UiT NORGES ARKTISKE UNIVERSITET

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Income inequality, taxation, collective bargaining and trade

A longitudinal analysis of 19 OECD countries in the period 1981-2011

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«Enten så går det bra, eller så går det over» -Rune Karlsen

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Abstract

This thesis studies determinants of income inequality using data from The World Top Incomes Database. The focus is on top tax rates, unions and trade openness. There is found that the erosion of unions and top tax rates are associated with the rise in top income shares in the sample of OECD countries. In addition, there is found that increase of trade openness is associated with the increase in top income shares.

There is support for a lag structure of tax changes, and a positive cross-level interaction between the level of taxation in the period and the effect of tax changes. In addition, there is support for a significant positive interaction between the level of trade openness and the effect of union density changes.

These associations are found utilizing a random-effects multilevel model, separating between and within effects, applied to annual longitudinal data covering the period 1981-2011. The results are largely supported by fixed-effects and first-differenced models.

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1 Introduction

The distribution of resources have long been recognized as an important element of organization and functioning of states. Indeed, Plato discussed how the distribution and hunger for gold could bring about an oligarchy where wealth is concentrated on ever fewer hands, and laws are twisted so that the wealthy does not have to oblige them (Plato, 2001, pp. 908-311)[1].

Distribution of resources have also been associated with a stable democracy: "*Increased wealth is not only related causally to the development of democracy by changing the social conditions of the workers, but it also affects the political role of the middle class through the shape of the stratification structure so that it shifts from an elongated pyramid, with a large lower-class base, to a diamond with a growing middle class*." (Lipset, 1959, p. 83)

As the title of this thesis suggest, it is not the distribution of wealth that is of concern here, but the distribution of income. The concepts are closely related, however, there is a difference. Wealth (accumulated resources at a given time), is the sum of income spent (the flow of resources in a given period) and previous wealth. A highly skewed distribution of income can thus be a first step toward a highly skewed distribution of wealth[2].

In the years after World War 2, and to the late 1970s, Lipset (1959)'s implicit assumption of economic development increasing the middle class seemed to hold in the United States. The economy grew steadily, as did wages of the average worker, and economic gains became more equally distributed. This changed somewhere in the late 1970s to early 1980s. Suddenly wages began a long downward trend, and even though more family members than ever before were working, median family income stopped growing. At the same time, the amount of people earning high incomes rose as well, leaving a declining proportion of employees receiving mid-level incomes (Harrison & Bluestone, 1990, pp. 4-5).

[1] The Republic, book 8, lines 550-552.
[2] Conditioned on consumption patterns, income mobility and demographics.

The status in 2013 was that ten percent of Americans claimed almost half (47%) of all gross income in the United States, the largest income share concentrated in this group since the 1930s[3]. Clearly, not all segments of the society have benefitted equally from economic development. The pyramid might have become more like a diamond for a while, but that is a trend long gone.

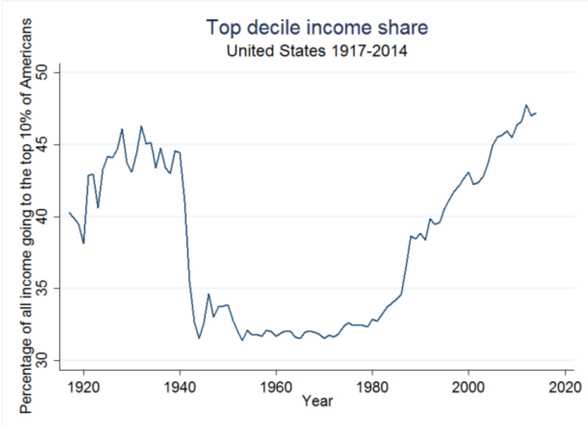

Figure 1 Top decile income share in the United States 1917-2014

The increasing income inequality is not unique to the US by any means. Top incomes have increased enormously in the US and other English-speaking countries over the past three decades (Piketty & Saez, 2006, p. 204). Meanwhile, European countries and Japan have had relatively stable top income shares, although there are increasing trends in most of these countries as well. The US inequality might, however, be the most pronounced, and have been the focus of the lion's share of research concerning inequality in developed countries (Mahler, Jesuit, & Roscoe, 1999, p. 368).

To make a comparison of differences concerning the income shares between countries, the highest-earning ten percent of Swedes claimed 28% of total gross income in 2013, and 23% in 1980. The rather large differences between Sweden and the US, both in level and growth of inequality, indicates that large inequalities are not inevitable. Markets may have created these inequalities, but laws, regulations and institutions shape the markets (Stiglitz, 2012, p. 66).

Understanding causes behind the rise in income inequality should be of concern for political scientists and policy makers. Inequality might not pose a direct threat to the stability of democratic institutions in the near future. However, high levels of economic inequality leads to political inequality (Stiglitz, 2015, p. 125). Moreover, inequality have major impacts on living conditions of substantial proportions of the population in both the long and the short

[3] Data from The World Top Incomes Database (October 31., 2015)

term. Income (and wealth) affects, for example, decisions and opportunities to get education, sufficient healthcare, and the ability to use the legal system (Stiglitz, 2012).

1.1 Brief overview of the research field

Explanations for the rise in inequality in the developed world focus either on market-driven forces or on institutional changes. According the market forces hypothesis, the rise in inequality reflects skill-biased technical change and globalization (Jaumotte & Buitron, 2015, p. 7). In this framework, wages are determined by supply and demand (the market) for labor. Technological change have increased demand for higher skilled workers, and decreased demand for low-skilled workers. Thus, market changes have increased the skill (educational) premium and increased inequality (consult Goldin and Katz (2007) for a study of the United States, see Brynjolfsson and McAfee (2014) for interesting ideas about potential future implications, also consult also Card and DiNardo (2002) for problems related to the skill-biased technological change hypothesis). In a similar fashion, globalization, working through increased global competition, have increased demand for capital, and decreased demand for labor (in developed countries) (consult Stolper and Samuelson (1941) for theoretical arguments).

Institutional features cited as determinants of income inequality includes top personal income tax rates (consult Atkinson (2004) for a long run descriptive study of taxes and top incomes, and consult Piketty, Saez, and Stantcheva (2011) for models on tax changes and responses), and financial deregulation (consult Jerzmanowski and Nabar (2013) for arguments how high skilled-labor can benefit relatively more than low-skilled labor).

Features related to the labor market, such as union density rates (consult Card (2001) for a study of unions and wage inequality in the US, consult Card, Lemieux, and Riddell (2004) for a study of the US, the UK and Canada) and minimum wage (consult Lee (1999) for a study of minimum wages and wage inequality in the US) are linked to inequality of incomes.

1.1.1 Research gap

The erosion of labor market institutions have been relatively little investigated in the context of income inequality (Jaumotte & Buitron, 2015, p. 5). This is especially true for cross-country analyses. Consequently, there have been little effort to investigate any potential interactions between market-driven forces and labor market institutions.

This thesis utilizes longitudinal analysis, which is seen as the natural next step in investigation of income inequality (Piketty, 2005, pp. 387-388). Previous databases have been haunted by various problems (Piketty, 2005, pp. 382-383) and opportunities to investigate the income distribution utilizing cross-country analysis in a rigorous way have therefore been limited. However, the possibility to use longitudinal analysis have increased by the publication of the World Top Incomes Database (WTID), motivated by dissatisfaction over existing databases. This database is fully homogenous across countries, annual and long-run (Piketty, 2005, p. 383), making it suited for longitudinal analysis.

This thesis investigates the proportion of the total income claimed by the top 10% (the top decile), and how institutional changes (represented with top tax rates and labor union density) and trade openness relates to it. In addition, this thesis investigates potential interactions between trade openness and labor unions. This is done by analyzing 19 OECD countries[4] (Organization for Economic Co-operation and Development), which are considered relatively developed in the period. This will test the theoretical assumptions and expectations, largely investigated and developed in the context of the US, in a broader context.

The use of top decile income shares and longitudinal models are not completely novel. Two studies investigating developed countries and top decile income share are Jaumotte and Buitron (2015) and Roine, Vlachos, and Waldenström (2009).

Jaumotte and Buitron (2015) investigates top decile income shares by labor market institutions (labor unions, extensions and minimum wages) and top tax rates, while controlling for market-driven forces. They use both event analysis and longitudinal analysis (three-stage least squares).

Roine, Vlachos, and Waldenström (2009) investigates the bottom nine deciles (the inverse of the top decile) by economic development, financial development, trade openness,

[4] Australia, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Korea, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom and the United States.

government expenditure and taxation. They use 5-year averages and a first-difference model including a lagged dependent variable.

The main novelty of this thesis lies in the statistical method used. A random-effects multilevel model which separates the between and within effects is utilized. This approach achieve the unbiasedness of the fixed-effects approach, but at the same time, it accommodates information about potential level effects of the explanatory variables. This approach allows for more exploration of the data, and especially between the level and changes of variables. As a result, this thesis goes somewhat longer in exploring potential interactions between labor market institutions and market-forces than earlier comparable studies.

1.2 Research question

The research question this thesis seek to answer is:

"*Can collective bargaining, tax policy and trade openness explain the increase in the top deciles' gross income share in OECD countries in the period 1981-2011?*"

These relationships are of interest because they are largely results of policy, and if they indeed affect the income distribution, then policy can be used actively to manage the distribution of income. As mentioned already, there are several reasons for why the income distribution should be of interest. If the inequality can be managed, there is surely of interest to know how this can be achieved.

1.3 Findings

The main findings can be summarized as follows: there is found support for the hypothesis that changes in trade openness affects the top decile income share. This relationship is positive, indicating that increasing trade openness could have increased the top decile income share. There is also support for the hypothesis that changes in top tax rates affects the top decile income share. This relationship is rather complex, with a negative lag structure of two years, in addition to country mean top tax rates acting as moderators of the country specific effects. Taken together, the relationship is negative, indicating that reduction of top tax rates could have increased the top decile income share. Lastly, it is found support for the hypothesis that changes in labor union density rates affects the top decile income share. This relationship is primarily negative, indicating that the decrease in labor union density could have increased the top decile income share. However, the effect is found to be moderated by the level of import/trade penetration of countries, with higher average import/trade penetration in the period indicating less (negative) effect of unions.

1.4 Structure

The next chapter outlines the theoretical and conceptual framework used in this thesis. Concepts of inequality, income distribution and income sources are introduced. Theoretical expectations about the association between the income distribution, trade openness, top tax rates and collective bargaining are outlined. The chapter ends with introducing a set of general hypotheses. In "Research design" arguments for utilizing the multilevel longitudinal analysis technique are presented, and concerns related to the choice of method are discussed. The chapter ends with presenting the modeling process. "Data collection" describes the data collection process. It provides reasoning behind the choice of indicators, and ends with a discussion of the case selection, statistical significance testing and generalization. "Descriptive statistics" presents numeric and graphical description of the variables. "Results" introduces empirical hypotheses, presents the result of a regression model utilizing all observations, and discuss the hypotheses in light of the model. In "Diagnostics and model specification" diagnostics of the model presented in Results are presented. In addition, alternative models and model specifications are presented to test the robustness of the model. Specific reasons for including the alternative models are also given. In "Discussion" the findings are reviewed and placed in the context of earlier research. The chapter also presents a final assessment of each component of the research question. In Concluding remarks the results are summarized and propositions for further research is given.

2 Theoretical and conceptual framework

This chapter starts with laying out the conceptual framework used in this thesis. The concept of income distribution and inequality, income sources and types of income is introduced. Following is the theoretical framework, which the thesis is built upon. After going through the theoretical assumptions, the chapter ends with the introduction of a set of hypotheses.

2.1 Income distribution – what is it?

In a general term, "distribution" refers to how values on a certain variable are spread across a defined population. Two extreme distributions are: 1) everyone in the population has exactly the same value on the variable, and 2) it is only one individual in the population having (a value on) the variable.

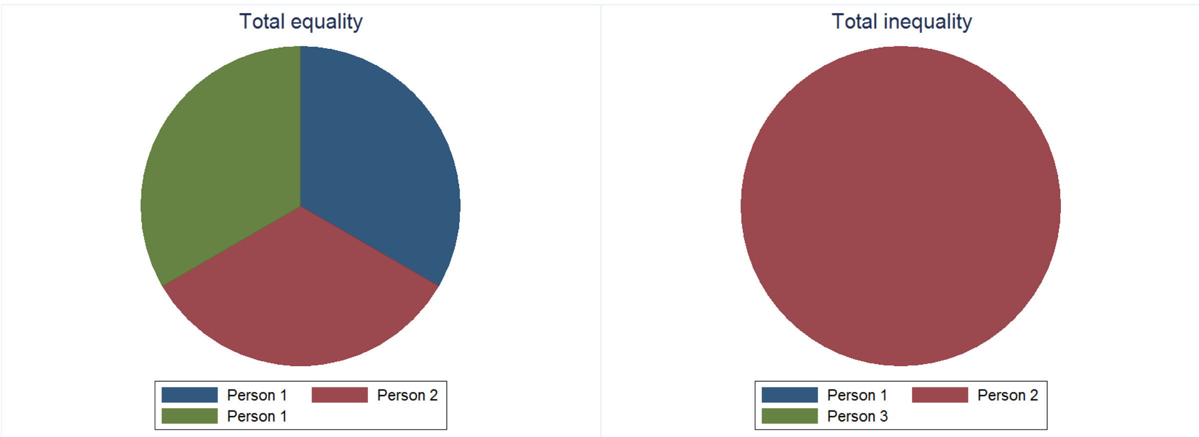

Figure 2 Two extreme distributions

When talking about inequality we also talk about the distribution of some variable. We state that the distribution is not equal – not everyone has the same value. Income inequality is thus a way to refer to how the income is distributed in the population. The degree of inequality lies somewhere between the two extremes, and the term "inequality" in itself does not indicate this degree.

2.1.1 Total, capital and labor income

By definition, the total income distribution is the result of adding up two components: inequality from income of labor and inequality of income from capital. It follows that the more unequally distributed each of these two components are, the greater the total inequality will be (Piketty, 2014, p. 242).

Even though it is true that the inequalities with respect to labor have always been much smaller than inequalities from capital, income from labor generally accounts for two-thirds to three-quarters of national income. There are also substantial differences between countries in the distribution of income from labor, which suggest that public policies and national differences can have major consequences for the labor income distribution. This in turn has a great impact on the living condition of large numbers of people (Piketty, 2014, p. 255). There is also the issue that capital accumulation by the "working rich" could lead up to the revival of top capital incomes in the following generation (Piketty, 2005, p. 387).

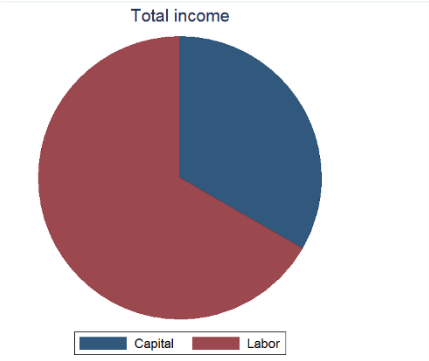

Figure 3 Income sources

Depending on the savings rate, the present income will affect the distribution of wealth in the future. This was recognized by Kuznets (1955), and it is one of the divergent forces he discusses. "According to all recent studies of the apportionment of income between consumption, only the upper-income groups save; the total savings of groups below the top decile are fairly close to zero. (…) Other conditions being equal, the cumulative effect of such inequality in savings would be the concentration of an increasing proportion of income-yielding assets in the hands of the upper groups – a basis for larger income shares of these groups and their descendants." (Kuznets, 1955, p. 7)

Newer studies support the relationship between savings and income (see for example Dynan, Skinner, and Zeldes (2004)). The distribution of total income can thus have quite substancial impact on the society, both in the short term (current income) and in the long term (capital accumulation). Since capital itself is a source of income, the inequality in capital and wealth will also induce larger income inequality in the future.

2.1.2 *Gross and net income*

The type of income that will be investigated in this thesis is the gross income, that is: income gained before taxes and transfers. The net or "disposable" income is the gross income after taxes and redistribution. The net income is the income we are free to spend as we choose, and ultimately what affects society.

Figure 4 From gross to net income

There are two ways to alter the net income distribution: we could alter the gross income distribution, and we could alter the tax and redistribution policies.

When we are looking at the net income distribution, we are really looking at the sum of two phenomena interacting: the gross income distribution and the tax and redistribution policies. It therefore makes sense to investigate policy impact on the gross income distribution, as it indicates how policy can alter the market-driven income distribution without disturbances from the redistribution.

2.2 *What is behind the rise in inequality?*

The factors concerning inequality have roughly been divided into two categories: market-driven forces and institutional changes. The rise in observed income inequality have coincided with the "second globalization" wave, which has been under way since the 1970s, and the "conservative revolution" starting around 1980s, characterized by a shift from "planning" to "market".

It can be argued that the conservative revolution around the 1980s was a response to the increased global competition and relative stagnation of the domestic economic growth (Piketty, 2014, p. 98). Thatcher and Reagan, state leaders in the United Kingdom in 1979-1990 and the United States in 1981-1989, relied on the doctrine of laissez-faire. Laissez-faire is the theory that commercial markets function best with minimal interfering from governments (Harrison & Bluestone, 1990, pp. 78-79). This period saw a reduction in taxation and a souring sentiment toward unions and collective bargaining, as both of were thought to distort markets and slow economic growth.

Globalization, like the shift in government policy have been seen as drivers for increasing inequality. One aspect of globalization thought to affect the distribution of income, is the economic openness of a country. Regarding the institutional factors, decreasing tax rates and the decreasing role of unions and collective bargaining are interpreted as potential explanations for the increase in inequality.

The factors under investigation here are largely related to the bargaining position of workers and the labor income distribution. The labor income accounts for around two-thirds of total income and is therefore of great importance in the total income distribution.

2.2.1 Unions and collective bargaining coverage

Collective bargaining is a process of decision-making between parties representing employer and employee interests. Creating institutions to improve the bargaining position of workers has historically been an important impetus to collective bargaining (Traxler, 1994, p. 168).

The industrial relations system, which constitute a "web of rules" relating the bargaining units, greatly affects the collective bargaining process – and results. Labor unions are organizations of workers whose primary objectives are to improve the wage and non-wage conditions of employment among their members, and union density is one indicator of the character of a country's industrial relations system (Ehrenberg & Smith, 2012, p. 444; Traxler, 1994, p. 167).

Unions have different strategies and tools to improve the conditions of their members. One strategy is bargaining for contracts and agreements on behalf of their members. The idea is that the bargaining position is better for unions as a group than individual employees bargaining for their wages and conditions on an individual level with their employer. The unions might bargain directly for higher wages, but unions can also push for staffing requirements, which in turn increase the demand for workers (or at least hinder future job cuts). Unions can also bargain for contracts that prohibit subcontracting, hindering the alternative of the employer to subcontract nonunionized and cheaper labor (lower wages and/or worse benefits).

Unions can increase the cost of other close substitutes of workers. They can for example lobby for import quotas, thereby increasing the cost of imports. By making import more expensive, the production of similar goods within the country becomes relatively cheaper, making it more profitable to produce those goods domestically. Increasing, or maintaining, production within a country will protect the jobs associated with that production. Unions could also bargain and lobby for minimum wages. Consequently, employing non-unionized workers is less attractive. However, bargaining for minimum wages also lift the least paid workers wages, compressing the income distribution.

Unions could also affect the wage distribution through more informal channels. Unions can, for example, promote norms of equity, not just at the lower part of the distribution, but also protesting the pay of the upper management (Western & Rosenfeld, 2011, pp. 517-518). They have also driven public relations campaigns to increase demand for products produced by union members (Ehrenberg & Smith, 2012, p. 462).

Perhaps the most powerful feature of a union is the ability to execute strikes and work slowdowns. These measures can impose potentially high costs to the employer if they do not agree to the terms and conditions specified by the union in question. The cost could be higher than the cost of agreement, in turn making it less attractive to fight for better agreements for the employer.

If unions increase the wages of their members, and the top earners are unaffected we should see a relative contraction of the income inequality. If the top wages are also constrained by social norms, the relative contraction will be even more pronounced. If, however, an increase in the wages of unionized workers is bought at the price of a higher unemployment rate, the contraction of the income distribution might be lower, or maybe even increase income inequality, depending on the relative effects of the unemployment rate and the wage effect.

2.2.2 Top tax rates

A decrease in the top tax rate can change the bargaining power of executives. It is always difficult for an executive to convince other parties involved in the firm that a large increase in his or her wage is truly justified. When the top tax rate is very high a large fraction of a potential wage increase goes directly to the government, and the executive will have little reason to fight for that wage increase. At the same time, other parties will be less inclined to accept the increase. However, if the tax rate were lowered, the incentive for the executive to chase the wage increase intensifies. The executive would gain more from an increase, and the executive will do more to persuade other interested parties to grant the raise (Piketty, 2014, p. 510).

