	Belarus	
Canada	Bolivia	
Chile	Brazil	
Czech Republic	Bulgaria	
Denmark	China	
Estonia	Colombia	
Finland	Costa Rica	
France	Dominican Republic	
Germany	Ecuador	
Greece	El Salvador	
Hungary	Georgia	
Ireland	Guatemala	
Italy	Honduras	
Japan	India	
Korea, Rep.	Indonesia	
Latvia	Iran, Islamic Rep.	
Lithuania	Jamaica	
Luxembourg	Jordan	
Netherlands	Kazakhstan	
New Zealand	Kyrgyz Republic	
Norway	Macedonia, FYR	
Poland	Malaysia	
Portugal	Mexico	
Singapore	Moldova	
Slovak Republic	Nigeria	
Slovenia	Pakistan	
Spain	Panama	
Sweden	Paraguay	
Taiwan, China	Peru	
United Kingdom	Russian Federation	
United States	Serbia	
Uruguay	Sri Lanka	
	Thailand	
	Turkey	
	Ukraine	
	Venezuela, RB	

Table 2.2: Description of Variables

Variables	Description	Source
Gini	Inequality measure	WDI
GDP per capita	Output-side real GDP per capita at chained PPPs (in mil. USD 2005)	WDI
Protest:		
- count	Number of protests occuring in country i in yeat t	GDELT
- number of mentions	Number of newspaper mentions of protests occuring in country i in year t	GDELT
Polity	Variable indicates if a country is democratic or autocratic,range -10,10	Polity IV
Life expectancy	Life expectancy	WDI
School enrollment	Primary and secondary enrollment rates, separated in two variables	WDI
Gross capital formation	Gross capital formation, % of GDP	WDI
Trade share	Share of trade in GDP	WDI
War dummy	Indicator that shows if there was a war in country i in year t	PRIO
Population	Size of total population	WDI
Inflation	Inflation, consumer prices (annual %)	WDI
Unemployment	ILO estimate of Unemployment (% of total labor force)	WDI
FDI	Foreign direct investment, net inflows (% of GDP)	WDI

Notes: WDI - World Bank Development Indicators, GDELT - Global Database of Events, Language and Tone, PRIO - UCDP/PRIO Armed Conflict Dataset, Version 4-2015. Gini index is a standardised data series from Luxembourg Income Study (LIS), Socio-Economic Database for Latin America (SEDLAC), Survey of Living Conditions (SILC) by Eurostat, World Income Distribution, World Bank Europe and Central Asia dataset, World Institute for Development Research (WIDER), World Bank Povcal, and individual long-term inequality studies.

Table 2.3: Descriptive Statistics

Variables	(1) N	(2) Mean	(3) St. Dev.	(4) Min	(5) Max
Gini index	1,306	38.1	10.2	16.6	67.6
GDP per capita	1,210	12551	14921	192	86129
Polity IV	1,233	5.9	5.6	-10	10
Life expectancy	1,277	71.8	5.7	45.8	82.5
Primary school enrollment	1,149	102.9	8.9	48.5	134.9
Secondary school enrollment	1,063	83.6	23.1	10.0	154.8
Gross capital formation	1,217	23.8	6.3	0.3	59.7
Trade share	1,216	72.1	48.3	9.7	439.6
War dummy	1,218	0.54	0.65	0	2
Log Population	1,264	16.6	1.5	12.8	20.9
Inflation	1,117	29.3	171.5	-1.4	3373.4
Unemployment	1,021	8.4	5.3	0.6	37.3
FDI	1,170	3.2	5.8	-57.4	88.1
Protest Variables:					
Count	1,306	28.3	180.1	0	5247
Number of Mentions	1,306	146.7	1316	0	41918
Number of Sources	1,306	36.2	310	0	9969

Table 2.4: Number of Protests: Baseline Specification

Dependent Variable: Gini Index

	(1)	(2)	(3)	(4)
Lag of Gini	0.549	0.547	0.544	0.518
	(6.86)***	(6.95)***	(7.32)***	(6.51)***
Number of Protests (log)	-0.3208	-0.4302	-0.9644	-0.9400
	(1.30)	(1.55)	(3.12)***	(2.56)**
Number of Protests Lags:				
First Lag		0.3939	0.6519	0.6401
		(1.49)	(1.49)	(1.35)
Second Lag		-0.0074	-0.0126	0.0516
		(0.02)	(0.03)	(0.12)
Third Lag		0.0648	0.1336	0.1015
		(0.24)	(0.40)	(0.30)
Forth Lag		0.1589	0.3022	0.2080
		(0.45)	(0.96)	(0.64)
Fifth Lag		0.2905	0.3603	0.3239
		(1.36)	(1.53)	(1.48)
Polity and its lags	No	No	Yes	Yes
Control Variables	No	No	No	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
F-test (F-statistic)		0.72	3.26	2.31
F-test (p-value)		0.63	0.01	0.04
Adjusted R-squared	0.40	0.40	0.41	0.40
Observations	362	362	362	362

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Standard Explanatory Variables: life expectancy, school enrollment (primary and secondary), gross capital formation, trade share, war dummy, population. Mean of number of protests - 28.3, Median - 1. Lags used: 5 lags of Polity and Interaction with Polity. F-test shows the t-statistics for a joint test that the coefficients of protest variable and its lags are 0.

Table 2.5: Intensity of Protests: Baseline Specification

Dependent Variable: Gini Index

	(1)	(2)	(3)	(4)
Lag of Gini	0.549	0.551	0.548	0.518
	(6.81)***	(6.91)***	(7.64)***	(6.76)***
Intensity of Protests (log)	-0.1742	-0.2100	-0.8633	-0.8583
	(0.87)	(0.88)	(4.02)***	(3.19)***
Intensity of Protests Lags:				
First Lag		0.1360	0.5854	0.5935
		(0.53)	(1.41)	(1.33)
Second Lag		0.0091	-0.0302	0.0010
		(0.04)	(0.09)	(0.00)
Third Lag		0.0211	0.1032	0.0607
		(0.10)	(0.38)	(0.22)
Fourth Lag		0.0211	0.1032	0.0607
		(0.10)	(0.38)	(0.22)
Fifth Lag		0.0035	0.0872	0.0333
		(0.02)	(0.42)	(0.18)
Polity and its lags	No	No	Yes	Yes
Control Variables	No	No	No	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
F-test (F-statistic)		0.15	3.01	2.60
F-test (p-value)		0.98	0.01	0.02
Adjusted R-squared	0.39	0.39	0.41	0.41
Observations	362	362	362	362

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Standard Explanatory Variables: life expectancy, school enrollment (primary and secondary), gross capital formation, trade share, war dummy, population. Mean of number of protests - 146, Median - 5. Lags used: 5 lags of Polity and Interaction with Polity. F-test shows the t-statistics for a joint test that the coefficients of protest variable and its lags are 0.

Table 2.6: Inequality: Intensity of Protests, Selected Lags

Dependent Variable: Gini Index

	(1)	(1)	(1)	(1)	(1)	(1)
Lag of Gini	0.522	0.518	0.517	0.521	0.518	0.521
	(6.33)***	(6.47)***	(6.29)***	(6.16)***	(5.95)***	(6.14)***
Intensity of Protests (log)	-0.4881					
	(2.01)**					
Intensity of Protests Lags:						
First Lag		0.3461				
		(0.92)				
Second Lag			0.2411			
			(0.78)			
Third Lag				0.1509		
				(0.37)		
Fourth Lag					0.2955	
					(0.88)	
Fifth Lag						-0.0249
						(0.11)
Polity and its lags	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.40	0.39	0.39	0.39	0.40	0.39
Observations	362	362	362	362	362	362

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Standard Control Variables: life expectancy, school enrollment (primary and secondary), investment share, trade share, war dummy, population. Mean of number of mentions - 146, Median - 5. Lags used: 5 lags of Polity and Interaction with Polity.

Table 2.7: 3–Year Average Effects

Dependent Variable: 3-year Average Gini Index

	Number of Protests			Intensity of Protests		
	(1)	(2)	(3)	(4)	(5)	(6)
Lag of Gini	0.186	0.191	0.185	0.186	0.190	0.184
	(2.48)**	(2.62)**	(2.51)**	(2.49)**	(2.64)**	(2.50)**
Number of Protests (log)	0.2908	0.3199	0.2351			
	(0.72)	(0.77)	(0.53)			
Lag of Number of Protests			0.3771			
			(0.62)			
Intensity of Protests (log)				0.2106	0.2313	0.2478
				(0.68)	(0.75)	(0.69)
Lag of Intensity of Protests						0.1068
						(0.25)
Adjusted R-squared	0.07	0.09	0.10	0.07	0.09	0.09
Observations	441	441	441	441	441	441
Polity and its lags	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	No	Yes	Yes	No	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Standard Control Variables: life expectancy, school enrollment (primary and secondary), investment share, trade share, war dummy, population.

Table 2.8: Intensity of Protests: Binary Specification

Dependent Variable: Gini Index

Number of Mentions	(1) >0	(2) >20	(3) >50	(4) >100	(5) >250	(6) >500
Binary (cutoff as shown)	0.413	0.080	-0.888	-0.453	-1.558	-2.050
	(0.29)	(0.10)	(1.12)	(0.64)	(3.91)***	(3.38)***
Lags:						
First Lag	0.745	0.678	0.582	-0.305	0.347	0.574
	(0.84)	(1.12)	(1.00)	(0.63)	(0.66)	(1.02)
Second Lag	1.645	0.146	-0.077	0.569	1.965	-0.402
	(1.41)	(0.18)	(0.14)	(0.96)	(2.31)**	(0.52)
Third Lag	1.150	0.099	0.595	-0.351	0.295	1.827
	(0.84)	(0.18)	(0.74)	(0.43)	(0.28)	(2.11)**
Fourth Lag	0.290	-0.489	-0.079	1.515	0.012	4.979
	(0.29)	(0.84)	(0.11)	(2.16)**	(0.02)	(3.06)***
Fifth Lag	0.151	-0.330	-0.118	0.047	1.499	-3.294
	(0.18)	(0.58)	(0.22)	(0.08)	(2.86)***	(2.40)**
Polity and its Lags	Yes	Yes	Yes	Yes	Yes	Yes
Explanatory Variables	Yes	Yes	Yes	Yes	Yes	Yes
Lags of GDP Growth	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
F-test (F-statistics)	1.23	0.48	0.99	1.37	4.75	12.05
F-test (p-value)	0.30	0.81	0.43	0.24	0.00	0.00
Adjusted R-squared	0.41	0.41	0.43	0.42	0.42	0.44
Observations	610	610	610	610	610	610

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Standard Explanatory Variables: life expectancy, school enrollment (primary and secondary), gross capital formation, trade share, war dummy, population, GDP per capita. Lags used: 5 lags of Polity and Interaction with Polity. Binary variable is based on the number of mentions and takes on the value of 1 if the number of mentions is as specified in the column headers (e.g. in column 2 number of mentions is above 20) and 0 otherwise. F-test shows the t-statistics for a joint test that the coefficients of protest variable and its lags are 0.

Table 2.9: Intensity of Protests: Lag Selection

	Dependent Variable: Gini Index								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lag of Gini	0.451	0.452	0.446	0.444	0.433	0.437	0.438	0.435	0.426
	(7.26)***	(7.19)***	(7.02)***	(6.81)***	(6.53)***	(6.64)***	(6.79)***	(7.26)***	(7.21)***
Intensity of Protests (log)	0.0023	-0.3611	-0.4613	-0.4623	-0.4647	-0.4682	-0.4553	-0.3522	-0.3591
	(0.01)	(1.11)	(1.64)	(1.64)	(1.67)*	(1.68)*	(1.56)	(1.28)	(1.34)
Intensity of Protests Lags:									
First Lag		0.4523	0.2759	0.2585	0.2771	0.2790	0.3354	0.3641	0.4103
		(1.52)	(0.79)	(0.75)	(0.84)	(0.84)	(0.94)	(1.06)	(1.13)
Second Lag			0.4112	0.3291	0.2885	0.2833	0.2824	0.1556	0.1684
			(1.37)	(0.94)	(0.79)	(0.79)	(0.80)	(0.44)	(0.47)
Third Lag				0.1102	0.0133	0.0464	0.0652	0.1293	0.0722
				(0.31)	(0.04)	(0.16)	(0.23)	(0.44)	(0.24)
Fourth Lag					0.1289	0.1903	0.2557	0.2943	0.2918
					(0.66)	(1.05)	(1.44)	(1.73)*	(1.55)
Fifth Lag						-0.1365	-0.1219	-0.0464	0.0048
						(0.66)	(0.68)	(0.28)	(0.03)
Sixth Lag							-0.3317	-0.1870	-0.0945
							(1.13)	(0.63)	(0.33)
Seventh Lag								-0.4439	-0.3752
								(1.65)	(1.49)
Eighth Lag									-0.2549
									(1.37)
Adjusted R-squared	0.34	0.35	0.36	0.36	0.37	0.36	0.37	0.38	0.38
Observations	563	563	563	563	563	563	563	563	563
F-test (F-statistic)		1.16	2.70	2.02	1.85	2.13	2.99	3.23	3.00
F-test (p-value)		0.32	0.05	0.10	0.11	0.06	0.01	0.00	0.00

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 2.10: Impact of Inequality on Protesting Activity

Dependent variable: Log of Intensity of Protests				
	(1)	(2)	(3)	(4)
First Lag of Intensity of Protests	0.0986	0.1029	0.3953	0.3395
	(1.32)	(1.40)	(5.94)***	(4.23)***
Gini Index	-0.022	-0.019	-0.018	-0.029
	(1.05)	(0.73)	(1.37)	(2.12)**
Gini Index Lags:				
First Lag		0.0205	0.0246	0.0238
		(1.07)	(1.53)	(1.63)
Second Lag		0.0036	-0.0186	-0.0151
		(0.13)	(0.85)	(0.68)
Third Lag		-0.0549	-0.0201	-0.0188
		(2.25)**	(1.04)	(0.97)
Fourth Lag		-0.0022	0.0052	-0.0071
		(0.10)	(0.28)	(0.33)
Fifth Lag		0.0294	0.0072	0.0124
		(1.09)	(0.52)	(0.91)
Polity and its lags	No	No	Yes	Yes
Control Variables	No	No	No	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
F-test (F-statistic)		1.16	1.31	1.58
F-test (p-value)		0.34	0.27	0.17
Adjusted R-squared	0.40	0.41	0.71	0.72
Observations	368	368	368	368

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Standard Control Variables: life expectancy, school enrollment (primary and secondary), gross capital formation, trade share, war dummy, population. F-test shows the t-statistics for a joint test that the coefficients of Gini index and its lags are 0.

Chapter 3

The Impact of WTO Accession on the Composition of Trade

3.1 Introduction

January 2015 marked the 20th anniversary of the World Trade Organization (WTO). It boasts 162 members as of November 2015, which is a majority of existing countries. Most of non-members are currently classified as observers, which means that the proceedings to join the WTO have already begun but have not concluded.

It appears that the WTO offers benefits that entice almost all countries (with an exception of a few holdouts). According to the mission statement of the organization, among its many goals the WTO negotiates "the reduction or elimination of obstacles to trade," ensures transparency in trade agreements and settles trade-related disputes between members. In other words, the WTO facilitates trade liberalization. Trade liberalization in its turn leads to an increase in the volume of trade (Subramanian and Wei, 2007) by increasing the size of current trade (intensive margin) and creating additional trading channels where non existed before (extensive margin).

Combination of intensive and extensive margins can change not only the volume but also the composition of trade, i.e. the proportions in which certain goods are traded. Why is a change in composition of trade significant and why do I devote this paper to the impact of WTO accession on trade composition?

Firstly, after accession countries might end up with strategically important sectors being crowded out due to more competitive goods from abroad (this does not generally happen as countries are able to protect such sectors). More importantly, when a country joins the WTO it expands trade in sectors with comparative advantage thereby increasing their share in total trade. Consequently, other sector contribute to a smaller share of trade (not necessarily a smaller volume). For example, in 2001 country X exported 2000 tons of coal and 5000 tons of apples, and in 2002 (after joining the WTO) it exported 2000 tons of coal and 10000 tons of apples. Country X grows apples cheaply and is able to sell them in other WTO member-countries, while coal goes to the pre-existing importers. In 2001 share of coal industry in imports was 28% and in 2002 only 16%. Even though the volume of coal import has not changed, its importance has.