Leaving out the bargaining aspect, there are generally two effects concerning taxation on wages. These are the substitution and income effect. The substitution effect is the tendency to substitute one good for another as the price of the first good increases. As the tax rate increases, the effect could be that the people affected will work less, as they are paid less and the "cost of leisure" decreases. If top earners work less their income decreases, and if the rest work just as much as previously this should compress the income inequality. The other effect is the income effect. The income effect is what affects people to work more, in order to keep their net income from going down and wanting to keep their standard of living (Gayer & Rosen, 2010, pp. 416-417). If the top earners work more, their gross income increase, and if everyone else work just as much as before, the gross income distribution would widen.

The effect of taxation on income inequality is thus dependent on which effect is the stronger. There is of course a practical limit to how many hours one can work any given day, and at some point, the substitution effect will appear.

This gives the top tax rates at least three potential effects on the income distribution. First, it could lower the incentives for high-income individuals to bargain for higher wages. This should result in an unchanged gross income if their work hours are unchanged. Two, it could discourage high-income individuals from working as much as before, lowering total working hours, thereby reducing their gross income. If the wages and working hours for the rest are unchanged, the effect should be a contraction of the income distribution. Third, it could encourage high-income individuals to increase working hours in order to keep their net income level, which should increase their gross income, ultimately widening the income distribution.

2.2.3 Trade and economic openness

The critics of globalization claims that the rapidly growing movement of goods, services, and capital throughout the world has forced workers into ruthless global competition, jeopardizing wages, benefits and job security previously extracted from employers during many decades (Mahler et al., 1999, p. 364).

The effects of trade on the income distribution could be different for how the relative supply of capital and labor is in the country. International trade is expected to lower the wage of the scarce factor of production. In countries where capital is relatively abundant, as is assumed is the case for most of the countries in the analysis, the increased trade openness is thought to reduce the wages of lower skilled labor (Stolper & Samuelson, 1941).

However, "trade" is comprised of both import and export, which could have adverse effects on the income distribution, and greater international trade generally means that both the country's imports and exports increase.

The increase in exports should increase the demand for workers involved in the production of the goods exported. Not only will more people be employed and become wage earners, but also the bargaining position for workers and unions will increase as the relative supply of workers decreases.

The increase in imports tends to directly, or indirectly, reduce the demand for some domestically produced goods. Some of the import is likely to substitute for goods that would have been produced domestically (Ehrenberg & Smith, 2012, p. 568). This is likely to reduce the amount of wage earners and to weaken the bargaining position of workers and unions, which ultimately reduces the wages of low-skilled labor (Harrison & Bluestone, 1990, pp. 35-36; Reuveny & Li, 2003, p. 579).

Even if import has a negative impact on the wages of lower paid workers, the effects of trade in the longer run might be less negative. If trade makes the country as a whole better off economically, then the domestic demand for goods and services should increase, assuming resources are spent, at least partially, on domestically produced goods and services. This in turn should increase the demand for workers producing these goods and services (Ehrenberg & Smith, 2012, p. 568).

The expected effects of trade on the income distribution is unclear. Import could hurt low-skilled workers, by the import acting as substitutes for their work, leading to a worse bargaining position for the workers and unions, ultimately increasing the income inequality. Export, on the other hand, is likely to create jobs and thus contribute to a compression of the income distribution. The total impact on trade, then, is conditioned on which effect is the greatest. Even if trade in the short run is negative for the income distribution, the effect could be less negative in the long run if the increase in cost effectiveness for consumers and corporations is used on domestically produced goods and services, which would produce more jobs in the country. This is again conditioned on what sort of jobs are created. If the new jobs are low-income jobs, this potential positive effect could be rather small.

2.2.4 Expectations

As is apparent from the brief overview, there is no general theoretical consensus on how and in what degree any of the factors affects the income distribution. Using earlier research in combination with these theoretical expectations, the following general hypotheses are formulated:

H1: Unions and collective bargaining reduces the income inequality

H2: Higher tax rates reduces the income inequality

H3: Trade and economic openness increases the inequality

H4: Trade reduces the effect of collective bargaining

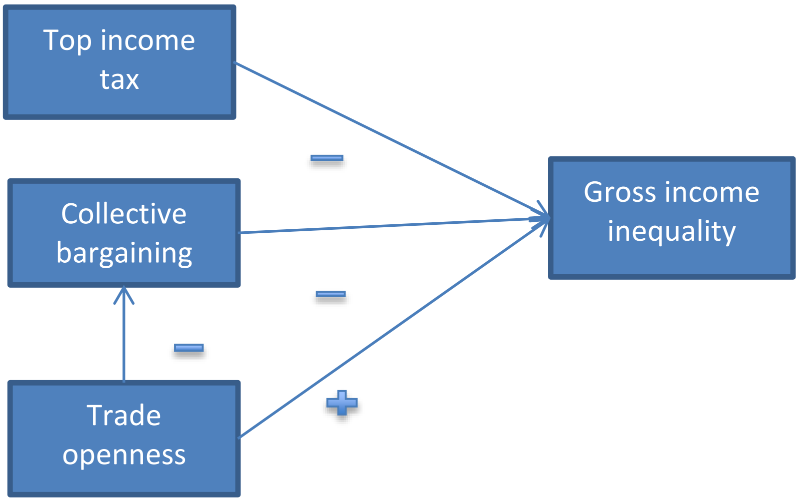

Figure 5 Theoretical model

These factors are in various degrees shaped by policies, and can thereby be altered. Import can be regulated, for example, through import quotas. This might not be optimal, as import is generally seen as beneficial for the economy as a whole. There might be better to use some of the benefits of import to compensate the workers hit by the import through other channels such as subsidy or redistributive measures (Stolper & Samuelson, 1941, p. 73). The Reagan administration have been criticized for both implicit and explicit attacking unions, and even the very principle of unionization (Harrison & Bluestone, 1990, p. 78). If this reduced the sentiment and bargaining power of unions, then government should also be able to improve and the sentiment and facilitate for collective bargaining. Export can be encouraged through increased competitiveness. There are several ways to increase this, for example to improve the infrastructure and increase the skill-level of the labor force through the educational system. The tax rates, however, are directly affected by legislation.

If these factors do affect the distribution of incomes, then knowledge about the relations and mechanisms can be used as a basis for policy. As noted in the introduction, the inequality of incomes bring about a host of negative consequences for a large proportion of the population. There is also reasons to believe that high inequality is bad for economic growth and economic stability (Stiglitz, 2012, pp. 106-115), which in turn have more negative consequences for society.

3 Research design

This chapter lays out the reasoning behind the choice of the longitudinal analysis. It continues with arguments for why a multilevel approach is appropriate for longitudinal research. Next follows a discussion about fixed and random effects estimators, which are two main estimators within the multilevel framework, and why an approach that separates between and within effects is chosen. The next section considers special concerns for longitudinal analysis, such as trends, stationarity, autocorrelation and cross-sectional correlation, and how these issues are tackled. The last section considers model specification and the building process. The issues of dynamics, estimation method, LR-tests and the choice of residual structure are considered.

3.1 Goals and tools

Collier, Brady, and Seawright (2004) suggests that the choice of tools is a pragmatic matter that should reflect the goals of the analysis. King, Keohane, and Verba (1994, pp. 4-6) argues that the differences between the quantitative and qualitative traditions are methodologically and substantively unimportant. According to King et al. (1994), all good research can be understood from the same underlying logic of inference. The rules of inference are relevant to all research where the goal is to learn facts about the real world.

Within the positivist tradition the statistical method is highly regarded. The statistical method is not as well regarded as the experiment, which in this topic, as often is the social sciences, a practical impossibility. The perceived strength of statistics for positivists lies in its ability to compare and control. Through control and comparison, the scientist is able to identify, isolate and explore regularities in the world (Moses & Knutsen, 2012, p. 50).

Even though statistics enjoy a highly regarded position within the positivist tradition, this is not the case within the constructivist tradition. The debate between the positivist and constructivist traditions can be boiled down to the ontological view. The worldview in turn affects what we can know about the world, and that in turn affects how we can obtain that knowledge. By using a statistical approach the assumption that it is possible to have some knowledge about the external world is implicitly made (King et al., 1994, p. 6; Moses & Knutsen, 2012, p. 91).

On a general ground, the positivist tradition is criticized for ignoring human agency, context, the connectedness of the world and meaning. The critique becomes clear just looking at the very process of quantification. The process involves that we interpret social phenomena, categorize and assign values in order to compare and analyze. This process necessitates losing the social context, and with it, a good portion of meaning. When we take social phenomena out of the context in order to compare the interpretation can become unclear, as it is unclear if we even compare the same phenomena. As Moses and Knutsen (2012, p. 260) writes: "(…) the first casualties of quantification are interpretation and context."

Admittedly, the statistical method simplifies the world and makes unrealistic assumptions. The costs of the particular may be great, but as King et al. (1994, p. 43) writes: "Systematic simplification is a crucial step to useful knowledge.".

3.2 Longitudinal analysis

The research question implies change over time in different units. Longitudinal data analysis seems to be a natural choice of statistical method. With longitudinal data, we can observe subjects over time, and we can observe many subjects. This allows us to study dynamics and cross-sectional aspects of a problem. As Frees (2004, p. 2) writes: "Longitudinal data analysis represents a marriage of regression and time-series analysis".

In addition to allowing us to study both cross-country and time effects, the longitudinal approach have the advantage of increasing the number of observations in the analysis. This is a strength when it comes to falsifiability, enhancing explanatory leverage and addressing multicollinearity (Collier et al., 2004, p. 157). However, the increasing of observations come at a cost.

Collier et al. (2004) discusses four trade-offs related to increasing the number of observations. All of them can be traced back to the issues of context and interpretation. The first and most elementary is whether the observations have a relevance for the research question. As noted above, the time aspect is of relevance for the research question. The second highlights that measurement validity is context specific. The third highlights that cultures and relevant aspects of history not only differ across states (which in itself is a manmade concept subject to change), but they also change in complex ways within a society over time. Thus, if we are comparing different states the phenomenon we investigate might not be the same across states. Even if we investigate a phenomenon in the same state in different time periods the phenomenon might not be the same. These are very real issues, and is something that the reader should keep in mind. The data sources and concepts used are well known, and an effort have been made to secure comparability. However, as the tradeoff implies, there is loss of context in this sort of analysis. For example, Germany of 1990 is surely different from Germany of 1989.

The last trade-off is related to independence of observations. A focus on temporal or spatial subunits can add observations that are not independent either from the initial set of observations, or from one another. This is a highly relevant critique when using longitudinal data, as measurements might be correlated over time (temporal dependence), and measurements within each country might be more similar than measurements in another country (spatial dependence). This issue can be mitigated through the choice of method, which the next section show.

3.3 Multilevel models and longitudinal data

A number of authors sees the use of multilevel models on longitudinal data as appropriate (Frees, 2004; Gelman & Hill, 2007; Hox, 2010; Luke, 2004; Rabe-Hesketh & Skrondal, 2012). In a multilevel framework, we see each period of observation as the lowest level in a hierarchy. In this thesis, the model will only contain two levels: countries, and years of observations nested within each country.

One of the reasons multilevel models are well equipped for longitudinal data is that it relaxes the independence assumption and allows for correlated error structures. Multilevel models can handle both spatial and temporal dependence, which is the forth concern Collier et al. (2004) points to when increasing observations. A standard OLS regression assume that the observations are conditionally independent given the covariates. If the assumption is violated the regression will give standard errors of the parameter estimates that are too small, which will inflate the t-values and alter the significance level. This increases the chance for obtaining spuriously 'significant' results. In a longitudinal framework, the multilevel model will correct for spatial dependence and it is possible to correct for temporal dependence by specifying a residual error structure. When such dependence are corrected for, we get more appropriate t-values and significance intervals (Luke (2004, pp. 21-22) , Hox (2010, pp. 4-5) , Rabe-Hesketh and Skrondal (2012, p. 2)).

Another reason why multilevel models are appropriate for longitudinal data is that it can easily handle missing data. The problem with missing data, except for the obvious loss of information and shrinkage of statistical power, is that missing data can produce biased results. If the data are missing at random (MAR) the bias will not be a problem using the maximum likelihood (ML) estimation (as long as the model is correctly specified). This means that the probability of missing data may only depend on the covariates or responses at previous/future occasions. They are not MAR if the probability of missing data depends on the response we would have observed if the response had not been missing (Rabe-Hesketh & Skrondal, 2012, p. 278).

Many traditional approaches to longitudinal data, such as repeated-measures MANOVA, are unable to easily handle unbalanced data. They often require balanced data, and list wise deletion is often used to achieve it. This means extra loss of data. Multilevel modeling is much more flexible and efficient, and it will use whatever data that are available (Luke, 2004, p. 64).

3.3.1 Fixed vs random effects models

There are two main estimators within the multilevel framework: fixed and random effects models. The fixed effects models are not biased by omitted country specific variables, but are generally less efficiently estimated than random effects models. The random effects models can be biased if there is an omitted country specific variable that both affects the level of an explanatory variable and the dependent variable. However, because it uses both between countries and within country information it is more efficient. Another advantage by the random effects models is that country level variables can be included. This is not possible in fixed effects models because of collinearity (the fixed intercepts occupies all the country heterogeneity).

The literature is full of advice when it comes to choosing estimator. As Gelman and Hill (2007, p. 245) writes: "A question that commonly arises is when to use fixed effects (…) and when to use random effects. The statistical literature is full of confusing and contradictory advice."

One of the more common methods to choose between the estimators is to use the Hausman test. The Hausman test is a statistical test for how severely biased the random effects estimator is, and an insignificant Hausman test is often interpreted to mean that the bias is insignificant and that a random effects estimator can be safely used. The test is not without criticism, and Clark and Linzer (2012) show how poorly the Hausman test perform in detecting and assessing the bias, and especially when the sample size is small.

There are methods for overcoming the bias of random effects models. Bartels (2008) and Rabe-Hesketh and Skrondal (2012) show how the bias can be overcome by including country specific means of the explanatory variables in the model, and centering the time-varying explanatory variables on the country specific mean variable.

This approach separates the within country and between country effects of the variables, removes the correlation between the intercepts (omitted country level variables) and the time-varying variables, thus eliminating the bias resulting from this correlation. This approach produces numerically identical within effects as a fixed-effects model (Rabe-Hesketh & Skrondal, 2012, p. 257).

Using this approach removes the bias issue of the random effects model, and allows us to include country level variables. Another advantage of this approach is that it allows estimation of the between country parameters for the variables of interest, meaning that we can estimate both the effect of a change of a variable over time, but also how the level of that variable affects the level of inequality between countries.

Using this approach do have costs, most of which is bared by the principle of parsimony. The inclusion of the mean explanatory variables doubles the amount of (time-varying) variables in the model, but the loss of parsimony is at least partially compensated through a more complete picture of the relationships, by giving both level effects and effects over time. In addition, this approach does not have the same advantage of efficiency as an unbiased random effects model without country mean variables over the fixed effects approach, as the mean explanatory variables occupies degrees of freedom.

Biases associated with the random effects approach is known as cluster-level confounding. The random effects estimator use a weighted average of between and within estimators. If the between and within effects are different, then the random effects model will give an estimate between these two estimators. Issues arise when not including country mean variables and centering the within variables. The parameter estimates ignore level differences, and we get parameter estimates based on both change over time and the level of the variable between the countries. This issue is closely related to the ecological fallacy where level differences are used to explain changes[5] (Rabe-Hesketh & Skrondal, 2012, p. 150).

Although this approach eliminates the problem with cluster level confounding, it does not eliminate the inconsistency of the parameter estimates of endogenous time invariant variables (country-level variables) (Rabe-Hesketh & Skrondal, 2012, p. 253). The problem is that time invariant variables (cluster means) could be correlated with the intercepts (the omitted country-level variables).

This is analogous to the assumption that the time-varying variables (level one variables) are not correlated with the residuals at the lowest level. That is, that there are no omitted variables that correlates with both the error term ("all omitted variables" affecting the top decile income share) and the time-varying explanatory variables in the model.

The problem with endogenous country-level variables could be partially overcome using the Hausman-Taylor method (Rabe-Hesketh & Skrondal, 2012, pp. 253-257). However, the exact coefficients of the time invariant variables are not a primary concern for the research question. In addition, the Hausman-Taylor method is highly dependent on the specification.

3.3.2 Model specification

Formally the model used becomes:

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[5] Alternatively, in a cross-sectional context: some attribute of the group is used to explain differences at the individual level.

$$y_{tc} = \alpha_j + \beta occ_{tc} + \sum \beta^W x_{tc} + \epsilon_{tc}$$

$$\alpha_c = \gamma + \sum \beta^B \bar{x}_c + \varepsilon_c$$

$$\beta^W x_{tc} = \beta(x_{tc} - \bar{x}_c)$$

Where α_c is the country intercept, occ_{tc} is a time variable and the associated beta coefficient represents a linear time trend, β^W represent the within parameters, ϵ_{tc} the error term for the individual year in a country, ϒ is the mean intercept controlled for the between variables, β^B represents the between parameters and ε_c represents the country level residuals.

When using this hierarchical equation structure it becomes clear that the model allows for different within (β^W) and between (β^B) effects. It also show that the mean explanatory variables only affects the intercepts (the level in 1980) and not the variation over time. By separating the level and variation, the model also removes potential bias associated with using a random effects model, as the level of the explanatory variables are not used when estimating variation over time.

In the context of a longitudinal analysis, the within parameters represent the effect of a change in time, and the between parameters represent the level effect of the explanatory variable. This is useful, as the time invariant variables (the country means) cannot explain changes occurring over time. They can only explain why some countries have a higher or lower *level* of inequality.

3.4 Special statistical concerns for longitudinal data:

3.4.1 Trends, stationarity and autocorrelation

The research question implies that there is a trend in the dependent variable. This could cause some problems for the regression estimation, especially if the variable is non-stationary. A series is non-stationary if the autocorrelation parameter (rho) is equal to or larger than one[6].

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[6] $\in_{i,t} = \rho \in_{i,t-1} + \eta_{i,t}$, $|\rho| \geq 1$ non-stationary process, $|\rho| < 1$ stationary process. Intuitively we can say that changes in a stationary variable, that is, a variable that wanders within some boundaries, cannot have a fixed linear relationship with a variable that wanders indefinitely far from its mean.

A non-stationary series is said to have a unit root. A series with a unit root will tend to wander far from its mean and the variance of the observations will grow larger and larger over time. In fact, it will tend to infinity as the number of observations go to infinity.

Beck and Katz (2011, p. 343) points out that proportions as a dependent variable have boundaries for how large their variance can become. In the case of the top decile income share, we know that the proportion of the total income must lie between 10% and 100%. Even though series with proportions are very persistent, they simply cannot be integrated of first order.

To avoid making an inconsistent regression, explanatory variables must be integrated of the same order, meaning they have to be stationary as well. Some explanatory variables are stationary by the same logic as the income share (for example union density and unemployment rate) while some have to be transformed. See Data collection for details about the variables.

Another problem with trends is autocorrelation, which will estimate standard errors that are too small, resulting in too much confidence to the estimates, and are frequent in time-series and longitudinal data. We have autocorrelation when the residuals are correlated, which violates of the assumption of independent residuals. This is one of the concerns Collier et al. (2004) had with introducing temporal subunits. If left uncorrected we could easily do a spurious regression, where we observe a significant relationship even though it is purely due to chance.

One way to eliminate autocorrelation is using a lagged dependent variable in the model. However, Rabe-Hesketh and Skrondal (2012, pp. 272-273) show that lagged dependent variable models produces inconsistent parameter estimates as a result of the initial-conditions problem, which will say that we assume that the initial response (the top decile income share in 1981) is uncorrelated with the random intercept (all country level variables omitted). It seems highly unlikely that the income inequality in the countries in 1981 is uncorrelated with the level of inequality in the countries and all aspects of inequality left out in the model, which means that a lagged dependent variable will produce biased estimates. Plümper, Troeger, and Manow (2005, pp. 342-343) advocates the use of lagged residuals to eliminate autocorrelation, as it produces consistent parameter estimates, in contrast to when a lagged dependent variable is included.

When using a multilevel model it is possible to correct for autocorrelation by specifying a residual covariance structure. As there are missing data it is important to specify a covariance structure that is as close as possible to the 'correct' structure in order to get consistent parameter estimates and to improve the efficiency (meaning estimated standard errors closer to the correct values) (Rabe-Hesketh & Skrondal, 2012, p. 298).

3.4.2 Cross-sectional correlation

In long panels one must also account for cross-sectional correlation (Frees, 2004, p. 286). Cross-sectional correlation is correlation because of linkage between countries. It could be that a global event affects the income distribution in all countries in the same year. This correlation can be estimated using a two-way error-components model (Rabe-Hesketh & Skrondal, 2012, pp. 435-436). The resulting cross-sectional correlation was estimated to 5.13e-21, indicating negligible cross-sectional correlation. An ordinary two-level random-intercept model is therefore the pragmatic choice, as adding a residual covariance-structure is easier in these models.

3.5 Model specifics and building process:

3.5.1 Dynamics

If dynamics are not taken into account, we are implicitly assuming that all variables only have an immediate impact on the income share. This seems unlikely to hold. Bartels (2008, pp. 13-14) advocate the use of a lagged dependent variable to account for dynamics when analyzing longitudinal data.

By using a lagged dependent variable[7], we are assuming that the effect of a variable declines geometrically and that the explanatory variables have identical persistent effects.

[7] That is, including the value of the dependent variable at the previous measurement occasion as an explanatory variable.

This is a strong assumption that might not be appropriate. In addition to this, as discussed in the section about autocorrelation, bias associated with the inclusion of a lagged dependent variable is undesirable.

Beck and Katz (2011, pp. 338-339) points to the possibility of including both a lagged dependent variable and potentially lagging independent variables to allow for both long lasting effects and immediate effects. This approach has the advantage of restricting the loss of observations, compared to fitting many lags, but it does not solve the issue of bias associated with the inclusion of a lagged dependent variable.

To account for potential lasting effects a model containing three period lags were fitted, and insignificant lags were removed. When lags are included in the variable, we are not only regressing the dependent variable on the explanatory variable, but we are also regressing it on previous values of the explanatory variables. When three lags are included, the model allows the variables to have effects lasting up to three years after the initial change of the variable. The advantage of this procedure is that it does not assume identical dynamics of the explanatory variables (Plümper et al., 2005, p. 335) and it will not bias the coefficients. However, this comes at the cost of losing observations[8], and potential long lag dynamics are not detected.

3.5.2 Estimation

When estimating a multilevel model the most commonly used method is maximum likelihood (ML). ML is generally robust, and produces estimates that are asymptotically efficient and consistent. With large samples, ML estimates are usually robust against mild violations of the assumptions, such as having non-normal errors (Hox, 2010, p. 40).

However, restricted maximum likelihood (RML) is more realistic and should improve estimation, especially when the number of groups is small. The differences in practice are usually small. If the differences are nontrivial then RML usually performs better. There are two advantages associated with using ML: computations are generally easier and it offers the

[8] We lose observations equal to the number of lags for each country at the start of the period, in addition to the same amount for each gap in the data of a country.

option to use an overall chi-square test based on the likelihood function to compare two models that differ in the fixed part.

RML has more attractive qualities regarding the limited sample (relatively few countries). RML accounts for the degrees of freedom lost in estimating the lowest level parameters, which ML does not. In addition, the differences between the ML and RML estimates will grow larger as the number of parameters grow (Frees, 2004, p. 103). However, Frees (2004, p. 103) recommends using “ordinary” likelihoods for LR-tests, even when evaluating RML estimators.

Regression results and the discussion will be based on result of RML estimation, except where indicated otherwise. However, ML was used when different models were fitted, and the LR-test functioned as a model selection criterion.

3.5.3 LR-test

The maximum likelihood procedure produces a log likelihood statistic, which can be transformed to the “deviance”. The deviance is obtained by multiplying the model log likelihood by minus two, and it indicates how well the model fits the data. If two models are nested, the deviance of the two models can be used to compare their fit statistically.

A lower deviance always implies a better fit, and the model with more parameters will always have a lower deviance. The LR-test helps us to test if the difference in deviance, and hence the parameter(s) of interest, are statistically significant.

The difference of the deviance is (approximately) distributed as a chi-square statistic with degrees of freedom equal to the difference in parameters estimated in the models. If the difference in the deviances exceeds the critical chi-square value, the model with all the parameters fits data significantly better than the reduced model.

As Stata gives the log likelihood and not the deviance the likelihood ratio test statistic is computed as follows: 2*(LL (full model) – LL (reduced model)). If this statistic should exceed the critical chi-square value given the parameter difference, the full model is accepted (Luke (2004, p. 34) , Hox (2010, p. 47) , Frees (2004, p. 99)).

3.5.4 Residuals and covariance structure

The likelihood is based on assuming multivariate normality of the total residuals. Even if this assumption is violated, point estimates of regression coefficients will remain consistent, as long as the fixed part of the model is correctly specified. The same applies to the model based standard errors, as long as the covariance structure is correctly specified (Rabe-Hesketh & Skrondal, 2012, p. 298). As long as the distribution of the total residuals is symmetric, ML not only produces consistent regression coefficients, but is also unbiased in small samples, even if the covariance structure is incorrectly specified. However, this is conditional on no missing data or that the missing data are random. Since there are missing data in the analysis, finding the best residual structure to reduce the downward bias of the standard errors is of interest.

The default residual covariance structure in Stata is independent, meaning that all residuals are independent and identically distributed with one common variance. In longitudinal analysis, this is inappropriate due to autocorrelation. As a result, multiple alternative residual covariance structures were tested. All covariance structures that are constant across subjects can be obtained by imposing restrictions on the unstructured model and are hence nested in the unstructured model. Therefore, we could conduct a likelihood-ratio test to compare a structured model to the unstructured model (Rabe-Hesketh & Skrondal, 2012, p. 322). An unstructured model has $n(n + 1)/2$ parameters, where n are the number of occasions (Rabe-Hesketh & Skrondal, 2012, p. 298). This is a huge matrix, and is in practice not possible to estimate in this data material.

Fortunately, all models are nested in the unstructured model, and the identity (called independent in Stata when talking about the residual covariance) structure is nested in all models (Rabe-Hesketh & Skrondal, 2012, p. 297). This means that we can reverse the procedure and test the independent model against structured models.

Rabe-Hesketh and Skrondal (2012, p. 325) recommends selecting a residual structure before selecting the mean structure (fixed-part) of the model. This is because the inferences for the regression coefficients depend on the specific residual structure. They recommend first adding all potentially relevant explanatory variables, then find the best fitting residual structure and keep the chosen residual structure when refining the model.

The modeling process is partly[9] following a bottom-up approach as suggested in the literature (Gelman & Hill, 2007, p. 69; Hox, 2010, p. 56; Luke, 2004, p. 23).

(1) A model with all the explanatory variables, country means at level 2 (country-level) and the country mean centered variable at level 1 (occasion-level), was fitted. Next, the residual structure were chosen.

(2) To account for dynamics, three-year lags were included for all within variables. The insignificant lags at 10% were removed.

(3) Cross-level interactions of country mean and the corresponding within variable were tested and insignificant interactions were removed. Other potential level 1 and cross-level interactions were tested.

The reason for exploring potential cross-level interactions between the country mean variables and the corresponding within variables is that there might be stronger or weaker effects depending on the average level of the variable.

[9] The usual step after fitting the level 1 structure is to test for random slopes before testing for cross-level interactions. However, as LaHuis and Ferguson (2009) points out, there is generally low power for tests of slope variation. The lack of power can give insignificant random slopes, even though the model is capable of estimate cross-level interactions.

4 Data collection

This chapter describes the data collection process. It provides reasoning behind the choice of each variable and issues related to the choice. The chapter ends with a discussion of the case selection, statistical significance testing and generalization.

The data used have been collected from widely recognized sources. Data on each variable have been collected from the same source in order to maintain comparability. Even though the sources are widely recognized, there may be different flaws. It is assumed that eventual flaws are minimal, and that they have a negligible impact on the results.

4.1 Income share

<u>Measure</u>

Inequality is a complex subject, and there are varieties of commonly used measures to capture the concept. Two of the more commonly used measures are the Gini-coefficient and inter decile ratios.

The Gini-coefficient is a synthetic measure that builds on the Lorenz curve. The Lorenz curve is a curve that plots the income share of each percentile of the income distribution. In a utopian society the line would be a straight line (each percentile have 1 percent of the income). Inequality is thus defined as the curve's deviation from this straight line. The Gini index is the area between the Lorenz curve and the straight line as a percentage of the entire area beneath the straight line (Jantzen & Volpert, 2012, p. 825).

The strength of the Gini coefficient lies in its ability to summarize the income distribution in one index value. The Gini coefficient makes technical sense, but it is an artificial statistical measure that can be difficult to interpret. Piketty (2014, p. 267) criticizes the Gini coefficient for giving an abstract and sterile view of inequality. Also, when we use the Gini index we simplify matters and ignore that there are different social realities, economic and political significance of inequality at different levels at the income distribution (Piketty, 2014, p. 266).

Interdecile ratios is the ratio between a given percentile and another. The most frequently used is the ratio between P90 (the lower income threshold for belonging to the upper 10% distribution) and P10 (the upper income threshold for belonging in the lowest 10% of the distribution).

The ratio gives more information about how skewed the distribution is compared to the Gini coefficient. However, the ratio ignores what is going on in the upper and the lowest decile, and ignores how much of the total income that the upper decile claims. It is also highly dependent on the exact threshold, which will vary depending on for example what period of work (monthly, weekly, annual etc.) the ratio is based on. The interdecile ratio could for example be quite high even though the bottom 50% of the labor income distribution draws a fairly stable share of the income from labor (Piketty, 2014, pp. 267-269).

Piketty (2014) promotes the use of deciles (or other breakdowns of the income distribution into percentages), justified by comparability, interpretation and transparency. His fundamental goal is to compare structures of inequality in societies that are different across both time and space. Different societies use different words and concepts when they refer to social groups. Even though the concepts of deciles and centiles are rather abstract they allows us to compare inequalities that would otherwise be incomparable, using a common language that should in principle be acceptable to everyone (Piketty, 2014, p. 252).

Interpreting the top decile income share is easier to interpret than for example the Gini-coefficient. While the Gini-coefficient gives a number for the total inequality, which is a highly abstract and technical value hard to grasp, the top decile income share tells how much of the total income the top ten percent earners get.

"The way one tries to measure inequality is never neutral" (Piketty, 2014, p. 270), and the top decile income share is no exception. It ignores the distribution of income in the top decile itself, and in the bottom 90%. It is also a relative measure, and as such, there is more than one way it can change. The share might increase because of the top earners earning more while the rest of the population have a stable income as a group. It may also increase because the bottom 90% earn less, while the income of the top ten percent is stable. A third possibility is that both groups experience an increase in income, but that the top ten percent gains more (equivalent for a decrease, if the top decile experience a lower decrease).

Data

Data on the top deciles' gross income share were collected from the World Top Income Database (WTID). See the Appendix for variable names and codes used for each country.

Canada has data on both the category "Top 10% income share" and "Top 10% income share-LAD". The solution was to use only the data from the LAD variable for two reasons: First, using only one measure ensure internal consistency (an alternative could for example have been to use the mean of any overlapping years). Secondly, when choosing a single variable, the LAD-variable offers most data. United Kingdom also has data from two sources, but no overlapping years. There appears to be a level difference between the two series, but the trend appears to be consistent. Using both series, a sensitivity analysis was conducted between the model with all data and on a model where the first series is set to missing (see Diagnostics and model specification).

The data are estimated from historical tax statistics. As the data are based on reported income, it may be that that they do not represent the real income. There may be both tax evasion and tax avoidance, likely to be correlated with the tax level (Piketty & Saez, 2006, pp. 200-201).

However, Piketty and Saez (2006, p. 200) affirms that their main motivation for the database came from dissatisfaction with existing income inequality databases. It is therefore expected that even though the data based on the tax statistics are not perfect, they offer more homogeneity across time and space than earlier databases.

The income share variable was converted to, and used, on the logarithmic scale. The reasoning is that the income share by construction cannot be negative. According to Gelman and Hill (2007, p. 59) it commonly makes sense to take the logarithm of outcomes that are all-positive. One reason for this is that a regression model imposes no constraint that would force the predictions to be all-positive on the original scale. When we take the logarithm of the outcome, make predictions on the log scale and transform back, the predictions are necessarily positive.

The interpretation changes with the transformation. It is hard to imagine a strict linear association between the explanatory variables and the top income share, as is assumed if the raw income share is used. It makes more sense that a unit change in for example top statutory tax rate to have a proportional relationship with the top income share rather than a fixed linear relationship.

The income share variable is also somewhat skewed and logarithmic transformations are convenient means of transforming a skewed variable into one that is more approximately normal (Benoit, 2011, p. 2). Normality of the dependent variable is strictly not an assumption (just normality of the residuals) but taken together with the benefit of all-positive estimates and a more realistic interpretation the log transformation makes sense.

4.2 Top statutory tax rate

Measure

To account for the top tax rates the top statutory tax rates are used. The top statutory tax rates are the tax rates as written in law. However, marginal tax rates (the tax payable on an additional currency unit of earnings) and average tax rates could be used.

The marginal tax rates is the rate that in theory should affect the incentives to work. The statutory tax rates are only one of more components that make up the marginal tax rates (tax deductions will make discrepancies between the statutory and marginal rates). However, marginal tax rates involve complex calculations that rely on a variety of assumptions, making comparison difficult (even over time within a country). The statutory tax rates are defined by legislation and do not require computations (OECD, 2012, p. 28).

The statutory tax rates have some advantages in international comparison. Policymakers cannot directly adjust marginal tax rates and changing the statutory tax rates is a powerful policy tool to indirectly modify incentives to work. In that manner, the statutory tax rate is a more direct measure of the actual policy and the policy tool.

The top statutory tax rates also have some weaknesses. First, they do not show the actual marginal top rates and are therefore only an approximation to the incentive driving marginal tax. Second, the tax brackets vary across both time and countries. Since this thesis investigates the top decile income share, the proportion of the top decile actually affected by the top tax bracket also varies across time and countries. Third, and related, tax progressivity varies across time and countries. The progressivity, or the degree to which tax rates increases with the income, is related to the tax bracket thresholds, the number of brackets and the difference between the tax rates in the brackets. Tax progressivity will presumably affect the incentives for workers in the bottom 90% to work, and is therefore relevant for the top decile income share. However, this is information not provided by the top statutory tax rates.

While acknowledging that the top statutory tax rate is not a perfect measure of tax policy and actual marginal top tax rates, it is generally accepted as a relevant indicator of taxation in international comparison (OECD, 2012, p. 28).

Data

Data on the top statutory tax rate in the period 2000-2013 were collected from OECDs Tax Database: "Table I.7. Top statutory personal income tax rate and top marginal tax rates for employees" the variable "Top tax rates" under the broader category "Top statutory personal income tax rates".

This database only contains data for the period 2000-2013. However, there are also some "historical tables" on OECDs webpages (OECD) that contains the information necessary to extend the top statutory tax rates series to include the period 1981-1999. In extending the series the explanatory annex (OECD, 2014) and the information in the spreadsheets were used. The general formula is: top central tax rate + top sub-central tax rate. Some countries have special surtaxes, which are also applied.

A special note concerning Switzerland: when calculating the top statutory tax rate the Tax Database uses the highest marginal central tax rate on Switzerland. In this thesis the highest *average* tax rate is used, which is 11.5% by law on the federal level. The data used in the whole time period (1981-2013) is thus adjusted for this. Country specific details concerning the calculation on the top statutory tax rates for the period 1981-1999 are listed in the Appendix.

4.3 Collective bargaining: Labor union density and extensions

Measure

While unions play an important part in the collective bargaining, the union density does not tell the whole story when it comes to people covered by the bargained agreements. Workers who are not union members may in fact be covered by the terms and conditions of union contracts by extension and enlargement. While a high rate of unionization leads to a high coverage rate, the opposite is not necessarily true (Traxler, 1994, p. 167).

This makes union density a crude measure of collective bargaining coverage. A more accurate picture could be painted by using the collective bargaining coverage rate. However, available data on the coverage rate is partial and fragmented. In addition, while the extension may increase wages for non-union members, it is unclear how the extension affects the union bargaining power.

It seems reasonable to assume that the bargaining power of any union is related to its member base. Members pay initiation fees, monthly dues and so on. More members means more resources for financing the activities previously mentioned in Unions and collective bargaining coverage. The effectiveness of the strike bargaining tool should also be closely related to the union member base. First, the more financial resources the unions have the more unionized workers the union can afford to take out to strike, and the longer the strike can go on thereby imposing a higher potential cost for the employer. Second, a higher unionization rate increases the rate of potential strikers within a firm or sector.

If a higher union density rate increases the bargaining position for the unions, then the higher union rate should increase both unionized and some of the non-unionized wages. The effect is two-fold: more workers covered by the bargained agreements, and more bargaining power. Extensions would only increase the amount of workers covered, but would not increase the bargaining power of the unions.

The collective bargaining coverage rate would in reality include two distinct groups, and using the collective bargaining coverage rate would treat all covered (either by being a union member or covered by extension) as one group, potentially diluting the bargaining power aspect. The effect of the collective bargaining coverage rate would probably depend on the proportion of the covered that are unionized. Consequently, it makes sense to treat unionized workers and workers covered by extensions as two groups. Optimally, we would have one variable as union density rate and one as the proportion of workers that are covered by extensions (coverage rate minus density rate). However, as mentioned, good data on coverage rates for the sample in question is hard to come by. A variable that captures extension mechanisms are included to account for any agreement benefits enjoyed by non-unionized workers.

Data

The data on labor union density were collected from the OECD database. The variable name in the database is: "Trade Union Density". It is *the ratio of wage and salary earners that are trade union members* to *the total number of wage and salary earners*. The data are mainly based on survey data and supplemented with administrative data.

Data on the extension score were collected from Visser (2013). The variable is named "Ext" in the database and is: 'mandatory extension of collective agreements by public law to non-organized firms.' The categories are as follows:

3: extension is virtually automatic and more or less general (including enlargements).

2: extensions is used in many industries, but there are thresholds and Ministers can (and sometimes do) decide not to extend (clauses in) collective agreements.

1: extensions is rather exceptional, used in some industries only, because of absence of sector agreements, very high thresholds (supermajorities of 60% or more, public policy criteria, etc.), and/or resistance of employers.

0: there are neither local provisions for mandatory extension, nor is there a functional equivalent.

4.4 Trade

Measure

Trade and trade openness have been measured in different ways in different studies. Roine, Vlachos, and Waldenström (2009) and Reuveny and Li (2003), for example, use the sum of imports and exports as a share of GDP as an indicator of economic trade openness. Mahler et al. (1999) take a different approach, separating trade penetration into import as a percentage of (sectoral share of) GDP and export as a percentage of (sectoral share of) GDP.

As indicated in Trade and economic openness there are theoretical reasons for expecting different effects from export and import. I therefore find Mahler et al. (1999)'s arguments for treating the import and export separately appealing.

Economic openness indicates that we are measuring the import/export/trade in relation to the rest of the economy. The reason for using the measures as a percent of GDP is to take into account the size of the rest of the economy. The larger the import/export/trade as a percent of GDP, the more open the economy is. An alternative measure could be the import/export/trade in value, or the annual percentage growth of the value. However, this would only measure the import/export/trade, and would not take into account the openness aspect.

Data

Data on exports and imports as a percentage of GDP were collected from the United Nations Conference on Trade and Development (UNCTAD). The dataset used is: "Goods and Services (BPM5): Trade openness indicators, annual, 1980-2013", and the flow of export and import as a percent of GDP is used.

4.5 Population

Measure

Kuznets (1955, p. 10) argued that demographics could reduce the income distribution. The argument is that the cumulative effect of savings raise the income for a progressively diminishing proportion of the total population. In other words, the rich becomes richer, but they are becoming a relatively smaller group of the total population.

There are also reasons to control for the population level. Small countries, for instance, tend to have a more open economy than larger countries. It is therefore of relevance to control for this, when the level of trade is of interest.

The population is the chosen indicator, but other measures could have been used, such as the labor force size. This could be a better measure given that it measures the economically active population plus the population actively seeking employment, but it does not include individuals out of the labor force (discouraged workers and people not seeking employment). A growing labor force could thus be due to workers entering the labor force after being discouraged. As such, an increase in the labor force is not necessarily reflecting an actual growth of the population (or working-age population), but rather an improved economic sentiment.

There are three population variables in the model. First, there is a level variable. This is the logarithm of the mean population size of the countries in the period. Second, the percentage growth of the population was used as a time varying population variable. Third, as with the other time varying variables, an average population growth rate in the period had to be included to account for potential country-level confounding.

Data

Population data were gathered from the OECDs dataset “Population”. “Population (hist5) All ages”. This variable is the basis for the country mean log population in the period. Data on the population growth rate were collected from OECDs dataset “ALFS Summary tables”, subject “Population growth rate”. The variable is the basis for the country mean population growth rate and the within population growth rate.

4.6 GDP

Measure

According to Kuznets (1955, p. 10) a dynamic economy should decrease the income inequality. In such a society, technological change is rampant and wealth is becoming less important as new industries are being born.