Acting according to ones comparative advantage follows the standard Ricardian model of trade. Exercising comparative advantage in trade is not generally perceived as a negative thing and usually it is not. Being able to expand production of commodities particular country is really good at producing benefits this country as well as those it trades with due to lower prices. Everybody wins. It does, however, matter how developed a country is and in some cases leaning too heavily on sectors with comparative advantage can be detrimental. Imbs and Wacziarg (2003) find that as countries with low income do not diversify but rather concentrate in a few labor-intensive sectors. As they get more developed these countries start branching out into multiple additional sectors and become diversified. Finally, high income countries get concentrated again, but in capital-intensive sectors instead.

So it does not matter as much whether joining the WTO changes the composition of trade of the new member but rather how the composition changes relative to member's level of development. In this paper I explore the impact of acceding to the WTO on the composition of both exports and imports based on countries' income levels and find that the shifts in traded sector shares is different depending on whether the country is low-, middle- or high-income. However, these shifts cannot be explained only by the economic well-being of the country. Another reason for the disparity of WTO membership effect stems from WTO rules and procedures that govern the process of joining the organization.

It is natural that countries wish to protect certain (usually strategically important) domestic industries from dying out (for example, agriculture) through tariffs and quotas on foreign goods that might be cheaper and/or of a higher quality than those produced domestically. In order to become a WTO member such tariffs and quotas have to be eliminated or at least lowered to an acceptable level, which is stipulated by the WTO and may vary from one country to the other. At least in theory.

In practice the implementation of these rules depends on other factors and is different across countries. For instance, countries that were members of General Agreement on Tariffs and Trade (GATT, the WTO predecessor) acceded to the new organization in 1995 in an almost automatic fashion. GATT was not quite as rigorous in furthering trade liberalization and as a result, former GATT members did not necessarily have to fulfill the same stringent requirements as the new members, especially if they joined GATT early. Notably, all the developed countries have been members of GATT before joining the WTO.

During the existence of GATT there have been 7 negotiation rounds that have all addressed lowering of trade barriers in one way or the other. So far the WTO has had 2 major negotiation rounds with a similar agenda. The newest changes to the WTO agreement were stipulated in the Bali package in 2013 (part of Doha Development Round from 2001) and they focused on lowering import tariffs and agricultural subsidies in order to make trade fairer for developing countries. The WTO itself accepts the reality that the developing countries are at a disadvantage.

Still researchers find that the rules of the WTO are skewed toward developed nations. Drabek and Woo (2010) explain that dispute resolution in the WTO favors developed countries. In another paper Drabek and Bacchetta (2010) explore the impact of membership on transition economies and find that the timeline for implementation of important reforms needed for accession to the WTO is too short, which lead the countries to struggle economically.

My findings seem to support the assumption that the differences in impact on composition from trade that stem both from economic development levels and differential treatment by the WTO. I show that middle-income countries utilize access to new markets granted by the membership in the most efficient way and follow the path predicted by the Ricardian model, but low-income countries appear to be stilted by the WTO rules and do not seem to be affected by the membership (I find no significant changes in the volume of trade for many sectors as well as its composition). However, part of this effect can be due to the presence of China in the sample which I test for as a robustness check. I find that indeed when trade with China is excluded from the sample, least developed countries seem to benefit more from joining the WTO than their developing or developed counterparts in terms of the increases in the volume of trade. I find similar changes in the composition of trade after acceding to the WTO for countries with different income levels. Namely, most of the 16 sectors increase their share by several percent with the exception of imports of Footwear and Machinery and exports of Textiles, Footwear and Machinery. It appears that Footwear and Machinery sectors become less traded relative to other sectors across the board for the WTO member countries.

These conclusions come from a two-step procedure that I use to arrive at the final numbers for changes in the composition of trade. First I estimate the impact of membership on the volume of trade using the standard gravity equation based off of the specifications in Anderson and van Wincoop (2003) and Subramanian and Wei (2007). I control for time trend and other variables with potential impact on the volume of trade, so it is reasonable to conclude that I arrive at the change in the volume of trade caused by the accession to the WTO. Then I take estimates from the gravity equations and calculate a counterfactual that shows me what trade would have been in the world without the WTO. By computing the difference between actual and counterfactual trade flows I arrive at the change in the composition of trade brought on by the WTO membership.

The changes in the composition of trade are computed for 16 major sectors which encompass all commodity trade between countries. I have a panel of all available world countries for a period of 14 years (1993-2006). The dataset is limited in time due to data availability as well as the bias that would be introduced by including the period of the Great Recession. I will expand on these details as I go on.

The work is divided into the following parts. The first section presents the literature review. It is followed by the theoretical and econometric specifications, data description, the discussion of the empirical results and possible extensions, and the concluding remarks.

3.2 Literature Background

3.2.1 WTO Membership

There is a considerable body of literature on the effects of accession to the WTO and the aspects of organizations policies. However, there is much debate over what is the actual impact of accession. Some researchers find no impact, some show that WTO increases the volume of trade and some find reduction in the volume of trade in certain instances.

According to the mission statement of the WTO its purpose is to stabilize trade and increase it through the extensive margin (the introduction of new export goods) and intensive margin(increase of trade in previously exported goods). Rose (2005) looks at trade flows after accession to the GATT/WTO and finds little evidence that it promotes stability in flows, as maintained in the organizations mission statement. The author uses a panel of 175 countries over the period of 50 years (1950-1999) and estimates a standard gravity model where the dependent variable is the coefficient of variation of the log of real exports between two countries. Across a series of specifications he finds that none show any effect of the WTO or the GATT on reducing the volatility of trade. Rose (2004) finds that accession does not have any effect on the level of trade (intensive margin). However, the author notes that this result applies definitively only to GATT. He does not have a long enough time series to estimate the impact of the WTO on the intensive margin, and concludes that it is very likely that the impact would be positive. The reason is that under GATT only trade in goods was agreed upon. Agreements under WTO are more ambitious and therefore are likely to have larger impact. Even though he does not find any impact in his paper as his time series ends in 1999, Subramanian and Wei (2007), who have a longer panel, do find a positive impact of the WTO on the intensive margin.

Subramanian and Wei (2007) claim that the establishment of the WTO increased world trade by 120%. There are two main differences between Subramanian and Wei (2007) and Rose (2004). The first is that the former include the multilateral resistance variables pioneered by Anderson and van Wincoop (2003) in their specifications. Second, the logarithm of bilateral imports is used as a dependent variable rather than total trade flow (which is justified by theoretical foundations of the gravity model). These differences create the divergence in results between the studies. However, Subramanian and Wei (2007) admit that the effect of membership differs for countries with different levels of industrialization (developing and developed countries) due to the different degrees of liberalization across sectors (e.g. agriculture is generally less liberalized than manufacturing). They estimate these differential effects through a set of sector-specific gravity equations, which serves as a basis for my study.

Subramanian and Wei (2007) do not distinguish between intensive and extensive margins, but Dutt, Mihov and Van Zandt (2011) consider the two separately and obtain conflicting results. The authors find that there is a negative impact on the intensive margin and a 25% increase in the extensive margin. Felbermayr and Kohler (2007) find similar results at the extensive margin. Dutt et al (2011) estimate two gravity equations one for intensive and one for extensive margins. The net effect still comes out positive. The authors differentiate between fixed and variable trade costs. The results suggest that the WTO is effective at reducing fixed costs but not variable ones. As fixed costs fall, trade appears where it did not occur before, but there is no incentive to increase the volume of existing trade as the variable costs have not changed. For a new WTO member this would mean that with lower fixed costs (keeping variable ones constant) it might be worthwhile to export new goods, rather than increase the volume of goods exported before the accession. New WTO members could shy away from their previous trading partners in favor of member-countries as the costs only decrease when trading with other WTO members. From Dutt et al (2011) it is unclear whether countries trade in different sectors, or just move their trade from non-WTO to WTO members.