A commonly used indicator for economic development is the gross domestic product (GDP). This is not a measure without criticism (see Stiglitz (2012, pp. 228-232)). Both gross national product and national income could have been used, but due to the availability of data and the convention of using GDP (it will be easier to compare these results with earlier and future research), the GDP was used for a proxy of economic development.

Data

Data on national GDP were collected from the IMF. “Gross domestic product per capita, current prices” measured in US dollars. These data are the basis for the country mean log GDP, which is the average logarithm of the GDP for each country in the period. Data on the GDP growth rate were collected from OECD “1.Gross domestic product (GDP)”, transaction “Gross domestic product (expenditure approach), measure “Growth rate”. These form the basis for the country mean GDP growth – the average growth rate of the GDP in the period. It also forms the basis for the within GDP growth rate variable, which is centered on the country mean GDP growth rate.

4.7 Unemployment

Measure

Unemployment indicates how the supply and demand for labor is balanced at the given time. High unemployment indicates an oversupply of labor, which tightens the competition for the jobs, presumably resulting in a downward pressure on wages. Krugman (1994, p. 30) suggests that the lowest “productivity”-segments (lowest paid workers) of the labor force might have higher unemployment than higher “productivity”-segments (highest paid workers). If this is true, a high unemployment rate should hurt the lowest paid workers more than the high paid workers, in turn contributing to higher inequality.

The unemployment rate seems a natural choice of unemployment, but the measure does not include discouraged workers – people who wants to work, but is not actively searching for employment. The labor force participation rate is an alternative measure that could have been used, but this measure ignores the difference between the unemployed (those actively searching for work) and people who does not want to work. The unemployment rate is used, as it seems like a milder violation to ignore the discouraged workers than to treat the proportion of the population not wanting or being able to work with the population actively seeking employment.

Data

The data were collected from the International Monetary Fund's "The World Economic Outlook Database" (October 2014 Edition). The country mean unemployment is the average unemployment rate for the country in the period, and the within unemployment is the unemployment centered on the country mean variable.

4.8 Case selection and generalizations

The countries in the analysis are all members of OECD, and it would be tempting to view the countries as a sample from the broader universe of OECD member states. However, the sample in this thesis was not a result of randomized draws or equivalent procedures. They were selected from two criteria: 1) being a member of the OECD and 2) having data on the top 10% labor income share in the WTID in the period 1980-2013.

The sample does not follow the assumptions of randomized draws and independence, and generalizations out of the sample would violate the very foundation of statistical generalization. There could be confounding reasons for why the countries are included in the WTID, or that the other OECD countries are not included. If this is the case, then the results of the analysis would not representative for the broader OECD universe.

The population under investigation is the 19 countries in the period 1981-2011. If there had been no missing data the population could have been claimed. When the data covers the population, there is no larger entity for which generalization is relevant. Not all researchers use statistical tests in these situations. However, Rubin (1985) advocate the use of significance even with population data. He argues that social researchers often have the broader purpose of linking their findings to theoretical analyses, and therefore must address whether the explanatory variables helps explain why the differences among the subpopulations exist. Significance testing would be required in order to determine the likelihood that the observed differences among subpopulations could have been generated by a random division of the population into subpopulations. With the results of the significance test one is in a better position to discuss the credibility of the notion that explanatory variables helps explain the differences in the dependent variable.

Rubin (1985) also argues that if one has missing data, then the population cannot be claimed, and significance tests would be appropriate. This is central for this thesis, as there are missing data. The statistical hypothesis tests are an attempt to generalize the relationships to the whole period under investigation, in all the countries in the analysis (the population). This is appropriate if the missing data are missing at random. If the data are MAR, then the data available can be seen as a randomized sample of the years under investigation in the countries, and the statistical conditions for generalizations are met. It is worth noting that the generalization is only appropriate for the total period under investigation in the countries included in the analysis.

At a higher level of abstraction, significance testing is appropriate because populations are always evolving. If research is done in connection to problems in the hope of generating implication for future action then significance testing should be used as any population is no more than a sample of that population at any given point in time.

5 Descriptive statistics

This chapter presents numerical and graphical description of the variables. The chapter starts with describing the dependent variable, next a description of the explanatory variables follows. The chapter ends by presenting the correlation matrix and discussing the effects of multicollinearity.

5.1 Top decile income share variable

Conducting a meaningful longitudinal study requires some variation in the dependent variable. After all, what is the point in investigating possible explanations for variation in the dependent variable if it does not vary (King et al., 1994, p. 129)?

Following Beck and Katz (2011) a box plot of the top decile income share and a time-series plot of the variable is examined to see if there is sufficient variation within and between the countries.

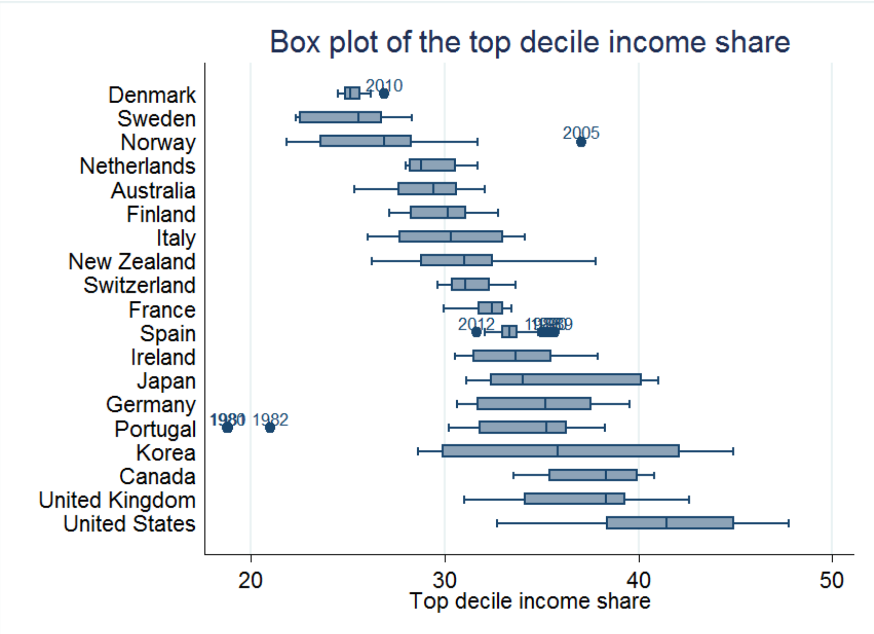

Figure 6 Box plot of the top decile income share by country

Figure 6 reveals significant differences regarding both the level of the top decile income share and the variation within the different countries. Some countries show little variation of their top decile income share, for example Denmark, France, the Netherlands, Spain and Switzerland, while other countries such as Korea and the United States show great variability over the period. Some countries show a persistently lower level on the top decile income share in the period than other countries. Denmark and Sweden, for example, have persistently lower levels than for example the United States. The plot makes it clear that there are some observations that is relatively far away from the other observations in the countries, notably in Denmark, Norway, Portugal and Spain.

Figure 7 below show how the top decile gross income share has evolved from 1980 up to 2013 in the 19 countries in this analysis. There is a trend toward a higher income share in most countries. However, Spain has actually had a declining trend, after an initial increase in the 1980s. It should be noted that each country is scaled differently.

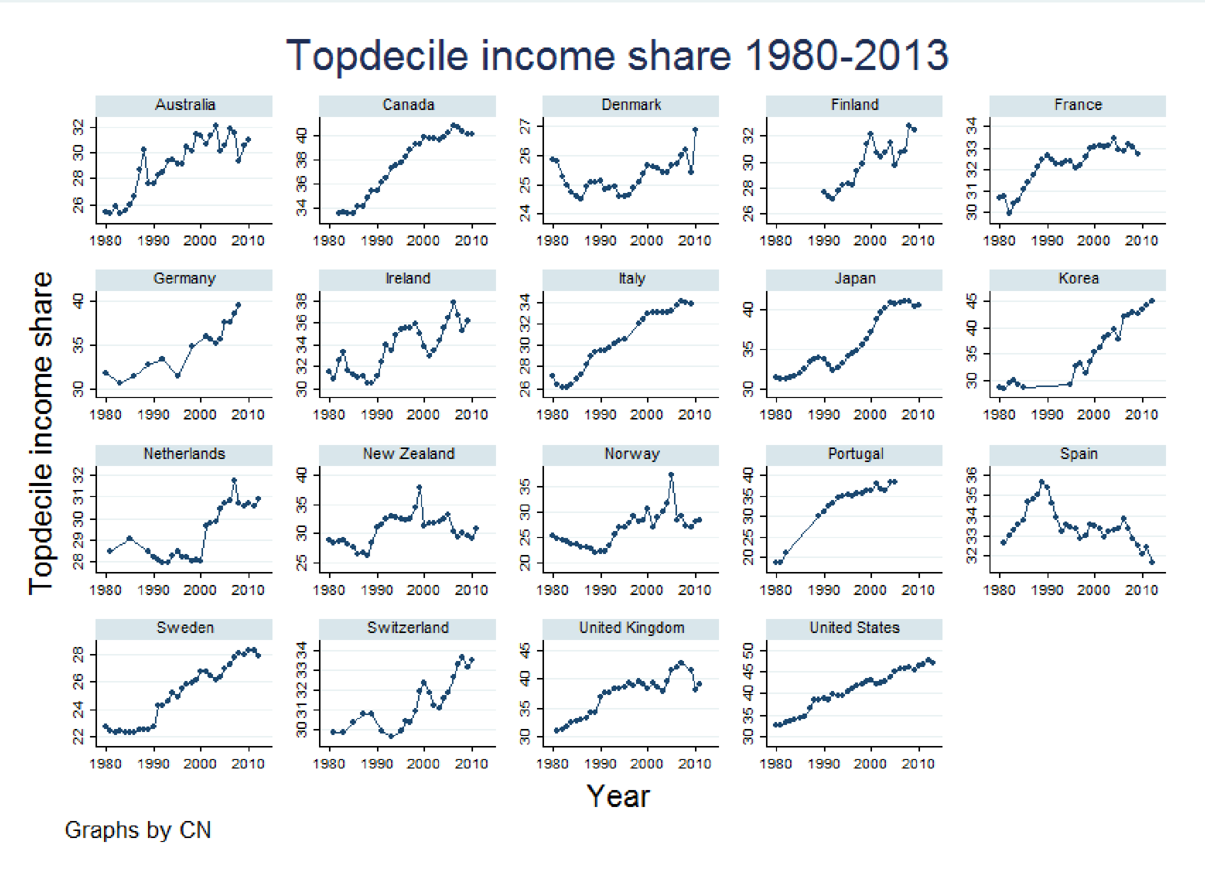

Figure 7 Top decile income share 1980-2013

We can see that there are different paths within each decade. The US and UK had a rising trend in the 80s, while Norway and New Zealand had declining trends. In the 1990s, Canada and Italy had increasing trends, while Spain and New Zealand had developments that are more inconclusive. In the 2000s, US continued to increase the share, as did Ireland, while

Spain reduced it and several other countries were quite stable. Overall, the development paths show substantial diversity.

Figure 7 also makes it clear that there are some missing values. There is, for example, no data on Finland before 1990, Korea have no observations between 1985 and 1995, and the Netherlands only have two observations in the period 1980-1988.

Table 1 displays the descriptive statistics of the raw income variable.

Table 1 Descriptive: Top decile income share

	Mean	St.dev.	Min	Max	Observations
Overall	32.1	5.23	18.77	47.76	531
Between		4.24	25.12	40.66	19
Within		2.94	18.05	42.65	27.95

There are 531 observations in total on the income share variable. The top decile income share in the sample varies from 18.77% to 47.76%, which is to say that across time and countries the observed average top decile income varies from 1.9 times the average income in the country in the given year, to 4.8 times the average income. The mean of 32.1 tells us that the average income share across both time and countries are 32.1% of the total labor income, and the average income in the top decile is 3.2 times the average income for the total population.

Looking at the differences within (over time) and between (across countries) we see that the standard deviation between the countries is larger than the standard deviation within, suggesting that, in the period under investigation, the difference across countries with respect to the top decile income share is greater than differences over time within the countries.

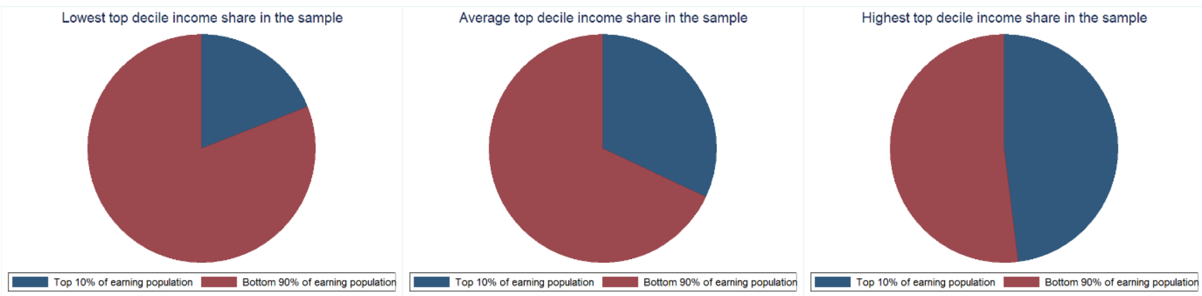

Figure 8 Top decile income share in the sample

Figure 8 above displays graphical how much of the total labor income that the top decile claims in the cases of the lowest, average and the highest income share in the sample. It is clear that here are substantial differences between the three scenarios.

5.1.1 Outliers

For Portugal, the outliers are in the early 1980s. There are missing data between these and up to 1989. If these are truly outliers, or just the start of an increasing trend is unclear. Knowing that the trends in the other south European countries (France, Italy and Spain) were a steep increase it seems likely that the outliers are outliers because of missing data, rather than being generated by another mechanism. The outliers for Spain seems to be a result of a period of higher income share rather than measurement issues.

We can see sudden spikes and trend breaks in Denmark in 2009 and 2010, in 1986 and 1987 in Australia, in 2000 in the Netherlands, in 1998 and 1999 in New Zealand, in 1990 in Sweden and in 2005 in Norway. There is also a small spike in the UK in 1990, which is related to the series break discussed in Income share. As it turns out, the Netherlands also has a break in the series between 2000 and 2001 (Salverda, 2013).

There were significant tax changes in Australia, Denmark, Norway and Sweden in the years close to the observed spikes in the income shares (Agell, Englund, & Södersten, 1995; Reinhardt & Steel, 2006; The Danish Ministry of Taxation, 2009; Thoresen, 2009). Saez, Slemrod, and Giertz (2012) discuss several behavioral changes associated with changing the tax system, some of which relates to income shifting and tax avoidance. This indicates that the observed spikes might not be because of 'secular' distributional changes, but rather a consequence of the tax reforms. Indeed, some of these tax reforms had a stated goal reducing incentives for tax avoidance. It is therefore reasonable to assume that the changes in the tax systems could potentially explain the spikes observed in the income share.

The relevance of these observations for the analysis could be discussed, as they are, at least partly, related to a phenomenon (tax reform) outside the scope of this thesis. The same goes for the Netherlands and the UK, as the break in the series introduce a level shock. The observations will affect the parameter estimates, and since they are not caused by the phenomenon of interest here, their impact will give skewed (biased) results.

The model found in Results is estimated using all available data. However, in Diagnostics and model specification the issue of outliers will be further discussed. In addition, models excluding the "outliers" are estimated to check for their influence, and to check if any results are substantially altered.

5.2 *Explanatory variables*

Table 2 Descriptive: all variables

Variable		Mean	Std. Dev.	Min	Max	Observations	Variable		Mean	Std. Dev.	Min	Max	Observations
log10	overall	3,46	0,16	2,93	3,87	N = 531	occ	overall	16,50	9,82	0,00	33,00	N = 646
	between		0,13	3,22	3,70	n = 19		between		0,00	16,50	16,50	n = 19
	within		0,09	2,92	3,80	T = 27,9474		within		9,82	0,00	33,00	T = 34
cm_tax	overall	51,36	6,79	39,99	63,57	N = 646	w_tax	overall	0,00	8,27	-14,84	33,86	N = 608
	between		6,97	39,99	63,57	n = 19		between		0,00	0,00	0,00	n = 19
	within		0,00	51,36	51,36	T = 34		within		8,27	-14,84	33,86	T-bar = 32
cm_logpop	overall	16,84	1,27	15,13	19,41	N = 646	cm_logGDP	overall	9,96	0,22	9,40	10,29	N = 646
	between		1,30	15,13	19,41	n = 19		between		0,22	9,40	10,29	n = 19
	within		0,00	16,84	16,84	T = 34		within		0,00	9,96	9,96	T = 34
cm_GDPgr	overall	2,48	1,09	1,28	6,33	N = 646	w_GDPgr	overall	0,00	2,36	-12,03	6,70	N = 646
	between		1,12	1,28	6,33	n = 19		between		0,00	0,00	0,00	n = 19
	within		0,00	2,48	2,48	T = 34		within		2,36	-12,03	6,70	T = 34
cm_unem	overall	7,22	3,25	2,44	17,04	N = 646	w_unem	overall	0,00	2,46	-8,82	9,06	N = 646
	between		3,33	2,44	17,04	n = 19		between		0,00	0,00	0,00	n = 19
	within		0,00	7,22	7,22	T = 34		within		2,46	-8,82	9,06	T = 34
cm_imp	overall	31,38	12,43	11,48	63,95	N = 646	w_imp	overall	0,00	5,73	-17,02	21,27	N = 646
	between		12,76	11,48	63,95	n = 19		between		0,00	0,00	0,00	n = 19
	within		0,00	31,38	31,38	T = 34		within		5,73	-17,02	21,27	T = 34
cm_exp	overall	33,18	14,90	9,74	72,43	N = 646	w_exp	overall	0,00	7,33	-29,56	35,01	N = 646
	between		15,30	9,74	72,43	n = 19		between		0,00	0,00	0,00	n = 19
	within		0,00	33,18	33,18	T = 34		within		7,33	-29,56	35,01	T = 34
cm_trade	overall	64,56	27,17	22,06	136,38	N = 646	w_trade	overall	0,00	12,73	-44,45	54,38	N = 646
	between		27,89	22,06	136,38	n = 19		between		0,00	0,00	0,00	n = 19
	within		0,00	64,56	64,56	T = 34		within		12,73	-44,45	54,38	T = 34
cm_popgr	overall	0,62	0,34	0,18	1,38	N = 646	w_popgr	overall	0,00	0,42	-2,12	2,88	N = 642
	between		0,35	0,18	1,38	n = 19		between		0,00	0,00	0,00	n = 19
	within		0,00	0,62	0,62	T = 34		within		0,42	-2,12	2,88	T-bar = 33,7895
cm_labor	overall	35,46	20,31	10,27	77,82	N = 646	w_labor	overall	0,00	6,78	-15,67	34,07	N = 621
	between		20,85	10,27	77,82	n = 19		between		0,00	0,00	0,00	n = 19
	within		0,00	35,46	35,46	T = 34		within		6,78	-15,67	34,07	T = 32,6842
cm_ext	overall	1,34	1,16	0,00	3,00	N = 646	w_ext	overall	0,00	0,39	-1,13	1,88	N = 607
	between		1,20	0,00	3,00	n = 19		between		0,00	0,00	0,00	n = 19
	within		0,00	1,34	1,34	T = 34		within		0,39	-1,13	1,88	T = 31,9474

Table 2 displays the overall, between and within variance of the variables in the regression models. We can see that the country mean variables (cm_*) show no variation over time (within), and that the variables centered on their country mean, (w_*), have close to no variation between countries.

The country mean variable all have 646 observations (N), over 19 countries (n) and 34 years (T). When looking at the 'within' variables it is clear that the mean time span for the variables varies. The GDP growth and unemployment rate are the only within variables with all observations, while within top statutory tax rate has a mean of 32 observations per country. This is due to the tax data starting in 1981, and that Korea is not included in OECD's historical tax tables. The first observation is also lost when calculating the import and export growth. Labor union density data stops in various years after 2010, and starts in 1981 for Spain. The data on extensions ends in 2012 for most countries, 2011 for Korea and the United States.

Looking at the country specific mean tax rate in the period (cm_tax) we can see that the mean top statutory tax rate in the period varies between 39.99% and 63.57% across countries, with a mean of the country mean top tax rate of 51.36%. The top tax rate over time varies between -14.84 and 33.86. That is, the country with the largest negative deviation of the tax rate from the period mean has a negative deviation of 14.84 percentage point from the country's average top tax rate in the period. The country with the largest positive deviation has a deviation of 33.86 percentage point over the period mean top tax rate.

Figure 9 below displays how the within variables have evolved over time in each country.