3.2.2 Estimation Techniques

The model used in this study is a variation of the gravity model, which was first introduced by Tinbergen (1962). The major challenge is to discern between the methodological approaches to the estimation of the gravity equation in order to be able to evaluate the impact of the accession to the WTO on the commodity composition of trade. The specific form of the model to be used in this research is derived from the paper presented by Anderson and van Wincoop (2003):

$$x_{ij} = \frac{y_i y_j}{y^w} \left(\frac{t_{ij}}{P_i P_j} \right)^{1-\sigma} \tag{3.1}$$

where x_{ij} is exports from area i to area j, y-variables represent GDP of respective countries, t_{ij} is the trade cost and P-variables are the price indexes for both countries. The main input of their study into the theoretical base is that it derives the gravity model according to the theory of international trade, which shows that the previous empirical specifications of the gravity equation are not correct as they omitted the two price index terms, referred to as the multilateral trade resistance variables. These variables are positively related to the trade barriers of one country relative to all other countries. To support their claim about the corrected gravity model, the authors present a range of successful sensitivity analysis reports, which are based on the changes in such variables as distance and income.

Once the theoretical foundation of the gravity model was resolved, the debate arose around the methods of empirical estimation. Most authors before (and including) Anderson and van Wincoop (2003) made use of the country fixed effects estimations. However, Baier and Bergstrand (2007) showed that due to the potential endogeneity in the model such an approach yields both biased and inconsistent estimates. The endogeneity is believed to stem from the fact that the dummy variables representing free trade agreements (in our case the membership in the WTO) are endogenous to the model, which in turn can come from three different sources, namely simultaneity, measurement error and omitted variable biases. To correct for these issues the authors estimate the so-called average treatment effects. They come to the conclusion that the preferential estimation technique is to use the first-differenced panel data with both country and time fixed effects.

There is yet another way to approach the issue of estimation proposed by Silva Santos and Tenreyro (2006). The authors build a case in favor of Poisson regression as a means to alleviate the heteroskedasticity that is present in the trade data. Due to Jensen's inequality under heteroskedasticity the elasticities calculated from the log-linear gravity equation are biased. An additional issue of trade data is that log-linearization leads to truncation of the sample due to elimination of zero trade flows. One way to solve these issues is to estimate the gravity equation using the Poisson pseudo maximum likelihood (PPML) methodology rather than OLS. The authors compare the estimates of the gravity equation from OLS, NLS, Tobit and PPML. The latter appears to yield consistent estimates regardless of the pattern of heteroskedasticity and alleviate the problem of zero trade flows. Using OLS to estimate the gravity equation leads to the loss of information on zero trade flows. This would not permit me to estimate the extensive margin of trade, therefore, use of PPML is logical.

3.3 Methodology

As it was mentioned before, the theoretical foundation for this research is the gravity model. Two sets of equations are specified for every sector: one for imports and one for exports. The countries considered for the estimation include both WTO members and non-members and various types of economies ranging from G-8 group to 3rd world countries. In order to control for the effect of membership on different groups of countries depending on their time of accession and economic status, various dummy variables are introduced (see Section 3.5 for details), similar to Subramanian and Wei (2007).

While the empirical form of the gravity equation has significantly evolved since its introduction by Tinbergen (1962), the version used here is a mix of the augmented gravity equation presented by Anderson and van Wincoop (2003) and its sector-specific derivation by Subramanian and Wei (2007):

$$LnImp_{ijt} = \alpha_0 + \alpha_1 W_{ijt} + \alpha_2 MRT_{ijt} + \alpha_3 WTO\_Membership_{it} + \alpha_4 Time_t + \epsilon_{ijt}; \quad (3.2)$$

$$LnExp_{ijt} = \beta_0 + \beta_1 W_{ijt} + \beta_2 MRT_{ijt} + \beta_3 WTO\_Membership_{it} + \beta_4 Time_t + \upsilon_{ijt}; \quad (3.3)$$

where the dependent variable is the log of volume of exports (imports) of a specific sector of country i to country j, W_{ijt} stands for the vector of standard gravity model variables such as log of GDP of countries i and j, log of distance between the countries, dummy variable for the existence of common border if any etc., MRT_{ijt} (multilateral resistance term) is a vector of similar variables that capture the unobservable trade costs. Based on the specification from Baier and Bergstrand (2009) I calculate MRT terms in the following fashion:

$$MRT_{ijt} = \left(\sum_{k=1}^{N} \theta_k X_{ik}\right) + \left(\sum_{m=1}^{N} \theta_m X_{mj}\right) + \left(\sum_{k=1}^{N}\sum_{m=1}^{N} \theta_m \theta_k X_{km}\right) \tag{3.4}$$

where θ_k and θ_m stand for the GDP shares of reporting and partner countries respectively in the total world GDP, and X_{km} could be the log of distance between two countries, RTA (regional trade agreements), common currency, common official language etc. For example, MRT for log of distance shows the trend in the log of distance that is correlated with the unobserved trade costs.$WTO\_Membership_{it}$ is a dummy variable that takes a value of 1 when country of origin is a WTO member.

Lastly, Time is a vector of dummy variables for years starting with 1994 to 2006 (1993 is a base year). These dummies were not considered in the previous works as most of the authors used crosssection data, which was averaged for a specific time periods (e.g. 25-year periods in Rose (2004) and 5-year periods in Subramanian and Wei (2007)). However, I find that variation in trade flows due to various shocks can have a significant impact on the estimation. These variables are intended to capture the general time trend so that the dummy variables concerning the WTO specifically would only show the impact of the accession and membership on the volatility of trade flows.

After the estimation of the coefficients for WTO membership dummy variable, the received values are transformed from the volume of trade into the change in its composition by calculating the following:

$$Composition_{ist} = \frac{Trade\_with\_WTO_{is}}{Total\_Trade\_with\_WTO_{i}} - \frac{Trade\_without\_WTO_{is}}{Total\_Trade\_without\_WTO_{i}} \quad (3.5)$$

where ist stands for a sector s in a country i at time t. The difference is taken between the share of sector s in the total trade (exports or imports) in the world with the WTO (utilizing the actual data) and the share of the same sector in total trade (exports or imports) in the world without the WTO, which is calculated using counterfactuals from gravity equation estimates of the impact of WTO membership on countrys trade by setting the WTO dummy variable to 0. The goal of this research is to determine the potential change in the composition of trade flows in connection with the accession and membership.

Concerning the econometric approach, again referring to Baier and Bergstrand (2007), given that the dataset is a panel, the superior approach seems to be to use fixed effects model (FEM), which includes country and time fixed effects. On the other hand, FEM may not yield convincing results due to the fact that it ignores the presence of time-invariant variables (for example, distance).

As mentioned in Silva Santos and Tenreyro (2006), it is likely that log-linearized models, such as the gravity equation, suffer from the heteroskedasticity when estimated with OLS. Therefore, Poisson estimation technique (PPML) with country-pair and time fixed effects is applied as suggested by the authors. In order to check the results for robustness OLS, FEM and PPML methods are employed.

3.4 Data

The data for the countries of the world used in the estimation come from UN COMTRADE and CEPII databases.

The dependent variable, which is a share of a particular sectors export (import) in the combined export (import) for a given country, is obtained from disaggregated data from UN COMTRADE. The coding used is HS 2-digit 1988/92 and various sections are compiled together into 16 sectors. The descriptive statistics are presented in Tables 2, 3 and 4 in the Appendix, where Tables 2 and 3 focus on the dependent variables and Table 3 on the explanatory ones. The means of trade flows range from 10.5 to 13.5 (note, the dependent variables are presented in logs) and the standard deviations do not differ significantly.

CEPII database provides the standard gravity model variables including the distance between countries, GDP, population, contingency, etc. The data for the WTO dummy variable is again taken from CEPII dataset. The rest of the dummy variables are constructed using the information on the accession dates from the WTO web site and the classification of the economies according to the World Bank nomenclature.

CEPII database terminates in 2006. I am, therefore, limited to a 1993-2006 period. However, one of the extensions I have in mind is to prolong CEPII dataset to include up to 2013 as that will allow me to look at a longer time span as well as observe more countries join the WTO.

3.5 Results

As mentioned in Section 3.3 there are seven different specifications of the model which are performed for every sector for both imports and exports. However, apart from the difference in dummy variables, which test different hypotheses, the remaining variables are standard for gravity equation and do not change from one estimation to another. Four estimation approaches were considered initially, but random effects model (REM) was rejected by the Hausman test. It is worth noting that both FEM and PPML utilize fixed effects, which omit time invariant variables such as the log of distance between two countries, common language etc. OLS on the other hand takes into account all the variables, but its estimates are biased due to endogeneity.