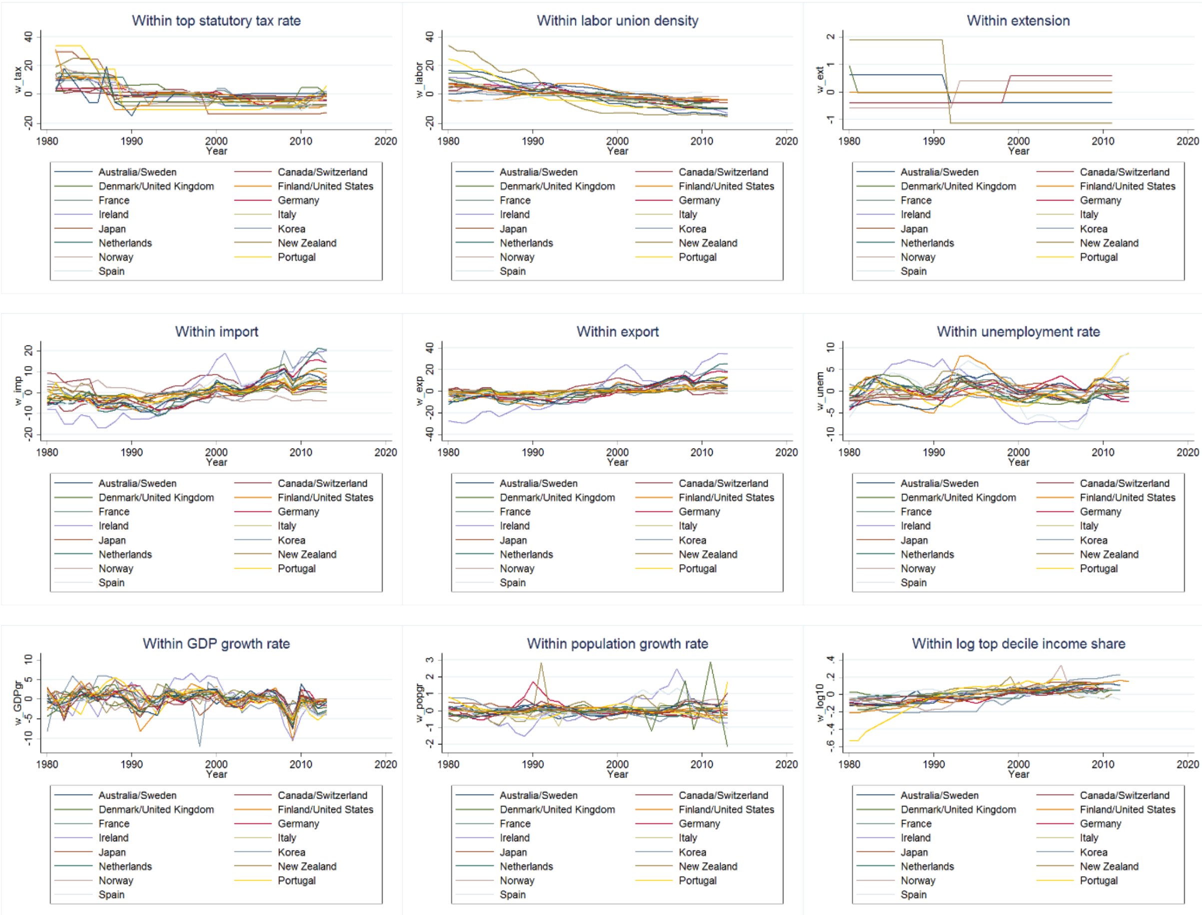

Figure 9 Evolution of variables over time

The top statutory tax rate and the union density show clear decreasing trends in the period, while the import and export variables have an increasing trend. As previously noted, the tax and labor union density variables cannot have a unit root by the same logic that applies to the income share. They cannot go below zero percent or higher than a hundred percent. The seemingly deterministic trend observed here is a result of the relatively short period of observation, and the long cycles of the variables. This may pose some problems concerning the standard errors. However, such problems should be mitigated by the choice of residual structure. There is also trends in the import and export variables; however, they not have any theoretical boundary. There is most likely a real limit. As with the tax and labor union density variables, choosing the correct residual structure can mitigate some of the problems concerning the standard errors. In addition to this, the alternative models introduced in Alternative measures and methods address the issue further.

The remaining variables show cyclical behavior, but there does not appear to be any problems concerning deterministic trends. It is worth noting that relatively few countries have actually changed extension classification in this period.

Table 3 displays the casewise correlation matrix for all the variables.

Table 3 Correlation matrix

	log10	occ	cm_tax	w_tax	cm_logGDP	cm_logpop	cm_GDPgr	w_GDPgr	cm_unem	w_unem	cm_imp	w_imp	cm_exp	w_exp	cm_trade	w_trade	cm_popgr	w_popgr	cm_labor	w_labor	cm_ext	w_ext
log10	1,00																					
occ	0,39	1,00																				
cm_tax	-0,31	-0,03	1,00																			
w_tax	-0,34	-0,67	-0,01	1,00																		
cm_logGDP	-0,15	-0,04	0,05	0,06	1,00																	
cm_logpop	0,59	-0,01	0,08	0,04	0,08	1,00																
cm_GDPgr	0,26	0,09	-0,39	0,01	-0,34	-0,12	1,00															
w_GDPgr	-0,03	-0,16	0,03	0,11	0,01	-0,01	-0,06	1,00														
cm_unem	0,19	-0,07	0,07	0,00	-0,40	0,13	0,03	0,06	1,00													
w_unem	-0,06	-0,21	0,00	0,20	0,08	-0,01	0,01	-0,06	-0,04	1,00												
cm_imp	-0,24	0,04	0,03	-0,06	-0,16	-0,64	0,26	0,03	0,08	-0,03	1,00											
w_imp	0,21	0,57	-0,06	-0,26	-0,04	0,03	0,07	0,07	-0,06	-0,42	-0,03	1,00										
cm_exp	-0,30	0,05	0,06	-0,04	-0,04	-0,67	0,26	0,02	0,00	-0,01	0,98	-0,03	1,00									
w_exp	0,25	0,63	-0,03	-0,33	-0,01	0,03	0,04	0,09	-0,08	-0,28	-0,05	0,89	-0,04	1,00								
cm_trade	-0,27	0,05	0,05	-0,05	-0,10	-0,66	0,26	0,02	0,03	-0,02	0,99	-0,03	1,00	-0,05	1,00							
w_trade	0,24	0,62	-0,04	-0,31	-0,02	0,03	0,05	0,08	-0,07	-0,35	-0,04	0,96	-0,04	0,98	-0,04	1,00						
cm_popgr	0,18	0,00	-0,55	0,03	0,14	-0,12	0,57	-0,02	0,05	0,01	-0,03	0,02	-0,03	0,00	-0,03	0,01	1,00					
w_popgr	0,04	0,23	0,04	-0,14	0,02	-0,01	-0,05	-0,07	0,07	-0,40	0,01	0,21	0,00	0,20	0,01	0,22	0,00	1,00				
cm_labor	-0,63	-0,01	0,31	-0,01	0,17	-0,63	-0,16	0,00	-0,21	0,06	0,29	-0,03	0,35	-0,01	0,32	-0,02	-0,29	0,00	1,00			
w_labor	-0,35	-0,71	0,02	0,59	0,05	-0,02	0,01	0,05	0,03	0,28	-0,01	-0,38	0,00	-0,44	-0,01	-0,43	0,03	-0,18	0,06	1,00		
cm_ext	-0,08	0,00	-0,04	-0,05	-0,36	-0,05	-0,14	0,01	0,42	-0,04	0,04	-0,01	-0,03	-0,01	0,00	-0,01	0,01	0,00	-0,38	-0,03	1,00	
w_ext	-0,05	-0,13	0,00	0,16	0,03	-0,01	-0,01	-0,07	-0,02	0,02	0,01	-0,07	0,01	-0,02	0,01	-0,04	-0,01	0,01	-0,01	0,57	0,02	1,00

There is much that can be said about the correlation matrix. I will limit my discussion and notes to the numbers highlighted in red. These correlations are above 0.6 in absolute value, and the reason for highlighting them is that they are so large that they will affect estimation of the standard errors. Due to the high correlation between some explanatory variables, the model has a hard time distinguishing the relative "effects" of the variables, inflating the standard error of the parameter estimates. A correlation of 0.6 yields a 25% higher standard error, and a correlation of 0.9 inflates the standard errors by 129% (Skog, 2004, p. 288).

The most severe correlation is between the import and export variables. The country mean import and export variables show a correlation value of 0.98. The within import and within export variables show a correlation of 0.89. There are also high correlations between the import and export variables and the trade variables. This is not surprising as trade it is the sum of the two. However, they do not appear in the same models, so any correlation between the trade and import/export is irrelevant.

Most of the high correlations are observed between country mean variables. This is particularly severe given the number of countries are only 19 (the number of units decrease the standard errors). Although the difference in the level of inequality is both important and interesting, the primary concern in this thesis is temporal change. Therefore, high correlations between country mean variables are not that crucial.

The within tax, within labor union density, within export, within import and within trade all substantially correlate with the time variable. The correlation with the time variable was clear when inspecting figure 9 (page 47).

It is worth noting that the correlation between the within variables and the country means are not completely gone. This is a result of missing data. As it is the casewise correlation matrix, cases without a value on all variables are dropped in the matrix, and this is tilting the correlation between the country mean and within variables. They are averaged using all of the data. When data points drop out, the mean value calculated with all data points is not identical to the mean value of all the data included in the matrix. This causes a slight correlation between some of the country mean variables and the within variables. The highest correlation is between the country mean GDP growth rate and the within country GDP growth rate, with a correlation of -0.06. This is a low residual correlation, and is expected to cause negligible bias to the parameter estimates. This is supported by a Hausman test, and by visual inspection of the difference between the parameters in the mixed and fixed models included in Alternative measures and models.

6 Results

The chapter starts with introducing technical hypotheses. Next, a regression model is introduced, and a primer for interpreting the parameters is given. Following next is a discussion of the hypotheses in light of the model.

6.1 *Hypotheses revisited*

In Theoretical and conceptual framework a set of general hypotheses were introduced. This section introduces a set of empirical hypotheses. The hypotheses in question are then tested using a regression model.

H1: *There is a significant negative relationship between the top statutory tax rate and the top decile income share*

H2: *There is a significant negative relationship between the labor union density rate and the top decile income share*

H3: *There is a significant negative relationship between the extension of collective agreements and the top decile income share*

H4*: There is a significant positive interaction between labor union density and import as a percentage of GDP*

H5: *There is a significant positive relationship between the growth of imports as a percent of GDP and the top decile income share*

H6: *There is a significant negative relationship between the growth of exports as a percent of GDP and the top decile income share*

6.2 *Regression model*

This is a log-linear model, meaning a unit increase in the associated variable multiplies the expected top decile income share by $e^{\widehat{\beta}}$. When the coefficient is small, we can use the approximation $e^{\widehat{\beta}} \approx 1 + \hat{\beta}$. This leads to the approximation $100 * \hat{\beta} =$ expected percentage change in the top decile income share for a unit change in the associated variable (Benoit, 2011, p. 4).

The “cm_logpop” and “cm_logGDP” variables are the logarithm of the mean population and GDP over the period, meaning a slightly different interpretation. The parameters are elasticities, and should be interpreted as the expected percentage change in the top decile income share when the variable changes by one percent. Increasing the explanatory variable by 1% multiplies the expected top decile income share by $e^{\widehat{\beta}*\log(1.01)}$.

The model below is built on all available observations, and the process leading up to this model is described in Model specifics and building process.

The coefficient is the average difference in the top decile income share when comparing two years (the lowest level of the analysis) that differ by 1 in the relevant explanatory variable while being identical in all other explanatory variables (Gelman & Hill, 2007, p. 34).

The expected (or estimated) effect, the phrasing used when describing the model, refers to the average difference when comparing two units (years) when these units differ by 1 measurement unit in the explanatory variable, controlled for all other variables in the model.

Table 4 Regression using all observations

```
Mixed-effects REML regression                   Number of obs      =       453
Group variable: id                              Number of groups   =        19

                                                Obs per group: min =         8
                                                               avg =      23.8
                                                               max =        28

                                                Wald chi2(24)      =    334.77
Log restricted-likelihood =  991.85899          Prob > chi2        =    0.0000
```

log10	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
occ	.0032779	.0007273	4.51	0.000	.0018524	.0047033
cm_tax	-.0103077	.0042173	-2.44	0.015	-.0185734	-.002042
w_tax	-.0067094	.0024342	-2.76	0.006	-.0114803	-.0019385
cm_logGDP	.2403548	.2512164	0.96	0.339	-.2520203	.7327299
cm_GDPgr	.0683415	.0525878	1.30	0.194	-.0347288	.1714117
w_GDPgr	.0015166	.0003943	3.85	0.000	.0007437	.0022895
cm_unem	.0150219	.0084189	1.78	0.074	-.0014789	.0315227
w_unem	-.0001219	.0008243	-0.15	0.882	-.0017375	.0014937
cm_imp	.0199159	.0109835	1.81	0.070	-.0016114	.0414432
w_imp	.0005072	.0008201	0.62	0.536	-.0011001	.0021145
cm_exp	-.0162247	.0103775	-1.56	0.118	-.0365644	.0041149
w_exp	9.24e-06	.0007547	0.01	0.990	-.00147	.0014885
cm_logpop	.0326228	.0526405	0.62	0.535	-.0705506	.1357962
cm_popgr	-.1717673	.1442111	-1.19	0.234	-.4544158	.1108811
w_popgr	-.0050979	.0030404	-1.68	0.094	-.0110569	.0008611
cm_labor	-.0008357	.0029683	-0.28	0.778	-.0066534	.0049819
w_labor	-.0069233	.00184	-3.76	0.000	-.0105296	-.003317
cm_ext	-.0026757	.0239269	-0.11	0.911	-.0495715	.0442201
w_ext	.0261798	.0090022	2.91	0.004	.0085359	.0438238
w_tax						
L1.	-.0005781	.0002313	-2.50	0.012	-.0010314	-.0001248
L2.	-.0004824	.0002257	-2.14	0.033	-.0009247	-.0000402
L3.	-.0004324	.0002044	-2.12	0.034	-.000833	-.0000319
c.cm_tax# c.w_tax	.0001107	.0000444	2.49	0.013	.0000237	.0001977
c.cm_imp# c.w_labor	.0001137	.0000545	2.09	0.037	6.84e-06	.0002205
_cons	.7635445	2.08583	0.37	0.714	-3.324607	4.851696

The regression model in table 4 contains a total of 453 observations. These are nested in 19 countries, with a minimum of 8 observations in a country, a maximum of 28, and an average of 23.8. The maximum amount of observations if there were no missing data is 532 (28*19). The first year of tax data is 1981, with three lags, we lose observations of the years 1981, 1982 and 1983. The extension data and the data on the labor union density limits the period to 2011, becoming the last year in the analysis. The actual period observed becomes 1984-2011 (28 years). With 453 observations, there are missing data on about 15% of the maximum amount of observations in the interval.

The model is estimated using restricted maximum likelihood, with the residual covariance structure set to AR1 (autoregressive of first order) by each country, estimating an AR1 autocorrelation coefficient for each country. The AR coefficients are included in the Appendix. The AR1-coefficients vary between 0.5748035 in the UK and 0.9985759 in Japan.

The intercepts are the average log-level of the top decile income share for countries with an average of zero in all the country mean variables, and a zero score on the within variables in the year 1980 and have not changed the tax rate the last three years. In short, the constant term is of little interpretative value in this model.

6.2.1 Tax:

Countries with a high average tax rate in the period tends to have a higher level of the top decile income share. For each percentage point increase in the average top statutory tax rate, the average change in the top decile income share is a 1.03% increase in the top decile income share, controlled for the other variables.

There is a negative relationship between the within variation of the top statutory tax rate and the top decile income share. On average, the top decile income share is 0.67% lower (in the year of impact) for each percentage point increase in the tax rate, controlled for the other variables. One of those other variables is a cross-level interaction between the average tax rate in the period and the change of tax rate in a country. This is what the somewhat cryptically labeled "c.cm_tax#c.w_tax" represents. This interaction is positive, meaning the estimate for the initial impact of tax is less negative the higher the average tax rate of the country. In fact, if we use the maximum and minimum average tax rate from Descriptive statistics we can calculate that the estimated initial impact for each percentage point tax increase lies between a reduction of 0.228% of the top decile income share and an increase of 0.033% (rounded). It is quite interesting that there is at least one country estimated to have a positive initial effect of a tax increase.

The use of the phrase “initial” is because there was found to be significant lags of a tax change. This means that the model estimates that the “effect” of a tax change is not limited to the year of implementation, but also affects the top decile income share over the following three years. The total estimated impact of the lag is a reduction in the top decile income share of 0.15% for each percentage point increase in the tax rate. This is more negative than the most positive estimated initial impact, indicating that the estimated total effect of a tax change is negative for all countries in the analysis.

The total estimated impact for each percentage point increase in the tax rate lies between a reduction of 0.3775% and a reduction of 0.1165% in the top decile income share in the sample.

Figure 10 displays the estimated total parameter for one percentage point change in the tax rate for each country. Multiplying the parameter by 100 yields the estimated effect of a one percentage point change in the tax rate for each country. It is clear that Korea, New Zealand and Switzerland are the three countries with the highest estimated impact of a tax change. Japan, Denmark and the Netherlands are the three countries with the lowest estimated impact of a tax change.

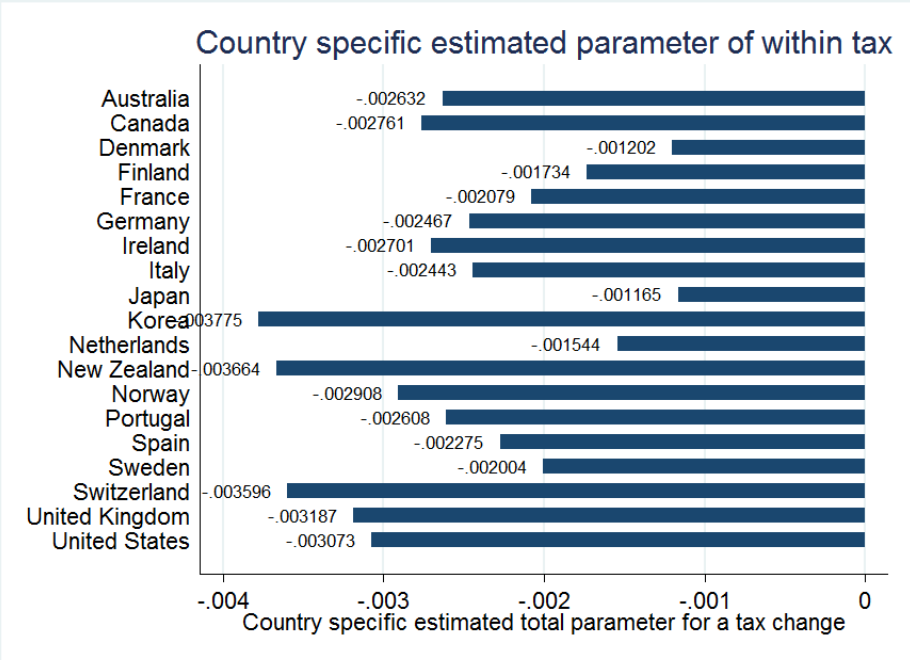

Figure 10 Country specific estimated total parameter of a tax change

H1: There is a significant negative relationship between the top statutory tax rate and the top decile income share

In this model, there is a negative and significant relationship between the top decile income share and the change of top statutory tax rate in the model, when controlling for the other variables. This relationship is complicated as there are both significant lags and an interaction between the average level of the tax rate and the within variation of the top statutory tax rate. Common for all countries, when accounting for the initial impact, the average tax level and the lag structure, the association between the within variation of the top statutory tax rate and the top decile income share is negative. The model thus supports the hypothesis of a negative association between the top tax rates and the top decile income share.

6.2.2 Collective bargaining:

There is a negative relationship between the average labor union density rate and the top decile income share. The estimated top decile income share is reduced by 0.08% for each percentage point of the average labor union density in the period, controlled for the other variables. There is a negative relationship between the average extension category in the period and the top decile income share. The estimated top decile income share is reduced by 0.27% for each integer value of the average extension category in the period, controlled for the other variables.

The association between the change of labor union density and the top decile income share is negative. The average estimated change in the top decile income share for each percentage point increase in the labor union density rate is a 0.69% reduction, controlled for the other variables. One of these other variables is the interaction between the average level of import as a percent of GDP in the period. Using the average country mean import as a percent of GDP in the period (31.59, see Descriptive statistics), we find that the average estimated "effect" of a percentage point increase of the labor union density is to reduce the top decile income share by 0.33%. The labor union density parameters in the sample lies between -0.005618 in Japan and 0.0003474 in Ireland.