Based on the theory behind the gravity model and the works of other researchers one should expect the coefficients for logs of GDP of origin and destination countries to be positive (although, a negative sign is also possible, but less likely). Dummy variable for RTA (regional trade agreement) should have positively signed coefficients in all the regressions as signing such agreements simplifies the procedures relating to trade and, therefore, lowers trade costs to some extent. While I do not display these estimates in the Appendix tables, all three are positive across different specifications and sectors, as expected.

3.5.1 Imports

As a whole joining the WTO seems to increase the volume of imports, but when the trade flow is broken down into sectors the effect is not uniform. For instance, joining the WTO appears to increase the imports of minerals by 113%, while only increasing the imports of animals by 13% (see Table 3.6). The results differ even more when I consider economies of various development levels (developed, developing and least developed countries, or otherwise termed as high, middle and low income countries) and timing of accession.

In Table 3.6 I show the estimates for WTO membership without distinguishing between countries on other characteristics. Estimates from OLS indicate that joining the WTO reduced imports in 6 sectors and increased them in the remaining 10. If one compares these estimates to ones from FEM and Poisson regressions they differ throughout by a significant amount. With the latter two approaches joining the WTO positively affects imports in most of the sectors. I expected OLS estimates to be lower than those from FEM and PPML as OLS is prone to downward bias due to endogeneity. Using estimations with fixed effects is one of the proposed solutions for this issue, but not the only one. Li and Wu (2004) propose using a dummy variable that they call Selection variable, which takes care of the endogeneity associated with the willingness (and opportunity) to join the WTO. Using their approach could serve as a possible robustness check.

Comparing FEM and Poisson to each other shows that estimates differ significantly. This supports the results received by Silva and Tenreyro (2006) and it can, therefore, be concluded that there indeed exists heteroskedasticity in the data (otherwise, coefficients would have been similar in two estimations), which is alleviated by Poisson estimation. I will only use coefficients estimated by Poisson PML from this point on.

Subramanian and Wei (2007) found the effect of accession differs depending on the specification, which is why I re-estimate gravity equations using several different formulations. Six additional specifications are considered. They vary by the inclusion of different dummy variables, while the remaining explanatory variables remain unchanged. In Table 3.7 I compare how membership impacts the imports if the country of origin is a member and if both trading partners are members. For 11 out of 16 sectors it appears that once a country joins WTO the boost in imports comes to a larger extent from existing WTO members, which is expected as joining the WTO opens new trade markets and lifts restrictions with respect to WTO member-states for the new members. Joining the WTO does not change existing tariffs and quotas with non-member states, which is why it is surprising that imports of vegetables, minerals, fuels, chemicals and miscellaneous items stemming from non-member countries increase after the reporter country joins the WTO.

In Table 3.8 I look at the impact of membership on developing, least developed countries and countries that joined WTO after 1995. Time of accession is represented by a dummy variable for the countries which have acceded after 1995. This dummy captures the effect of the accession for the most liberalized countries on average. A possible issue here is that the effect of trade liberalization might appear well before accession. For example, China began preparing for the accession 13 years prior to 2001, when it finally became a member (Subramanian and Wei, 2007). This is due to the fact that every new member has more restrictions to comply with as every member has a right to impose restrictions on the prospective members and as the number of members grows so does the number of restrictions. Notably, the developed countries have been members of the GATT/WTO for the longest and, as a result, new members (after 1995) are mostly developing countries.

Column (1) in Table 3.8 shows that compared to other WTO members developing countries import more in 10 sectors when they join WTO. The sectors which benefit the most are the manufacturing ones. However, this might not mean that developing countries increase their imports in these sectors after the accession, but rather that the decrease in the volumes traded is not as significant as for developed countries.

Least developed countries (or LDCs) are considered separately in column (2) of Table 3.8. In most sectors increase in the volume of imports is dramatically lower than in more developed countries. Even though on average developing countries generally take a greater advantage of WTO membership when it comes to imports, membership has a much lower impact on LDCs. Compared to other members of the WTO least developed countries only expand imports of textiles. LDCs might not be importing other goods as the income level of the population would be prohibitively low for people to enjoy these likely more expensive foreign goods.

Lastly, in column (3) of Table 3.8 I present the effects of joining the WTO on those countries that were not original member of GATT and acceded to the WTO after 1995 and were likely forced to liberalize their economies to a larger degree than the existing members. I find that indeed these countries appear to increase the volume of imported goods compared to the original member-states in such sectors as Minerals, Fuels, Chemicals and more (9 sectors altogether).

3.5.2 Exports

I estimate same specifications as above but for exports in Table 3.9. As with imports joining WTO increases the volume of exports for most of the 16 sectors. Notable exception is trade in minerals which decreases by 15% for WTO members; however, the coefficient is not statistically significant.

In Table 3.10 I compare the changes in the volume of exports between a WTO member and the rest of the world to exports between two WTO members. In most sectors increase in volume of trade comes to a large extent from non-WTO member countries which contradicts the notion of preferential treatment between WTO members. In any case joining the WTO should not directly increase trade with non-members, but it is possible through indirect channels. Namely, greater trade openness after accession can lead to improved trade relations as with members so with non-members.

Similarly to imports I look at the different types of countries by economy status and the timing of accession in Table 3.11. Developing countries export more in the majority of sectors compared to their developed counterparts, with the exception of fuels and vegetables. The former is not surprising as I would not expect exports of fuel to depend on WTO membership due to high demand of such resource. The exports of vegetables are only lower by about 2% and is not statistically significant.

When it comes to LDCs the amount exported is larger than the rest of the world only in 7 out of 16 sectors. Out of these only 3 have statistical significance: fuel sector with a 38% increase in volume of exports after accession, mineral sector with

34% and chemicals with 51%. It appears that least developed countries cannot take advantage of the membership to the same extent as other members, apart from several sectors which consist mostly of those supplying raw materials.

Countries that acceded after 1995 export more in 14 sectors than the rest of the world, which can be seen in column (3) of Table 3.11.

It is impossible to draw reliable conclusions based only on the changes in the volume of trade without calculating changes in composition. As of now it is unclear whether, for example, a decrease of 24% in exports of footwear should be a concern or whether it reflects a closure of merely several firms across LDCs for other reasons unrelated to the WTO accession rather than a major crowding out of such firms by foreign competitors. A change of 24% in itself is not straightforward as it is unknown whether the volume of trade in that sector was large or small prior to the inclusion into WTO.

3.5.3 Robustness Check: Exclusion of China

Before I get to the calculation of composition of trade I want to make sure that the estimates described above are reliable.

I was concerned that Chinese data might be driving the results. China has taken great advantage of the membership. Due to the sheer size of its economy, the success of WTO accession for China can potentially be imposing a bias on the results and, instead of showing the global picture, skewing the estimates towards those of China itself. To check I perform the same set of regressions on a dataset without China using exports only.

Table 3.12 compares the fluctuations in the volume of exports between the sample with and the sample without China. For all sectors the estimates in Column (2) (shortened sample) are lower and coefficients for 6 sectors lose statistical significance, i.e. the difference between members and non-members is not as pronounced once China is excluded. Notably, the exports of chemical industry changes from an increase of 16% after the accession to a decline of 18% when China is no longer accounted for. This finding supports the hypothesis that the size of China's economy coupled with their increased involvement in trade has impacted overall trade flows to a great extent.

The impact of membership on different types of economies is also different once China is no longer in the sample (see Table 3.13). Now it appears that developing countries export less than developed ones in 12 sectors (compared to only 2 when the entire sample was considered). On the other hand, LDCs are shown to export more than the rest of the world in 11 sectors rather than just 7, out of which 7 coefficients are statistically significant compared to only 3 in the full sample. The reason in such changes is that China is classified as a developing country, which creates bias not only when this group is considered explicitly, but also when it is included in control group (i.e. the rest of the world).

It might be worthwhile to re-estimate not only the coefficients for exports but also for imports on the smaller sample in order to get more reliable picture of the impact of WTO accession on an average member.

3.5.4 Composition of Trade

After obtaining the coefficients from the Poisson PML estimations for both trade flows I am able to compute the changes in the commodity composition of trade resulting from a membership in WTO of an average member as well as developing and least developed ones.

Using Equation 3.5 I estimate changes in the composition of trade during a year of WTO membership in Table 3.14. In Column 1 I find that on average membership in WTO increases the share of most sectors by several percentage points. These numbers can be interpreted as follows: if before the accession import of Fuels in a given country i amounted to 10% of total volume of imports, after the accession the share of Fuel sector in imports rose to 15.5% as the change in the share of Fuels was found to be 5.5%. Understandably, if one sector receives a larger share of imports, then another sector must have a shrinking share to balance out the change. It is the case here as Footwear and Machinery sectors appear to be declining in importance as imports. It is worth mentioning that the fact that a share of certain sector has declined does not meant that the volume of trade in that sector has gone down. The decline is rather an indicator of sector's importance relative to other industries.

Exports (Table 3.15 Column 1) seem to be more volatile than imports and respond to the WTO membership with more pronounced changes in the composition. In this case sectors that become relatively less important are Footwear, Textiles and Machinery, with Textiles showing the largest change of -33.5%. It is not surprising as Textile business has largely shifted to low income countries with cheap labor over the last decade or so.

A worthwhile extension would be to see how changes in the composition of imports fluctuate depending on a how far removed from the date of accession particular year is. Namely, one would expect more shifts in imported goods by sector in the years immediately following the accession rather than 10 years into the future. Such differences could explain such small changes in the composition as shown in Tables 3.14 and 3.15. On the other hand, if these results hold regardless of the time passed since the accession to the WTO, it would seem that countries are not making use of comparative advantages they might have.

3.6 Conclusion

In this chapter I looked at the impact of joining the World Trade Organization on the composition of trade flows, which could be expected to change when the country gets access to new markets with a preferential treatment.

I find that the accession to the WTO appears to increase the volume of exports and imports as a whole and has varying effect when separate sectors are considered. I also show that least developed countries are generally unable to take full advantage of WTO membership and fare worse compared to other countries in most sectors. The situation changes for the better for the LDCs when I consider a shortened sample without China. However, the improvement is mostly in sectors catering to trade in raw materials. It is worth noting that no distinction between intensive and extensive margin has been made.

Changes in composition of trade are not as pronounced as changes in the volumes traded after the accession. It appears that on average countries do not change the composition of trade significantly to make use of their comparative advantages after they become a member of WTO but rather increase the volume of trade across the board. I find that most of the 16 sectors increase their share in the trade flow (export or import) by several percent with the exception of imports of Footwear and Machinery and exports of Textiles, Footwear and Machinery. Footwear and Machinery sectors become less traded relative to other sectors across the board for the WTO member countries, which could be a general WTO trend relative to non-members.

Table 3.1: List of Countries

Albania***	Ecuador**,***	Malawi**	St. Kitts and Nevis***
Algeria	Egypt, Arab Rep.**	Maldives**	St.Vincent & the Gren.
Andorra*	Estonia*,***	Mali**	Sudan**
Anguilla	Fiji***	Malta*	Suriname
Antigua & Barbuda	Finland*	Mauritania**	Swaziland**
Argentina	France*	Mauritius	Sweden*
Armenia**,***	French Polynesia*	Mexico	Switzerland*
Aruba*	Gabon	Moldova**,***	Syrian Arab Republic**
Australia*	Gambia, The**,***	Mongolia**,***	Tajikistan**
Austria*	Georgia**,***	Montserrat	Tanzania**
Azerbaijan	Germany*	Morocco**	Thailand**
Bahamas, The*	Ghana**	Mozambique**	Togo**
Bahrain*	Greece*	Namibia	Tonga**
Bangladesh**	Greenland	Nepal**,***	Trinidad &Tobago*
Barbados*	Grenada***	Netherlands*	Tunisia**
Belgium*	Guatemala**	New Zealand*	Turkey
Belize**	Guinea**	Nicaragua**	Turkmenistan**
Benin**,***	Guinea-Bissau**	Niger**,***	Tuvalu**
Bhutan**	Guyana**	Nigeria**	Uganda**
Bolivia**	Haiti**,***	Norway*	Ukraine**
Bosnia & Herzegovina	Honduras**	Oman*,***	UAE*,***
Botswana	Hong Kong, China*	Pakistan**	United Kingdom*
Brazil	Hungary*	Panama***	United States*
Brunei*	Iceland*	Papua N.G.**,***	Uruguay
Bulgaria***	India**	Paraguay**	Vanuatu**
Burkina Faso**	Indonesia**	Peru	Venezuela

Burundi**	Iran, Islamic Rep.	Philippines**	Vietnam**
Cambodia***	Ireland*	Poland*	Yemen**
Canada*	Israel*	Portugal*	Zambia**
Cape Verde**	Italy	Qatar*,***	Zimbabwe**
Central African Republic**	Jamaica	Romania	
Chile	Japan*	Russian Federation	
China**,***	Jordan**,***	Rwanda**,***	
Colombia	Kazakhstan	Salvador**	
Comoros**	Kenya**	Samoa**	
Congo, Rep.**,***	Kiribati**	Sao Tome &Principe**	
Costa Rica	Korea, Rep.*	Saudi Arabia*,***	
Cote d'Ivoire**	Kyrgyz Republic**,***	Senegal**	
Croatia*,***	Latvia*,***	Seychelles	
Cuba	Lebanon	Sierra Leone**	
Cyprus*	Lesotho**	Singapore*	
Czech Republic*	Lithuania***	Slovak Republic*	
Denmark*	Luxembourg*	Slovenia*	
Dominica	Macao*	South Africa	
Dominican Republic	Macedonia, FYR***	Spain*	
East Timor	Madagascar**	Sri Lanka**	

Note: * Developed countries, ** LDCs and Lower Income countries, *** Countries that have acceded after 1995.

Table 3.2: Descriptive Statistics: Imports

	(1)	(2)	(3)
Sectors	N	Mean	St. Dev.
Animals	105,077	10.473	5.611
Vegetables	140,614	12.615	3.529
Food Products	71,933	13.585	4.221
Minerals	76,230	12.349	3.487
Fuels	71,933	13.585	4.221
Chemicals	147,660	12.858	3.784
Plastic/Rubber	137,025	12.191	3.765
Hides/Skins	97,373	11.061	3.522
Wood	145,778	11.881	3.806
Textiles	162,804	12.265	3.753
Footwear	97,774	10.921	3.502
Stone/Glass	123,910	11.864	3.654
Metals	145,729	12.617	3.956
Machinery	178,678	12.571	4.097
Transportation	120,999	12.433	3.905
Miscellaneous	162,160	11.855	3.724

Table 3.3: Descriptive Statistics: Exports

	(1)	(2)	(3)
Sectors	N	Mean	St. Dev.
Animals	97,962	12.630	3.191
Vegetables	118,437	12.930	3.209
Food Products	130,643	13.015	3.088
Minerals	69,651	12.090	3.311
Fuels	72,276	13.022	3.827
Chemicals	137,685	13.179	3.392
Plastic/Rubber	126,877	12.578	3.381
Hides/Skins	83,773	11.313	3.335
Wood	134,938	12.127	3.542
Textiles	140,047	12.667	3.469
Footwear	83,211	11.233	3.307
Stone/Glass	114,324	12.151	3.342
Metals	133,631	13.056	3.521
Machinery	151,837	13.455	3.697
Transportation	110,491	13.217	3.530
Miscellaneous	146,882	12.347	3.456

Table 3.4: Descriptive Statistics: CEPII Database

Variables	(1) N	(2) Mean	(3) St.Dev.	(4) Min	(5) Max
Log Distance	1,934,228	8.594	0.920	-0.005	9.898
Log GPD (Origin)	1,758,013	10.290	2.415	3.498	16.40
Log GDP (Destination)	1,753,649	10.631	2.412	3.498	16.40
Common Currency	1,934,228	0.019	0.137	0	1
Ever a Colony	1,934,228	0.020	0.140	0	1
Regional Trade Agreement	1,930,104	0.105	0.306	0	1
WTO Member (Origin)	1,934,228	0.756	0.428	0	1
WTO Member (Origin and Destination)	1,934,228	0.582	0.493	0	1
Contiguous Countries	1,934,228	0.031	0.174	0	1
Official Common Language	1,934,228	0.167	0.373	0	1

Notes: This table includes various variables common to gravity model. Their short description is presented in Table 4.