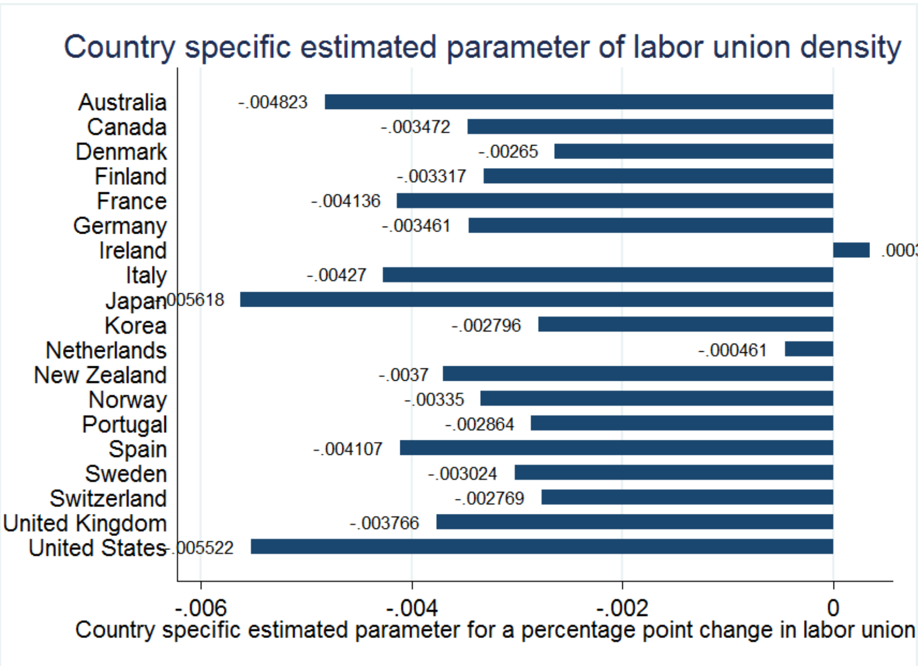

Figure 11 Country specific estimated parameter of within labor union density

Figure 11 displays the country specific parameter of the within labor union variable. Ireland and the Netherlands stands out as having the least negative parameters. Ireland even has a positive estimated effect of labor unions.

The association between the change of extension category and the top decile income share is positive. The estimated change in the top decile income share for each increase in the category of the extension variable is an increase of 2.62%, controlled for the other variables.

H2: There is a significant negative relationship between the labor union density and the top decile income share

In the model, there is a negative association between the union density rate and the top decile income share and this association is significant, when controlling for the other variables. The relationship is modified by the average level of import as percent of GDP in the period. The range of the within parameter of labor union when accounting for the country level of import is negative for all countries with the exception of Ireland. The model show support for the hypothesis.

H3: There is a significant negative relationship between the extension of collective agreements and the top decile income share

There is a positive and significant association between the change of the extension classification and the top decile income share in the model, when controlling for the other variables. There is thus no support for the hypothesis in the model.

H4*: There is a significant positive interaction between labor union density and import as a percentage of GDP*

There is a significant and positive interaction between labor union density and the average level of import as a percentage of GDP in the model, when controlling for the other variables. This model show support for the hypothesis.

6.2.3 Trade:

Countries with a higher average import as a percent of GDP had a higher level of the top decile income share in the period, controlled for the other variables. On average, the top decile income share is increased by 1.99% for each percentage point of the average import as a percent of GDP in the period. There is a negative association between the average export as percent of GDP in the period and the top decile income share. The expected top decile income share is reduced by 1.62% for each percentage point of the average export as a percent of GDP in the period, controlled for the other variables.

Regarding the change of import as a percent of GDP, the relationship with the top decile income share is positive. The model estimates that the top decile income share is expected to increase by 0.05% for each percentage point increase in the import growth, controlled for the other variables. The relationship is also positive for the change of growth of export as a percent of GDP and the top decile income share. The “effect” however, is both statistically insignificant, and substantively negligible.

H5: There is a significant positive relationship between import as a percent of GDP and the top decile income share

In the model there is a positive relation between import as a percent of GDP and the top decile income share, when controlling for the other variables. The relationship however, is statistically insignificant. There is no support for the hypothesis in the data.

H6: There is a significant negative relationship between exports as a percent of GDP and the top decile income share

There is a positive association between import as a percent of GDP and the top decile income share, when controlling for the other variables. The relationship is not significant. There is not support for the hypothesis in the data.

6.2.4 Control variables:

<u>Unemployment:</u>

There is a positive relationship between the average level of unemployment and the top decile income share. The estimated effect of unemployment on the top decile income share is that for each percentage point of average unemployment rate in the period, the top decile income share is increased by 1.5%, controlled for the other variables. The relationship between the change of unemployment rate and the top decile income share is negative. The estimated effect on the top decile income share is that it is decreased by 0.01% for each percentage point increase in the unemployment rate, controlled for the other variables.

<u>GDP:</u>

The association between the top decile income share and the average GDP per capita is positive. The estimated impact of a 1% increase of the average GDP per capita in the period, the top decile income share is increased by 0.24%, controlled for the other variables. The association between the average growth rate of GDP and the top decile income share is positive. The estimated effect on the top decile income share for each percentage point of average GDP growth in this period is an increase of 6.83%, controlled for the other variables. There is also a positive relationship between the change in the GDP growth rate and the top decile income share. The estimated impact of a one percentage point increase in the GDP growth rate is to increase the top decile income share by 0.15%, controlled for the other variables.

Population:

There is a positive association between the average population in the period and the top decile income share. The estimated effect of a 1% increase in the average population is to increase the top decile income share by 0.11%, controlled for the other variables. The association between the average population growth rate and the top decile income share is negative. For each percentage point of average population growth rate in the period, the top decile income share is reduced by 15.78% (not approximated), controlled for the other variables. The association between the change of population growth rate and the top decile income share is also negative. The estimated effect of each percentage point increase in the population growth rate is to decrease the top decile income share by 0.5%, controlled for the other variables.

Time:

Even after controlling for the other variables in the model there is a positive association between the time variable and the top decile income share. On average, the top decile income share is increased by 0.33% for each year, controlled for the other variables.

7 Diagnostics and model specification

This chapter presents a number of diagnostic plots of the model in the previous chapter. A qq-plot of the standardized residuals, a scatterplot of standardized residuals against fitted values, a time series plot of standardized residuals by country, a histogram of the estimated intercepts, a box plot of residuals by country and a missing data pattern figure are included. Next, different estimators challenge the model. The model is tested without the outliers detected, a fixed effects estimator, and first-differenced models. The growth rate of import and export is replaced with import/export as a percent of GDP, and a trade (the sum of export and import) growth rate and as a percent of GDP is tested.

7.1 Diagnostics

The diagnostics of multilevel models are often in form of graphical plots. The most commonly utilized plots are the qq-plot (quantile-quantile) of the standardized residuals (standardized residuals against their normal score), standardized residuals against the model estimated values (fitted values) and histograms of intercepts (Gelman and Hill (p. 46-48), Hox (p. 23-28), Luke (p. 37-42), Rabe-Hesketh and Skrondal (p. 204-206)).

Gelman and Hill (p. 46) argue that the most important mathematical assumption of the regression model is that its deterministic component is a linear function of the separate predictors. That is, the dependent variable is a linear function of the explanatory variables. After linearity, they rank the assumptions, in descending order of importance: the independence of errors, equal variance of errors and last normality of errors. Luke (p. 38) argues that two of the most important assumptions that can be empirically checked in a multilevel model are that the level-1 errors are independent and normally distributed, and that the random effects are normally distributed and independent (the only "random effects" in this model are the intercepts).

The qq-plot is useful to test for normality of the errors, and if normality is present, the plot should display a straight line. Plotting residuals against fitted values is a useful way to check for nonlinearity and heteroscedasticity. The assumption that the intercepts are normally distributed can be inspected by a qq-plot or by a histogram. To check for spatial and temporal independence of the residuals a time series plot of the standardized residuals and a box plot of the standardized residuals by country is included.

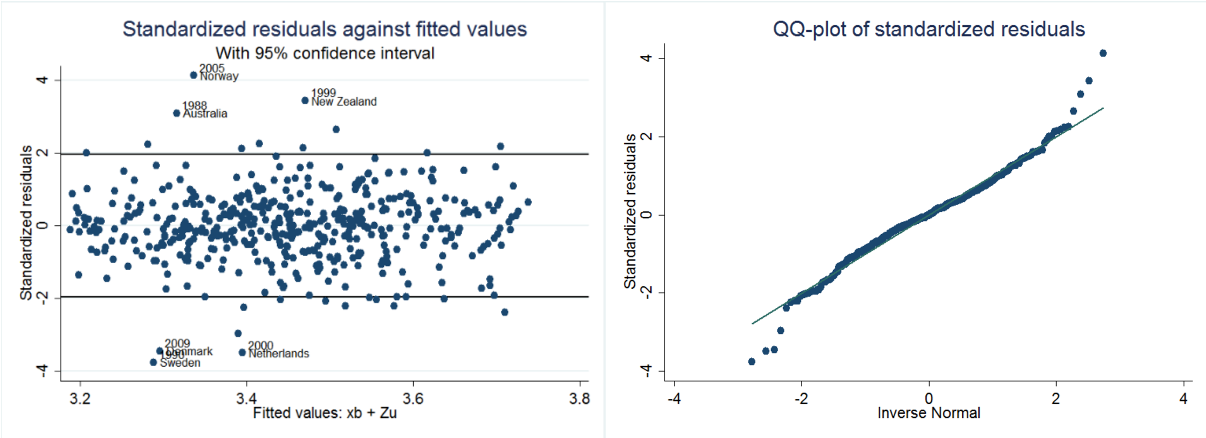

Figure 12 Standardized residuals against fitted values and QQ-plot of standardized residuals

Figure 12 to the left displays a plot of the standardized residuals versus the fitted values. The figure does not reveal any clear patterns, and the residuals seem to be quite equally distributed over the fitted values, indicating homoscedasticity. Overall, the assumption on linearity seems to be reasonably met. The observations marked by the country and year are the observations that are further than three standard deviations from zero.

We can see that the outliers corresponds to Norway in 2005, New Zealand in 1999, Australia in 1988, Denmark in 2009, the Netherlands in 2000 and Sweden in 1990. In Descriptive statistics these observations were pointed out, and there are reasons to believe that these observations are at least partially generated by other mechanisms.

Figure 12 to the right displays the QQ plot of the standardized residuals. The residuals follow the line quite nicely, except for the residuals at the ends. The normality assumption is not of the most crucial assumption, and overall the residuals seems to be distributed with a close conformity to the normal distribution.

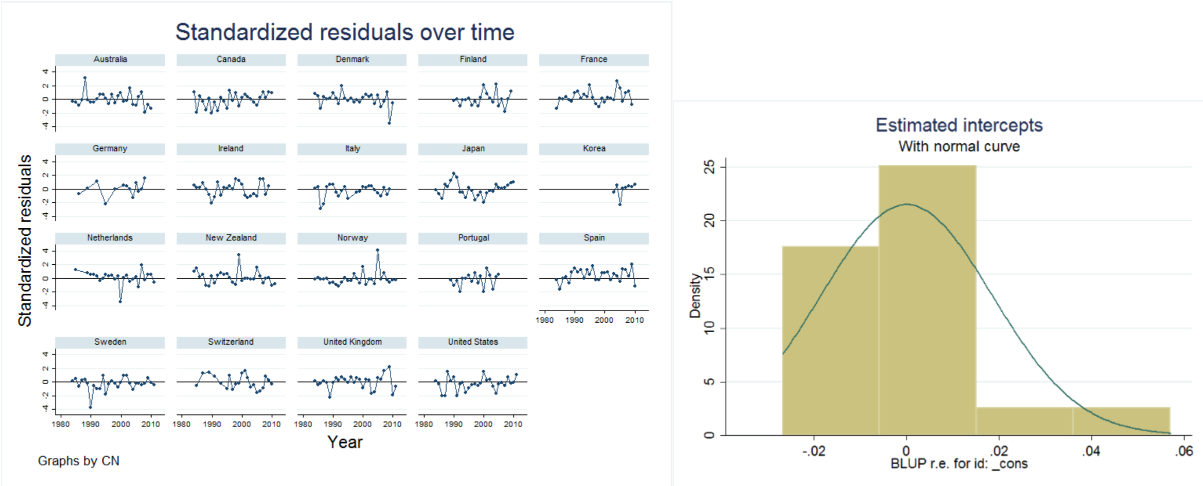

Figure 13 Standardized residuals over time and histogram of estimated intercepts

Figure 13 to the left plots the standardized residuals over time. The graph reveals that there are still patterns to detect in the residuals, even after fitting the residual structure. This does not affect the point estimates of the parameters, but will affect the standard errors and p-values, which could be somewhat underreported.

The histogram in figure 13 show the estimated intercepts. They appear to meet the normality assumption reasonably, given the sample size (19 countries), although they are biased toward normality. Consequently, it is hard to judge just how much the apparent of normality is due to bias. However, normality of the random intercepts and level-1 residuals is not required for consistent estimation of model parameters and standard errors, nor is it required for asymptotic normality of the estimators (Rabe-Hesketh & Skrondal, 2012, p. 101).

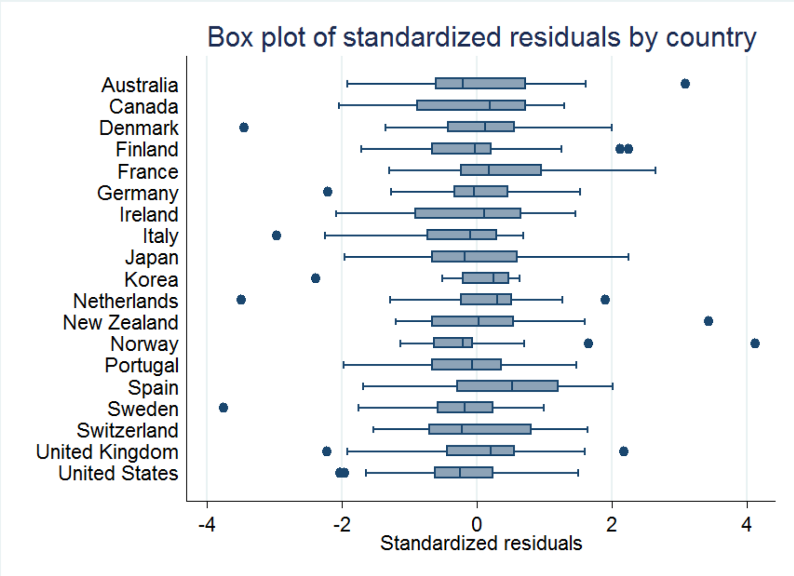

Figure 14 Box plot of standardized residuals by country

Figure 14 show the standardized residuals and their distribution for each country. They are primarily centered around zero, although the weight is somewhat scattered. The plot is an indication of whether the variance of the residuals are constant across countries. There appears to be uniform variance, although Korea stands out as country with below average variance. This could be due to the smaller amount of observations in the analysis of Korea.

Missing data

```
       id:  1, 2, ..., 19                                    n =         19
     Year:  1984, 1985, ..., 2011                            T =         28
            Delta(Year) = 1 unit
            Span(Year)  = 28 periods
            (id*Year uniquely identifies each observation)

Distribution of T_i:   min      5%     25%       50%       75%     95%     max
                         8       8      21        26        27      28      28

     Freq.  Percent    Cum. |  Pattern
 ---------------------------+------------------------------
        3     15.79   15.79 |  111111111111111111111111111.
        2     10.53   26.32 |  11111111111111111111111111..
        1      5.26   31.58 |  ...................11111111.
        1      5.26   36.84 |  ......11111111111111111111..
        1      5.26   42.11 |  .....11111111111111111......
        1      5.26   47.37 |  ..1..1..1..1..1..1111111111...
        1      5.26   52.63 |  .1...11111111111.11111111111
        1      5.26   57.89 |  .1.1.1.1.1.1111111111111111.
        1      5.26   63.16 |  1111.1111111111111111111111.
        1      5.26   68.42 |  111111.111111111111111111111
        1      5.26   73.68 |  111111111111..111111111111..
        1      5.26   78.95 |  111111111111111.111111111111
        1      5.26   84.21 |  111111111111111111111.111111
        1      5.26   89.47 |  111111111111111111111111.111
        1      5.26   94.74 |  1111111111111111111111111.1.
        1      5.26  100.00 |  1111111111111111111111111111
 ---------------------------+------------------------------
       19    100.00         |  XXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

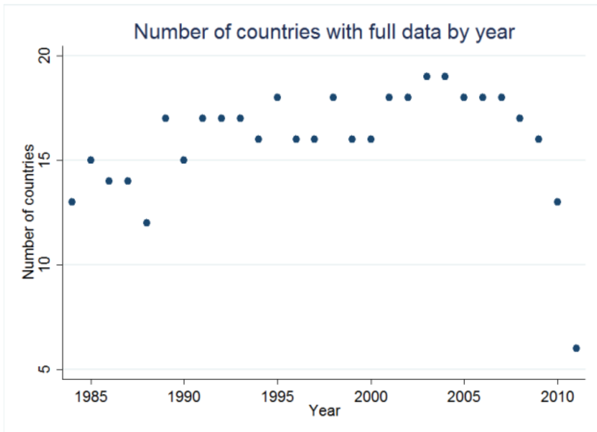

Figure 15 Missing data patterns

As mentioned in Research design, missing data could bias the coefficients. This only applies if data are not missing at random, meaning that missing data are missing because of the value the data would have had. There are two sources of missing data in this thesis: missing data on the dependent variable, and missing data on the explanatory variables.

The table in figure 15 displays the patterns of years with data on all explanatory variables and the dependent variable. “1” marks complete cases, while cases with missing data on one or more variables are marked with “.”. There are differences between the countries with respect to how much data they contribute. The country with the least amount of observations is Korea, which is not included in OECD’s historical tax tables. The figure to the right is the number of countries with full data in the given year, over the period with data. We can see that there is a slight tendency to be less data on earlier years, increasing slightly over time. However, in 2010 and 2011 there is a clear drop in the number of countries with full data.

As noted in Research design, the multilevel models utilize whatever data that are available. As long as data on the explanatory variables exist, the model utilizes this information to estimate a fitted value (Hox, 2010, p. 106).

Table 5 Missing estimated values

```
      id:  1, 2, ..., 19                                     n =         19
    Year:  1984, 1985, ..., 2011                             T =         28
           Delta(Year) = 1 unit
           Span(Year)  = 28 periods
           (id*Year uniquely identifies each observation)

Distribution of T_i:   min      5%     25%       50%       75%     95%     max
                         8       8      27        28        28      28      28

     Freq.  Percent    Cum. |  Pattern
 ---------------------------+------------------------------
       13     68.42   68.42 |  1111111111111111111111111111
        4     21.05   89.47 |  111111111111111111111111111.
        1      5.26   94.74 |  ...................11111111.
        1      5.26  100.00 |  1111111.11111111111111111111
 ---------------------------+------------------------------
       19    100.00         |  XXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

Table 5 displays the missing occasions of the estimated values. There is a substantially smaller amount of missing data in this table. This show some of the strength of multilevel models.

Clearly, there are more missing data earlier in the period. Combined with the general time-trend of increasing inequality could cause some bias. However, it is hard to tell how severe the problem is, as the result that would have been observed is by definition unknown.

7.2 Alternative measures and models

This section presents some alternative models. These models include a model estimated in the analogously to the model shown in Results excluding the outliers detected in the previous section. The same model (excluding outliers) will be presented using a fixed effects estimator, and a first difference approach. Analogous models will be presented using trade as a percentage of GDP, instead of import and export as a percentage of GDP.

Why the outliers are dropped

An outlier is, according to Barnett and Lewis (1994, p. 7)'s definition: "(…) an observation (or a subset of observations) which appears to be inconsistent with the remainder of that set of data.". If the outliers are generated by other mechanisms than the other observations, these outliers produce bias the parameter estimates of the phenomenon of interest. The problem with detecting outliers through fitting a statistical model to the whole data is that these outliers influence the choice of the model used to detect them. Through iteration, the identification of the error-prone observations is improved (Ecob & Der, 2003, pp. 3-4).

The approach taken is similar to the proposed method of Ecob and Der (2003) to handle outliers in longitudinal analysis. Their iterative approach starts with fitting a model on the complete data. Then, observations considered as outliers are temporarily deleted from the dataset and the model refitted. The data are then examined in the context of the updated model. Should outliers still be present, the procedure of deleting and refitting is repeated until convergence is achieved (Ecob & Der, 2003, p. 6). Using this approach poses the question whether we are adjusting the model to the data, or the data to the model. However, there are reasons to believe that the observed outliers are, at least partly, caused by other processes. Dropping the outliers is therefore considered uncontroversial.