Table 3.5: Description of CEPII Database Variables

Variables	Description
Log Distance	Log of weighted distance (pop-wt, km)
Log GDP (O)	Log of GDP for the country of origin(current mn US$)
Log GDP (D)	Log of GDP for the destination country(current mn US$)
Common Currency	1 for common currency in both countries
Ever a Colony	1 for pair ever in colonial relationship
Regional Trade Agreement	1 for regional trade agreement in force
WTO Member (O)	1 if origin country is GATT/WTO member
WTO Member (O and D)	1 if both countries are GATT/WTO members
Contiguous Countries	1 for contiguity
Official Common Language	1 for common official of primary language

Notes: "O" stands for "Origin," "D" — for "Destination."

Table 3.6: WTO Membership Effect Using OLS, FE and PPML (Imports)

Sectors	(1) OLS	(2) Fixed Effects	(3) Poisson PML
Animals	-0.270	0.072	0.134
	(9.89)***	(1.32)	(1.67)*
Vegetables	-0.270	0.114	0.308
	(11.89)***	(2.64)***	(2.26)**
Food Products	-0.393	0.052	-0.037
	(18.29)***	(1.26)	(0.65)
Minerals	0.134	0.386	1.134
	(4.07)***	(5.77)***	(8.93)***
Fuels	0.537	-0.124	0.383
	(13.64)***	(1.55)	(2.71)***
Chemicals	0.033	0.168	0.311
	(1.72)*	(4.37)***	(3.08)***
Plastic/Rubber	0.131	0.248	0.319
	(6.37)***	(5.82)***	(4.60)***
Hides/Skins	0.455	0.482	0.204
	(16.53)***	(8.22)***	(0.94)
Wood	0.019	0.219	0.147
	(0.82)	(4.97)***	(1.40)
Textiles	0.303	0.207	-0.112
	(14.48)***	(4.58)***	(1.32)
Footwear	0.313	0.090	-0.099
	(11.63)***	(1.56)	(0.81)
Stone/Glass	0.134	0.180	0.054
	(6.02)***	(3.79)***	(0.54)
Metals	0.132	0.262	0.283
	(5.99)***	(5.82)***	(3.62)***
Machinery	-0.148	0.097	0.620
	(7.59)***	(2.35)**	(5.73)***
Transportation	-0.168	-0.136	0.096
	(7.01)***	(2.47)**	(0.94)
Miscellaneous	-0.143	0.148	0.840
	(7.74)***	(3.61)***	(4.16)***

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Dependent variable: log of imports. Estimates are taken from separate regressions. Explanatory variables used in all regressions: GDP of origin and destination countries, RTAs, dummy variables for common language, currency, border, dummy for colonies and log of distance, as well as multilateral resistance terms.

Table 3.7: WTO Membership Redefined: Both Trading Partners are Members (Imports)

Sectors	(1) Dummy variable for reporting country WTO member	(2) Dummy variable for both countries WTO members
Animals	0.134	0.175
	(1.67)*	(2.66)***
Vegetables	0.308	0.230
	(2.26)**	(2.56)**
Food Products	-0.037	0.180
	(0.65)	(2.34)**
Minerals	1.134	0.742
	(8.93)***	(5.98)***
Fuels	0.383	-0.009
	(2.71)***	(0.18)
Chemicals	0.311	0.261
	(3.08)***	(3.73)***
Plastic/Rubber	0.319	0.411
	(4.60)***	(7.87)***
Hides/Skins	0.204	0.413
	(0.94)	(5.45)***
Wood	0.147	0.398
	(1.40)	(3.71)***
Textiles	-0.112	0.276
	(1.32)	(4.53)***
Footwear	-0.099	0.111
	(0.81)	(1.34)
Stone/Glass	0.054	0.499
	(0.54)	(6.60)***
Metals	0.283	0.511
	(3.62)***	(8.91)***
Machinery	0.620	0.807
	(5.73)***	(13.61)***
Transportation	0.096	0.271
	(0.94)	(2.86)***
Miscellaneous	0.840	0.593
	(4.16)***	(4.84)***

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Estimates from Poisson PML regression. Dependent variable: log of imports. Estimates are taken from separate regressions. Explanatory variables are same as in Table 3.6.

Table 3.8: WTO Membership by Economy and Accession Status (Imports)

Sectors	(1) Dummy variable for Developing WTO member	(2) Dummy variable for Least Developed WTO member	(3) Dummy variable for Accession after 1996
Animals	0.235	0.189	0.133
	(1.85)*	(0.27	(1.66)*
Vegetables	0.325	-0.600	0.308
	(1.81)*	(3.28)***	(2.26)**
Food Products	-0.118	-0.137	-0.042
	(1.35)	(0.94)	(0.74)
Minerals	1.039	-1.592	1.134
	(6.47)***	(8.58)***	(8.93)***
Fuels	0.398	-1.064	0.382
	(2.06)**	(4.38)***	(2.70)***
Chemicals	0.405	-0.358	0.311
	(3.29)***	(2.20)**	(3.08)***
Plastic/Rubber	0.310	-0.331	0.320
	(3.28)***	(3.63)***	(4.60)***
Hides/Skins	-0.183	0.263	0.204
	(0.75)	(0.94)	(0.94)
Wood	0.057	-0.298	0.146
	(0.44)	(1.64)	(1.40)
Textiles	-0.121	0.406	-0.113
	(1.24)	(2.90)***	(1.32)
Footwear	0.390	-0.638	-0.102
	(1.69)*	(2.30)**	(0.83)
Stone/Glass	0.311	-0.524	0.054
	(1.95)*	(1.28)	(0.54)
Metals	0.138	-0.423	0.285
	(1.30)	(1.68)*	(3.63)***
Machinery	0.468	-0.545	0.621
	(3.79)***	(3.90)***	(5.74)***
Transportation	0.012	0.180	0.096
	(0.08)	(1.24)	(0.95)
Miscellaneous	0.922	-0.220	0.841
	(3.87)***	(0.54)	(4.16)***

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Estimates from Poisson PML regressions. Dependent variable: log of imports. Estimates are taken from separate regressions. For developed countries coefficients are the same in magnitude as those for developing ones, but with an inverted sign. Explanatory variables are same as in Table 3.6.

Table 3.9: WTO Membership Effect Using OLS, FE and PPML (Exports)

	(1)	(2)	(3)
Sectors	OLS	Fixed Effects	Poisson PML
Animals	0.492	0.184	0.130
	(15.50)***	(2.72)***	(1.38)
Vegetables	0.057	0.209	0.168
	(2.14)**	(3.87)***	(2.13)**
Food Products	0.892	0.212	0.355
	(33.74)***	(4.04)***	(3.35)***
Minerals	0.304	-0.075	-0.146
	(7.43)***	(0.82)	(1.09)
Fuels	-1.035	0.341	0.187
	(22.82)***	(4.34)***	(1.80)*
Chemicals	0.281	0.132	0.161
	(10.91)***	(2.79)***	(2.42)**
Plastic/Rubber	0.641	0.344	0.483
	(22.99)***	(5.78)***	(6.33)***
Hides/Skins	-0.102	0.281	0.474
	(2.89)***	(4.10)***	(6.81)***
Wood	0.627	0.287	0.750
	(22.85)***	(5.12)***	(7.95)***
Textiles	0.210	0.283	0.453
	(8.13)***	(5.68)***	(4.52)***
Footwear	-0.265	0.277	0.301
	(6.56)***	(3.85)***	(2.83)***
Stone/Glass	0.584	0.422	0.550
	(19.59)***	(7.49)***	(5.85)***
Metals	-0.298	0.378	0.659
	(11.16)***	(7.00)***	(9.18)***
Machinery	0.694	0.202	1.111
	(28.01)***	(4.35)***	(18.52)***
Transportation	-0.001	0.361	0.683
	(0.03)	(5.12)***	(5.90)***
Miscellaneous	0.445	0.236	0.711
	(18.61)***	(4.80)***	(6.87)***

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Dependent variable: log of exports. Estimates are taken from separate regressions. Explanatory variables are same as in Table 3.6.