Why the fixed effects model?

As noted in Research design, the mixed model eliminates the country level confounding (bias). Due to missing data, some correlation still exist between some of the country mean variables and the within variables, as noted in Descriptive statistics, which bias the mixed model parameters. In addition, there could be some cluster level confounding between the lag of the tax variable and the estimated country intercepts. These issues do not affect the fixed effects model. Using the same estimation method and residual structure, we can investigate if the parameter estimates and standard errors are (significantly) different.

Why the FD model?

When we are using a first difference (FD) model, we regress the change of the dependent variable on the change of the explanatory variables. As in the fixed effects model, the FD model solves the problem of omitted time invariant variables. The parameter estimates of the FD model are, however, dependent on the values of the explanatory variables to change for a substantial portion of countries over time. In other words, since we are regressing changes, there have to be enough change in the variable. If a variable show little variation, the estimate of the parameter becomes unreliable.

The advantages of using a FD model over a cross-sectional (pooled) model are greatest when unmeasured omitted variables bias the cross-sectional estimates, and when errors in the explanatory variables are strongly autocorrelated. However, the advantages of the FD model are weakened when the explanatory variables are highly correlated over time (multicollinearity) (Liker, Augustyniak, & Duncan, 1985, pp. 82-85).

The FD model should increase the confidence in the model, as it accounts for omitted time invariant variables, and should mitigate the issue of autocorrelation. However, this estimation comes at a cost. Differentiating the series filtrates away some of the variance in the data, resulting in larger standard errors and increases the risk of committing type two errors (Skog, 2004, p. 341). We also lose the observation at the start of the series, that is, one more than with the mixed models, in addition to one observation per country for each gap in the data. In addition, as in the fixed effects models, we cannot investigate what affects the level differences across countries while using the FD model.

As noted in Trends, stationarity and autocorrelation the trend of the variables might pose problems regarding the p-values of the regression models. In Descriptive statistics it was noted that the tax, labor union, import and export variables showed noticeable trends in this period. The associations and significance levels observed might be a construct of similar trends with the top decile income share, rather than any causal relationship.

The problems concerning trends also applies to the first difference model if there are trends in the change of the variables. Even though the top decile income share show a persistent trend over time, this might not be true for the *change* of the top decile income share over time. A time series plot of the change of all the variables are included in the

Appendix. There does not appear to be any problems regarding trends in the difference of any of the variables.

7.2.1 *Import and export models*

Table 6 Regressions: import and export

Variable	Mixed (all)		Mixed (no outliers)		Fixed (ML)		First-difference (mixed)		First-difference (fixed)	
	Coef.	P>|z|	Coef.	P>|z|	Coef.	P>|z|	Coef.	P>|z|	Coef.	P>|z|
occ	.0032779	(0.000)**	.0034643	(0.000)**	.0035426	(0.000)**				
cm_tax	-.0103077	(0.015)**	-.0090701	(0.002)**						
w_tax	-.0067094	(0.006)**	-.007846	(0.001)**	-.0078015	(0.000)**	-.0077666	(0.001)**	-.0074365	(0.001)**
cm_logGDP	.2403548	(0.339)	.9806193	(0.000)**						
cm_GDPgr	.0683415	(0.194)	.2177735	(0.000)**						
w_GDPgr	.0015166	(0.000)**	.0009845	(0.007)**	.0009253	(0.010)**	.0007783	(0.016)**	.0007549	(0.020)**
cm_unem	.0150219	(0.074)*	.0221265	(0.000)**						
w_unem	-.0001219	(0.882)	.0003624	(0.647)	.0006094	(0.427)	-.0001098	(0.886)	-.0003588	(0.637)
cm_imp	.0199159	(0.070)*	.0427789	(0.000)**						
w_imp	.0005072	(0.536)	.0005743	(0.441)	.0008666	(0.232)	.0005296	(0.430)	.0005166	(0.441)
cm_exp	-.0162247	(0.118)	-.036903	(0.000)**						
w_exp	9.24e-06	(0.990)	.0001592	(0.816)	.0000851	(0.898)	.0005113	(0.410)	.0005697	(0.361)
cm_logpop	.0326228	(0.535)	.029853	(0.405)						
cm_popgr	-.1717673	(0.234)	-.5064368	(0.000)**						
w_popgr	-.0050979	(0.094)*	-.004673	(0.112)	-.004825	(0.094)*	-.0058038	(0.021)**	-.0057228	(0.021)**
cm_labor	-.0008357	(0.778)	-.0002856	(0.892)						
w_labor	-.0069233	(0.000)**	-.0074177	(0.000)**	-.0070351	(0.000)**	-.0078994	(0.006)**	-.005822	(0.069)*
cm_ext	-.0026757	(0.911)	.0463821	(0.003)**						
w_ext	.0261798	(0.004)**	.0200617	(0.019)**	.0228688	(0.004)**	.0162444	(0.042)**	.0150633	(0.062)*
w_tax										
L1.	-.0005781	(0.012)**	-.0005375	(0.012)**	-.0006007	(0.003)**	-.0002807	(0.148)	-.000278	(0.156)
L2.	-.0004824	(0.033)**	-.0006749	(0.002)**	-.0007696	(0.000)**	-.0003498	(0.082)*	-.000352	(0.083)*
L3.	-.0004324	(0.034)**	-.0001255	(0.564)	-.0002244	(0.288)	-.0000925	(0.630)	-.0000713	(0.710)
c.cm_tax# c.w_tax	.0001107	(0.013)**	.0001324	(0.002)**	.000131	(0.001)**	.0001354	(0.001)**	.0001292	(0.002)**
c.cm_imp# c.w_labor	.0001137	(0.037)**	.0001335	(0.013)**	.0001259	(0.004)**	.0001687	(0.047)**	.0001173	(0.215)
_cons	.7635445	(0.714)	-6.9855	(0.009)**	3.315389	(0.000)**	.0040879	(0.000)**	.0051434	(0.374)
n		453		447		447		409		409

The first model, "Mixed (all)", is the same model as in Results. The second model, "Mixed (no outliers)", is the same model without the noted outliers. The third model, "Fixed (ML)", is the same model with the same residual structure (unique autoregressive parameters of first order for all countries) including country dummies, estimated using the mixed command in Stata with the "noconstant" option. This model is estimated using maximum likelihood, due to non-convergence using restricted maximum likelihood (as is used estimating the other models). The fourth model, "First-difference (mixed)", is a first differentiated model using the data with no outliers, the same relationships as the other models, and the same residual structure. The fifth model, “First-difference (fixed)” is also a first differentiated model on the data without outliers, with the same residual structure. However, it is a fixed effects estimator, estimated with country dummies using the mixed command in Stata, with the “noconstant” option.

The numbers in parentheses are the p-values of the coefficients with two stars indicating significance at the 5% level and a single star indicates a significance at the 10% level. The full Stata output of the models are listed in the Appendix, along with residual plots of the mixed model discarding outliers and the first-difference (fixed) model.

Results

The third lag of the tax lag is not significant in any of the models besides the mixed model with all observations. An LR-test on the mixed model without outliers reveals that the lag is insignificant. Only the second lag of the tax variable is significant at the 10% level in the FD models. As noted, the FD models are sensitive to multicollinearity, and the lags of the tax variable are highly correlated with each other. This combined with fewer observations and lower variation could be the cause behind the insignificant lags in the FD models. The interaction between the average level of taxation and within tax variable is significant in all models.

The labor union variable is significant at the 5% level in all models, except the fixed FD model, where it is significant at the 10% level. The interaction between the within labor union density and the country mean import as a percent of GDP is significant in all models except for the fixed FD model. The coefficient is similar to the estimates of the other models.

The within extension variable is positive and significant in all the models. The coefficient estimates are notably lower in the FD models. This could be due to the difficulties the FD models have with variables rarely changing, resulting in unstable parameter estimates.

The within import and export variables are positive, but statistically insignificant in all models.

One thing to note is that due to collinearity there cannot be included a time variable in the FD models. However, the constant term is the estimated change holding the other variables constant, in other words, change not accounted for. The intercepts in FD models are therefore closely related to the time variable in the other models[10].

The mixed model without outliers, the first series for UK and observations after the year 2000 for the Netherlands can be found in the Appendix. The results are not fundamentally different from the mixed model without outliers.

7.2.2 Trade models

The table below displays the same estimators as the table above, but instead of using import and export as a percent of GDP as two separate variables, trade (the sum of the two) is used.

[10] The time variable is the linear time trend not accounted for by other variables in the model.

Table 7 Regressions: trade

Variable	Mixed (all)		Mixed (no outliers)		Fixed (ML)		First-difference (mixed)		First-difference (fixed)	
	Coef.	P>|z|	Coef.	P>|z|	Coef.	P>|z|	Coef.	P>|z|	Coef.	P>|z|
occ	.0036649	(0.000)**	.0038316	(0.000)**	.0035806	(0.000)**				
cm_tax	.0014753	(0.418)	.001609	(0.396)						
w_tax	-.0063819	(0.008)**	-.0073286	(0.002)**	-.0077213	(0.000)**	-.0077564	(0.001)**	-.0074251	(0.001)**
cm_logGDP	-.482416	(0.000)**	-.5005867	(0.000)**						
cm_GDPgr	-.0258107	(0.248)	-.0294796	(0.208)						
w_GDPgr	.0015087	(0.000)**	.00097	(0.008)**	.0009109	(0.011)**	.0007735	(0.017)**	.0007515	(0.020)**
cm_unem	.0121739	(0.033)**	.0120924	(0.040)**						
w_unem	-.0001829	(0.809)	.0002458	(0.735)	.000437	(0.537)	-.0001121	(0.876)	-.000348	(0.627)
cm_trade	.0009661	(0.224)	.0010368	(0.208)						
w_trade	.0002711	(0.183)	.0003691	(0.050)**	.0004565	(0.012)**	.0005221	(0.003)**	.0005457	(0.002)**
cm_logpop	.0829268	(0.003)**	.0844466	(0.004)**						
cm_popgr	.1184186	(0.094)*	.1262046	(0.078)*						
w_popgr	-.0051424	(0.088)*	-.0047599	(0.104)	-.0046696	(0.105)	-.0057942	(0.020)**	-.0057283	(0.019)**
cm_labor	.0018403	(0.247)	.001904	(0.249)						
w_labor	-.0066218	(0.000)**	-.0071316	(0.000)**	-.007241	(0.000)**	-.0078789	(0.006)**	-.0057903	(0.070)*
cm_ext	-.0704292	(0.000)**	-.0719214	(0.000)**						
w_ext	.0275275	(0.002)**	.023016	(0.007)**	.0227265	(0.005)**	.0162298	(0.041)**	.0150849	(0.060)*
w_tax										
L1.	-.0005893	(0.010)**	-.0005434	(0.010)**	-.0006056	(0.003)**	-.0002809	(0.146)	-.0002773	(0.155)
L2.	-.0004843	(0.031)**	-.0006694	(0.002)**	-.0007605	(0.000)**	-.0003499	(0.082)*	-.0003521	(0.083)*
L3.	-.0004366	(0.032)**	-.0001197	(0.581)	-.0002132	(0.313)	-.0000923	(0.630)	-.0000713	(0.710)
c.cm_tax#										
c.w_tax	.0001043	(0.017)**	.0001228	(0.004)**	.0001296	(0.001)**	.0001352	(0.001)**	.000129	(0.002)**
c.cm_trade#										
c.w_labor	.000052	(0.031)**	.0001311	(0.012)**	.0001332	(0.002)**	.0001682	(0.047)**	.0001165	(0.217)
_cons	6.611103	(0.000)**	6.755589	(0.000)**	3.314521	(0.000)**	.0040896	(0.000)**	.0051685	(0.372)
n		453		447		447		409		409

First of all, the models are similar to the other models concerning the explanatory variables. We can see that the within trade variable is positive in all the models, which we would expect given that both import and export were positive in the earlier models. The variable is significant in all the models, except for the mixed model with al observations.

Interesting to note is that the interaction between the country mean trade variable and the within labor union density is positive, as earlier when the country mean import variable was used. As in previous models, the interaction is significant in all models except for the FD fixed model.

8 Discussion

This chapter reviews the findings of this thesis, answer the research question and places the results in the context of earlier research. First, the models and robustness are discussed. Second, a remainder of the sample and population is given, before a clarification about what support for hypotheses actually means. The rest of this chapter goes through the relationships of interest one by one.

Method

The main model used is a random effects model with between and within variables, separating level effects from changes over time. Because of the separation of the effects, the model is very close to a fixed effects model. The advantage of this approach, as opposed to a regular fixed effects model, is that the random effects model yields estimates of the level effects of the variables. These are consumed in the regular fixed effects model by the dummy variables. Due to the sample size and the likely omitted country level variables there are limits to what we can read out of the country level coefficients, but they can give valuable indications discarded in the fixed effects model. In addition, this approach allows for estimating other country level variables of interest, as well as incorporating random coefficients. These opportunities, however, can only be exploited with a sufficient sample, which is rarely the case in cross-national studies (Möhring, 2012).

Robustness of the findings were tested by omitting outliers, using a fixed-effects model, a first-difference mixed model, and a first-differenced fixed model. The models largely agree, with a few exceptions discussed below. The strong agreement between the models gives confidence in the results. In addition, this agreement reflects the model performance, despite considerable challenges, such as clear trends in the dependent variable and some of the explanatory variables.

Diagnostics were performed, and the results was encouraging, as no severe violations seems to have been made. There is always the issue of missing data, and whether these are missing at random. This is of course unknown. There were perhaps slight time trends in the missing data, possibly biasing the estimates, as we know that the trend in the top decile share have seen a general increase in the period.

The time trends in the tax, labor union, import, export, trade and the income share variables causes some problems concerning hypothesis tests and potential spurious findings. In the mixed and fixed models, this was handled using a residual structure (unique AR1 parameters). However, specifying a residual structure is no guarantee, and the analysis was supplemented with first differenced models. This increases the confidence in the results, as the trend issue seems to be overcome with the first differencing. The same residual structure was also specified in the FD models to tackle potential autocorrelation left after first differencing the variables.

Sample and generalizations

The sample here is the countries and the years where the countries have complete data. The population is the full period for the countries. The statistical tests is thus a test if the findings can be generalized to the whole period, for all the countries.

Since the selection of the sample of observations is correlated with the dependent variable (we know that the trend has generally been an increase in the top decile income share in the period under investigation), these findings need not be valid for other periods. The sample does not cover the full range of variation on the top decile income share. The "cycles" are extremely slow, and at present, there does not exist good, comparative data for the variables of interest to cover a full cycle on the top decile income share. This should be partly overcome by the use of longitudinal analysis, as we also get the cross sectional variation. Nonetheless, when the selection rule is correlated with the dependent variable, the numerical estimates of causal effects will be closer to zero than they really are (King et al., 1994, p. 130).

Causality and the hypotheses

The hypotheses implies causality, and indeed, this can be viewed as the overarching goal (to use Collier et al. (2004)'s terminology). When the hypotheses are evaluated, they are evaluated from a falsifying principle. The support for a hypothesis is not the same as claiming causality. It is simply a statement that in the data and with the analytical methods used; there is sufficient support for the hypothesis, relative to the null-hypothesis (of no relationship). Support for the hypothesis is *not* a validation of a causal relationship.

This thesis aims at answering the question:

"Can collective bargaining, tax policy and trade openness explain the increase in the top deciles' gross income share in OECD countries in the period 1981-2011?"

Each part of the research question is discussed below, before a final assessment of each component is made.

8.1 Tax

In Theoretical and conceptual framework the channels through which taxation can alter the income distribution were discussed. These were connected to the income and substitution effects, and the bargaining position for executives. These are theories operating at the individual level, and conclusions about the specific effects requires individual-level data with information about the hours worked and indicators of bargaining power. This thesis cannot conclude on these specific effects and their relative contribution. What we can conclude is how the aggregated effect of these and other effects concerning taxation and behavioral change relates to the top decile income share.

There were three significant negative lags in the model using all observations. However, the third lag was not significant in any of the other models. There is a possibility that the significance of the third lag is a construct of one or more of the observations dropped from the other models. Two lags are supported in the mixed and fixed models without outliers. The second lag was also significant at the 10% level in the FD models, although neither the third nor the first was significant.

The insignificance of the lags in the FD models could be due to some of the weaknesses with FD models in general. The models are less efficient when multicollinearity is present. The approach also filtrates variance and induce more missing data, lowering the statistical power of the model.

There could also be that the significant lags are a construct of the period under investigation. As the FD models lose more observations at the beginning of the period, there is necessarily more data lost at the start of the period. There is the possibility that the lags are only applicable to the earlier part of the period. However, using the mixed approach on the same observations as the FD models reveals that the two first lags are still significant. This poses the question: are there any theoretical reasons to expect a lag structure of the tax rate on the income distribution?

Saez et al. (2012) discuss several potential individual behavior responses to tax changes, some of them related to timing. If, for example, individuals anticipate a tax increase, they have incentives to accelerate taxable income realizations before the tax change takes place. As a result, reported taxable income just after reform will be lower than otherwise. In addition, if current income tax rates increase while long-term future expected income tax rates do not, individuals might decide to defer some of their incomes. Adjusting to changes in taxation could also take time, as individuals might decide to change career or educational choices or businesses might change their long-term investment decisions (Saez et al., 2012, pp. 12-13).

There is a significant and positive interaction between the initial impact of the tax variable and the country mean tax rate in the period in all the models, suggesting that the effect of a tax change relates to the average tax level in the country. The effects of a tax change becomes less negative the higher the average tax level.

Piketty (2014, p. 520) writes that the tax is more than just a tax. Taxation is also a way of defining norms. In this perspective, the average tax level could reflect confounding social norms about equality and redistribution. It could mean greater acceptance for taxation, and a lower degree and social acceptance of tax avoidance and evasion.

If the social norms reduces tax avoidance and/or evasion, while tax changes alters the incentive for tax avoidance/evasion, this could explain the observed interaction. Tax avoidance and evasion should decrease the top decile income share, as a proportion of the top incomes are underreported, and the reported income distribution (misleadingly) contracts.

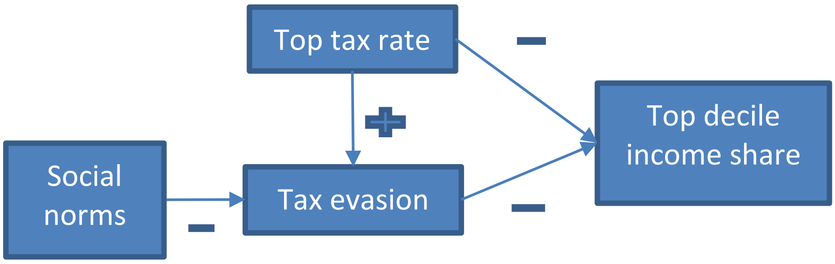

Figure 16 Social norms, tax evasion and the income distribution

Thus, the observed change in the income distribution should be lower in the case where social norms hinder tax evasion. This is conditional on the mitigating effect of social norms being stronger than the economic incentives associated with the higher tax rate. This relation is illustrated in figure 16.

The income effect could also be more pronounced in the countries with a higher average tax rate in this period. In this case, the contracting effect of the substitution effect is in part offset by the widening effect of the income effect[11].

A third explanation relates to the bargaining power of top executives. The bargaining power, and incentives for chasing wage increases, of top executives are thought to decrease with the tax level. If the combined effect of the bargaining power and incentives is to moderate the responses of top executives to tax changes, we should experience less movement in the income distribution the higher the initial tax level.

Final assessment

The results show a strong support for the hypothesis that decreasing tax rates leads to an increase in the top decile income share. There appears to be a lagging effect, and the total effect appears to be moderated by the average tax rate in the country over the period.

The data supports that the decreasing trend in the top statutory tax rates could have caused the top decile income share to increase in the period.

[11] See Theoretical and conceptual framework for a reminder on the effects

8.2 Trade

Import:

The within import as a percent of GDP was not significant in any of the models. The coefficient was, as expected, positive in all models. There is a chance that the standard errors of the import and export variables are inflated by collinearity. LR-tests on whether models without the variables was significantly worse than when they were included, was not significant. This applied to models where they were left out one at a time, and when both were excluded simultaneously.

The level of import as a percent of GDP was positively associated with the top decile income share. This indicates that the countries that had a higher level of import as a percent of GDP in this period also tended to have a higher level of the top decile income share, controlled for the other variables. The variable was significant, but the coefficients and significance of the country level variables should be interpreted with caution. One obvious critique is that country mean variables varies with the period under investigation.

Export:

The within export as a percent of GDP variable was not significant in any of the models. The coefficient was positive, contrary to the theoretical expectations. However, the level of export as a percent of GDP was negatively associated with the top decile income share. The variable was significant in the model with the outliers dropped, but not in the model with all observations included. The same issues related to the collinearity with import also applies to the export variable.