Table 3.10: WTO Membership Redefined: Both Trading Partners are Members (Exports)

Sectors	(1) Dummy variable for reporting country WTO member	(2) Dummy variable for both countries WTO members
Animals	0.130	0.104
	(1.38)	(1.54)
Vegetables	0.168	0.227
	(2.13)**	(2.21)**
Food Products	0.355	0.191
	(3.35)***	(1.93)*
Minerals	-0.146	0.703
	(1.09)	(5.60)***
Fuels	0.187	0.136
	(1.80)*	(1.52)
Chemicals	0.161	0.227
	(2.42)**	(3.41)***
Plastic/Rubber	0.483	0.408
	(6.33)***	(6.10)***
Hides/Skins	0.474	0.313
	(6.81)***	(2.86)***
Wood	0.750	0.412
	(7.95)***	(4.19)***
Textiles	0.453	0.259
	(4.52)***	(3.52)***
Footwear	0.301	0.155
	(2.83)***	(1.87)*
Stone/Glass	0.550	0.399
	(5.85)***	(6.28)***
Metals	0.659	0.541
	(9.18)***	(9.40)***
Machinery	1.111	0.829
	(18.52)***	(12.33)***
Transportation	0.683	0.194
	(5.90)***	(1.62)
Miscellaneous	0.711	0.601
	(6.87)***	(6.51)***

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Dependent variable: log of exports. Estimates from Poisson PML regressions. Estimates are taken from separate regressions. Column (1) is provided for comparison. Explanatory variables are same as in Table 3.6.

Table 3.11: WTO Membership by Economy and Accession Status (Exports)

Sectors	(1) Dummy variable for Developing WTO member	(2) Dummy variable for Least Developed WTO member	(3) Dummy variable for Accession after 1996
Animals	0.100	0.004	0.131
	(0.61)	(0.00)	(1.38)
Vegetables	-0.018	0.470	0.166
	(0.13)	(1.06)	(2.09)**
Food Products	0.263	0.161	0.356
	(1.56)	(0.25)	(3.35)***
Minerals	0.098	0.344	-0.146
	(0.50)	(2.20)**	(1.09)
Fuels	-0.352	0.382	0.187
	(2.11)**	(3.80)***	(1.80)*
Chemicals	0.375	0.511	0.161
	(3.62)***	(2.03)**	(2.42)**
Plastic/Rubber	0.313	-0.738	0.483
	(1.74)*	(3.20)***	(6.33)***
Hides/Skins	0.307	-1.433	0.476
	(1.59)	(1.91)*	(6.82)***
Wood	0.535	-0.220	0.752
	(4.22)***	(1.72)*	(7.97)***
Textiles	0.452	-0.079	0.454
	(2.58)***	(0.68)	(4.52)***
Footwear	0.841	-0.243	0.301
	(5.29)***	(1.12)	(2.83)***
Stone/Glass	0.331	-1.301	0.550
	(2.54)**	(11.09)***	(5.85)***
Metals	0.612	-0.964	0.659
	(6.23)***	(3.65)***	(9.18)***
Machinery	0.920	-1.463	1.111
	(8.50)***	(3.23)***	(18.52)***
Transportation	0.891	-0.693	0.683
	(4.93)***	(1.40)	(5.90)***
Miscellaneous	0.244	0.646	0.711
	(1.92)*	(1.13)	(6.87)***

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Estimates from Poisson PML regressions. Dependent variable: log of exports. Estimates are taken from separate regressions. For developed countries coefficients are the same in magnitude as those for developing ones, but with an inverted sign. Explanatory variables are same as in Table 3.6.

Table 3.12: Robustness check: WTO Membership with and without China (Exports)

Sectors	(1) Dummy variable for reporting country WTO member in original sample	(2) Dummy variable for reporting country WTO member in amended sample
Animals	0.130	-0.106
	(1.38)	(0.86)
Vegetables	0.168	0.138
	(2.13)**	(1.83)*
Food Products	0.355	0.084
	(3.35)***	(0.95)
Minerals	-0.146	-0.323
	(1.09)	(1.97)**
Fuels	0.187	0.203
	(1.80)*	(1.76)*
Chemicals	0.161	-0.183
	(2.42)**	(2.76)***
Plastic/Rubber	0.483	0.200
	(6.33)***	(1.29)
Hides/Skins	0.474	0.177
	(6.81)***	(1.19)
Wood	0.750	0.351
	(7.95)***	(5.11)***
Textiles	0.453	0.183
	(4.52)***	(1.30)
Footwear	0.301	-0.287
	(2.83)***	(1.74)*
Stone/Glass	0.550	0.297
	(5.85)***	(2.46)**
Metals	0.659	0.075
	(9.18)***	(1.18)
Machinery	1.111	0.220
	(18.52)***	(2.18)**
Transportation	0.683	-0.070
	(5.90)***	(0.47)
Miscellaneous	0.711	0.461
	(6.87)***	(3.79)***

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Dependent variable: log of exports. Estimates from Poisson PML regressions. Estimates are taken from separate regressions. Column (1) is provided for comparison. Explanatory variables are same as in Table 3.6.

Table 3.13: Robustness check: WTO Membership by Economy and Accession Status in amended sample (Exports)

Sectors	(1) Dummy variable for Developing WTO member	(2) Dummy variable for Least Developed WTO member	(3) Dummy variable for Accession after 1996
Animals	-0.363	0.439	-0.107
	(1.73)*	(0.50)	(0.86)
Vegetables	-0.059	0.506	0.128
	(0.42)	(1.12)	(1.69)*
Food Products	-0.125	0.444	0.082
	(0.77)	(0.70)	(0.93)
Minerals	-0.607	0.677	-0.323
	(2.14)**	(3.83)***	(1.97)**
Fuels	-0.234	0.376	0.199
	(1.27)	(3.39)***	(1.74)*
Chemicals	0.002	0.818	-0.183
	(0.02)	(3.06)***	(2.77)***
Plastic/Rubber	-0.298	-0.417	0.199
	(1.38)	(1.54)	(1.28)
Hides/Skins	-0.185	-1.150	0.197
	(0.68)	(1.45)	(1.29)
Wood	-0.359	0.267	0.352
	(3.41)***	(2.37)**	(5.06)***
Textiles	0.508	0.352	0.190
	(1.37)	(1.94)*	(1.34)
Footwear	0.590	0.438	-0.287
	(2.53)**	(1.70)*	(1.74)*
Stone/Glass	0.088	-1.037	0.297
	(0.34)	(7.14)***	(2.45)**
Metals	-0.150	-0.303	0.075
	(1.00)	(1.10)	(1.18)
Machinery	-0.557	-0.577	0.220
	(3.68)***	(1.16)	(2.18)**
Transportation	-0.196	0.065	-0.070
	(0.83)	(0.13)	(0.47)
Miscellaneous	-0.873	0.974	0.461
	(4.68)***	(1.68)*	(3.79)***

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Estimates from Poisson PML regression. Dependent variable: log of exports. Estimates are taken from separate regressions. For developed countries coefficients are the same in magnitude as those for developing ones, but with an inverted sign. Explanatory variables are same as in Table 3.6.

Table 3.14: Change in Composition of Trade during a Year of WTO Membership (Imports)

Sectors	(1) Average WTO member	(2) Average Developing WTO member	(3) Average Least Developed WTO member
Animals	1.2%	1.2%	1.2%
Vegetables	2.3	2.8	2.8
Food Products	2.3	2.6	2.6
Minerals	0.7	0.7	0.7
Fuels	5.5	6.5	5.0
Chemicals	4.1	4.7	5.2
Plastic/Rubber	2.0	2.2	2.2
Hides/Skins	0.2	0.5	0.2
Wood	1.1	2.1	2.1
Textiles	2.9	0.5	1.4
Footwear	-0.1	-12.2	-7.2
Stone/Glass	1.2	0.9	1.1
Metals	3.3	5.7	3.6
Machinery	-37.0	-21.8	-28.0
Transportation	5.0	6.3	5.0
Miscellaneous	5.3	-2.6	2.1

Table 3.15: Change in Composition of Trade during a Year of WTO Membership (Exports)

Sectors	(1) Average WTO member	(2) Average Developing WTO member	(3) Average Least Developed WTO member
Animals	3.5%	3.5%	3.5%
Vegetables	11.5	11.5	11.5
Food Products	8.4	8.4	8.4
Minerals	3.4	3.3	3.3
Fuels	9.8	9.8	9.8
Chemicals	6.3	6.3	6.3
Plastic/Rubber	1.6	1.6	1.6
Hides/Skins	0.9	0.9	0.9
Wood	2.1	2.0	2.0
Textiles	-33.5	-33.6	-34.1
Footwear	-12.2	-10.0	-12.0
Stone/Glass	4.1	4.0	4.0
Metals	5.4	5.4	5.4
Machinery	-14.7	-16.2	-14.9
Transportation	0.7	0.4	0.4
Miscellaneous	2.7	2.7	2.7

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