Trade:

The within trade as a percent of GDP variable was positive in all models. This is not surprising since we know that the two variables it is comprised of both had a positive coefficient separately. The variable was significant at the 5% level in all models, except for the model including all observations.

The level of trade is positive, but insignificant, in both the mixed models. Thus, there is no significant association with the level of trade and the level of the top decile income share.

There is support for the hypothesis that trade openness, as measured as the sum of import and export as a percent of GDP, increases the top decile income share, contrasting the findings of Reuveny and Li (2003). They investigated the income inequality by the use of the Gini-coefficient, and found a significant negative association between trade openness and the Gini-coefficient in OECD countries. Roine, Vlachos, and Waldenström (2009) found a positive and insignificant association between the change of trade openness and the bottom 90% income share. Since the bottom 90% income share is the inverse of the top decile, this translates to a negative association for the top decile income share.

Final assessment

There is support for the hypothesis that the increase in trade openness (as measured as the sum of import and export as a percent of GDP) could have caused the top decile income share to increase in this period. However, there is no support for separate effects of import and export as a percent of GDP.

8.3 Collective bargaining

There was a significant negative association between the union density rate and the top decile income share in all models. The variable was significant at the 5% level in all models with the exceptions of the FD fixed models, where it was significant at the 10% level.

The cross-level interaction between the change of labor union density and the country mean import variable (trade in the model using trade) was significant in all models, with the exception of the FD fixed models.

The theoretical reason for testing this interaction is that international trade is thought to decrease the bargaining position for unions. Some of the arguments are based on competitiveness: in order to be able to compete with global markets, firms must decrease their expenses, for example by cutting wages. The unions and workers then face the choice: decrease wages and keep employment, or keep wages and accept job cuts.

If international trade decreases the bargaining power of unions, then we would expect countries with a greater exposure to international markets to be more affected than countries with less exposed economies. The reason for using the country mean import as a percent of

GDP in the interaction, instead of the yearly change, is that there could be significant inertia between the openness and the ultimate effect on the bargaining power. The effect of international trade on the bargaining power presumably relates to the expectations of both unions and corporations on future exposure to international markets. If import grows substantially in a given year, and the long term expectations of the unions and corporations remains unchanged, the bargaining power would probably only be marginally changed. If, however, the economy should be highly exposed over a substantial period, the expectations would probably change as well. There is also the issue that a collective agreement usually covers more than a year. Even if the bargaining power was de facto changed in the same year, the effects on the income distribution should only take effect when new agreements are bargained for.

The reduction of the union "effect" on the income distribution is in line with findings of Abraham, Konings, and Vanormelingen (2009). Investigating firms in Belgium, they find that sectors with high import penetration rates tends to have lower union bargaining power. The sectors of the firms can be viewed as countries in this thesis, and the sector import penetration as the country's import as a percent of GDP. They explicitly seek to measure the bargaining power of unions, and find that it is reduced by import penetration. This lends support to the hypothesis that the observed lower expectation in the top decile income share, as a result of a change in the union density rates given the (mean) import as a percent of GDP, is related to the bargaining power of the unions.

Somewhat surprisingly, the extension variables was positive in all the models, and the change of extension was significant in all the models at the 5% level, except for in the FD fixed models where it was significant at the 10% level.

The expectation was that with more inclusive extension mechanisms, the less inequality would be observed. As indicated earlier, this measure is rather crude. It is hard to believe that extensions of union agreements should increase the top decile income share. The positive association is likely to be confounded by other factors. Jaumotte and Buitron (2015) also found a positive association between broad extensions and inequality. They think the positive association might be due to higher unemployment. However, in this study, the unemployment is included as a control variable. Therefore, a higher unemployment rate cannot be the sole explanation for the positive relationship.

Final assessment

There is support for the hypothesis that the decreasing trend in labor union density rates could have caused the top decile income share to increase in the period. The estimated effects of union density is moderated by the trade openness of a country, with a higher degree of openness reducing the estimated effects of unions.

The data does not support the hypothesis that the extensions and enlargements of collective agreements have decreased the top decile income share.

8.4 Controls

GDP

Besides the main findings, it was interesting that the GDP growth variable was significant and positive in all models, indicating that economic growth is more beneficial for the top decile group than for the bottom 90%. This is in line with Roine, Vlachos, and Walderström (2009)'s findings. They find that this is likely a cause of top incomes being more closely related to actual performance than incomes on average.

The causal direction between inequality and growth is not clear-cut. While growth might affect the inequality, for example through high incomes being linked to the economy (bonuses, dividends etc.), the case can be made that the inequality affects growth. Stiglitz (2012, pp. 104-147) discusses several channels through which inequality can hinder growth. One channel is through the demand and spending of the middle class. As they generally spend a larger proportion of their incomes, a greater demand would have been produced by shifting income in their direction. Thus, demand is less than it could have been, and the economy is producing less than it could have done.

The findings goes against Kuznets (1955) hypothesis. However, it is not completely fair to draw any conclusions from the models here, as technological change, which is central to the hypothesis, is not included.

Population

The population growth variable was significant in most of the models, and negative in all. This lends support to the hypothesis that a growing population contracts the income distribution.

Unemployment

The change in unemployment rate was not significant in any models, and the sign was not conclusive. However, the level of unemployment was positive and significant at the 10% level in the models that can estimate level effects. This indicates that countries with a higher unemployment rate in this period also have a higher level of income inequality. Perhaps there is a long lag before the unemployment rate starts to affect the income distribution that was not found with the three lags included here. The bottom line, though, is that there is no support for the hypothesis that a change of unemployment is increasing the top decile income share.

9 Concluding remarks

This thesis set out to empirically analyze the relationship between the top decile income share and top tax rates, collective bargaining and trade openness. While these relationships have been studied before, the unique contribution of this thesis lies in the statistical approach utilized, and the additional data exploration it offers.

There were found significant relationships between most of the variables of primary interest. The only variables without any significant relationship over time was import and export penetration. Treated together, however, the trade variable was significant and positive over time. This suggests that increased international trade have benefitted high-income groups more than proportionally. This thesis cannot give the answers to which mechanisms this effect works through. However, the theoretical framework suggests that the lower demand for domestic jobs associated with a greater trade penetration might reduce wages of already low-wage workers.

Trade penetration was found to affect the income distribution through an additional channel: through an interaction with union density rates. The level of trade penetration (and import penetration) appears to mitigate the negative (and significant) effect of unions. Countries with a higher penetration appears to have a lower negative effect of unions. This supports the argument that international trade lowers the bargaining power of unions.

The association between top tax rates and the income distribution is rather complex. First, tax rates appears to have a negative impact in the year of implementation. Second, the effect seems to last for two to three years after the implementation. Third, the initial impact appears to be mitigated by the average tax level in the period under investigation, with countries having higher average tax rates experiencing a less negative initial impact. Three potential explanations are offered. First, the tax level might be confounded by social norms, such as a lower social tolerance for tax avoidance and evasion. If norms reduce incentives for these activities, the effect of tax changes on the (reported) income distribution should be less pronounced. Second, the income effect might be stronger in these countries, counteracting the contracting effects of the substitution effect. Third, higher tax rates could moderate responses of top executive, through lower bargaining power and incentives to chase wage increases.

9.1 Further research

This thesis found interesting associations, but offer few answers to the mechanisms at work. The theoretical framework offer potential explanations and can function as a guide; however, further research is needed to put these explanations to test.

There are some findings worthy of further inquiry. I will encourage more research regarding the relatively complex tax association, and especially regarding the interaction between the average tax level and the effect of tax changes. Three potential explanations are offered, and it is of interest to find out if they have any explanatory power.

The interaction between labor unions and trade openness is little investigated in the context of income distribution, and further inquiry is needed to increase the confidence of the finding.

The significant positive association between the change and level of extensions and the top decile income share is surprising. Jaumotte and Buitron (2015) found a qualitative similar result, and hypothesized that this could be due to a trade off with a higher unemployment. This cannot be the whole story, as this thesis control for both the level and change of unemployment. This is worthy of further investigation.

This thesis cover a relatively short time span relative to distributional cycles, and a small sample of countries. As larger quantities of good quality data becomes available, the associations found here ought to be tested in a longer time span and in a larger sample of countries. In addition, many stones are left unturned in this thesis. Potential factors affecting the income distribution, such as minimum wages, financial developments and technological change are not addressed. Since leaving out relevant explanatory variables increases the chance of confounding and spurious findings, I would like to encourage investigation of the findings in this thesis where these and other potential factors are accounted for.

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Appendix

Research design

Two-way error components model

Mixed-effects ML regression Number of obs = 500

Group Variable	No. of Groups	Observations per Group Minimum	Average	Maximum
_all	1	500	500.0	500
occ	31	6	16.1	19

Wald chi2(21) = 1149.58
Log likelihood = 783.92054 Prob > chi2 = 0.0000

log10	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
occ	.0027034	.0004637	5.83	0.000	.0017946	.0036123
cm_tax	-.0038202	.0036353	-1.05	0.293	-.0109452	.0033049
w_tax	-.0026907	.0003715	-7.24	0.000	-.0034188	-.0019626
cm_logGDP	.1382998	.1738312	0.80	0.426	-.2024031	.4790026
cm_GDPgr	.07894	.070549	1.12	0.263	-.0593336	.2172136
w_GDPgr	.0043798	.0011403	3.84	0.000	.0021449	.0066147
cm_unem	.0141539	.0066765	2.12	0.034	.0010682	.0272395
w_unem	.0044664	.0009987	4.47	0.000	.002509	.0064238
cm_imp	.0145064	.0100955	1.44	0.151	-.0052803	.0342932
cm_impgr	.0096223	.0995443	0.10	0.923	-.1854809	.2047256
w_impgr	-.0008767	.0004113	-2.13	0.033	-.0016829	-.0000706
cm_exp	-.0130606	.009938	-1.31	0.189	-.0325388	.0064176
cm_expgr	-.03187	.0556085	-0.57	0.567	-.1408607	.0771207
w_expgr	.0003944	.0004173	0.94	0.345	-.0004236	.0012123
cm_logpop	.0054271	.0317501	0.17	0.864	-.0568019	.0676561
cm_popgr	-.1183556	.1032354	-1.15	0.252	-.3206933	.083982
w_popgr	-.0135545	.0058763	-2.31	0.021	-.0250718	-.0020372
cm_labor	-.0040134	.0015178	-2.64	0.008	-.0069883	-.0010385
w_labor	-.0071324	.0007016	-10.17	0.000	-.0085076	-.0057572
cm_ext	-.0430693	.0178166	-2.42	0.016	-.0779892	-.0081495
w_ext	.0637066	.0074723	8.53	0.000	.0490612	.078352
_cons	2.267827	1.46632	1.55	0.122	-.6061079	5.141762

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
_all: Identity				
var(R.CN)	.0025398	.0008526	.0013153	.0049041
occ: Identity				
var(_cons)	2.45e-23	2.22e-22	4.62e-31	1.30e-15
var(Residual)	.0022369	.0001442	.0019713	.0025382

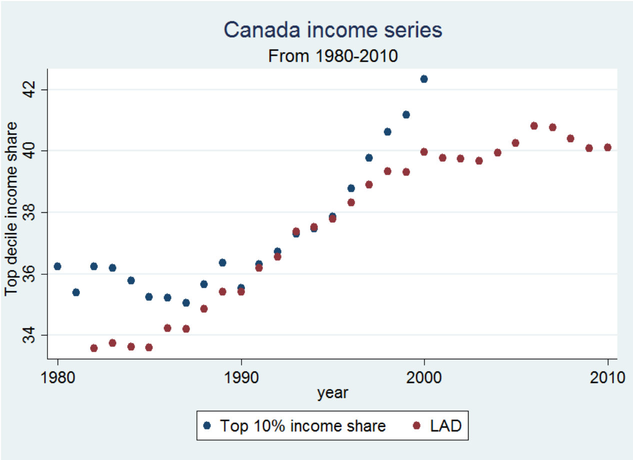
LR test vs. linear model: chi2(2) = 307.05 Prob > chi2 = 0.0000

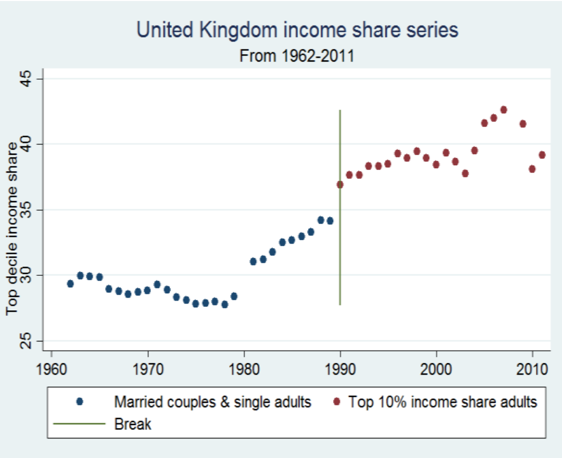
The two-way error-components model was used to estimate the cross-sectional correlation. The model was estimated using RML. The formula for the cross-sectional correlation is:

$$\frac{var(occ)}{var(occ)+var(CN)+var(Residual)} = \frac{2.45e{-23}}{(2.45e{-23})+0.0025398+0.0022369} \approx 5.13\text{e-}21$$

Data collection

Top decile income share:





Var code	"1110101"	"1110104"	"1110103"	"1110102"	"1110106"
Var name	"Top 10% income share"	"Top 10% income share-adults"	"Top 10% income share-married couples & single adults"	"Top 10% income share-LAD"	"Top 10% income share-IDS"
Countries	Australia, Norway France, Portugal Germany, Spain Italy, Sweden Korea, Switzerland Netherlands, United States	Denmark New Zealand United Kingdom (1990-2011)	United Kingdom (1980-1989)	Canada	Finland

Top statutory tax rates:

Countries with only the central level taxation:

Australia (with surtaxes), France (with surtaxes), Germany, Ireland, Japan, Korea (problems), Netherlands, New Zealand, Portugal, United Kingdom.

Countries with a sub-central level:

Canada (see explanation), Denmark, Finland (see explanation), Italy (see explanation), Norway (see explanation), Spain, Sweden, Switzerland (see explanation), United States (see explanation).

Canada:

Canada have a basic provincial tax, and some of these have an additional surtax, calculated as a percentage of the provincial basic tax. For the representative province, Ontario, this is 20-56 % of the basic tax of 11,16 for the year 2000. That gives total tax of: 29 (central tax) + 1,56*11,16. For the time period 1981-1999 this surtax is provided in the dataset as surtax in a percent. For 1981 then, the top tax is calculated as central tax + sub-central representative tax (Ontario) + surtax for the representative province. This is the same as for the period 2000-2013, but we operate with an additive surtax instead of the percentage of the provincial tax.

Finland:

The only information about the sub-central taxation for Finland is the maximum sub-central rate for the period 1981-1999. Top statutory: central + sub-central rate.

Italy:

Central government tax rates + representative regional taxes (Lazio)(From 1998-) + representative local taxes (Rome)(From 2002-)

Norway:

Central government tax rate + surtax + sub-central tax rate

Portugal:

The top statutory tax rate that is stated in table 1.8 seems to contain the Social Security Contribution (SSC). In the data calculated and reported here the top tax rate is the same as the top tax rate at central level, i.e. without SSC.

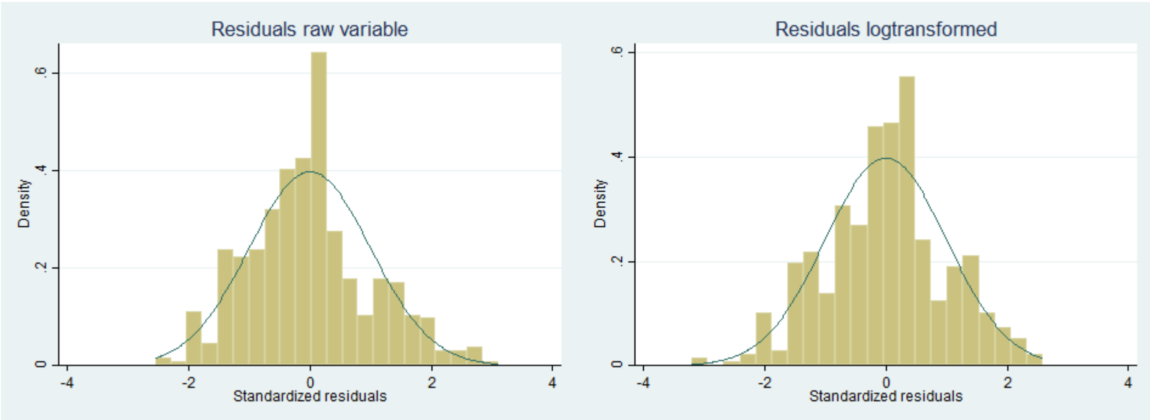
Switzerland:

Central government tax rate + sub-central.

United States:

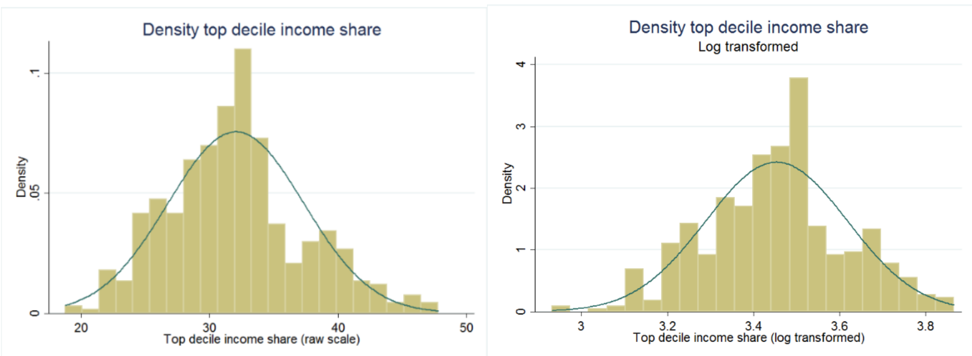
The calculated data is the top central tax + local and state level taxes. That is: central tax rate + representative sub-central rate (S) + representative sub-central rate (L)

Descriptive statistics



These figures show the distributions of the standardized residuals of an empty mixed-model.

Inspecting the distribution graphical, it is clear that the top decile income share is not perfectly normally distributed. The figures below display a histogram of the raw variable (top decile income share) at the left and the log-transformed variable at the right.



The figure displays the two distributions, with a normal curve overlaid. As we can see, the raw income share variable seems to be slightly skewed to the right. The log transformation appears to make the distribution more normal. Below are the results of the skewness test performed on both distributions.

Skewness-test of income share variables:

Skewness/Kurtosis tests for Normality

Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	joint adj chi2(2)	joint Prob>chi2
share10	511	0.0004	0.8561	11.49	0.0032

Skewness/Kurtosis tests for Normality

Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	joint adj chi2(2)	joint Prob>chi2
log10	511	0.5379	0.7872	0.46	0.7962

The test is a test of normality, and a significant test indicates that the distribution is significantly different from normal. The test rejects that the raw variable is not skewed, and that it is normally distributed (joint test), while it fails to reject normality of the log transformed variable.

<u>Results</u>

Mixed-effects REML regression | Number of obs = 453
Group variable: id | Number of groups = 19

Obs per group: min = 8
avg = 23.8
max = 28

Wald chi2(24) = 334.77
Log restricted-likelihood = 991.85899 | Prob > chi2 = 0.0000

log10	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
occ	.0032779	.0007273	4.51	0.000	.0018524	.0047033
cm_tax	-.0103077	.0042173	-2.44	0.015	-.0185734	-.002042
w_tax	-.0067094	.0024342	-2.76	0.006	-.0114803	-.0019385
cm_logGDP	.2403548	.2512164	0.96	0.339	-.2520203	.7327299
cm_GDPgr	.0683415	.0525878	1.30	0.194	-.0347288	.1714117
w_GDPgr	.0015166	.0003943	3.85	0.000	.0007437	.0022895
cm_unem	.0150219	.0084189	1.78	0.074	-.0014789	.0315227
w_unem	-.0001219	.0008243	-0.15	0.882	-.0017375	.0014937
cm_imp	.0199159	.0109835	1.81	0.070	-.0016114	.0414432
w_imp	.0005072	.0008201	0.62	0.536	-.0011001	.0021145
cm_exp	-.0162247	.0103775	-1.56	0.118	-.0365644	.0041149
w_exp	9.24e-06	.0007547	0.01	0.990	-.00147	.0014885
cm_logpop	.0326228	.0526405	0.62	0.535	-.0705506	.1357962
cm_popgr	-.1717673	.1442111	-1.19	0.234	-.4544158	.1108811
w_popgr	-.0050979	.0030404	-1.68	0.094	-.0110569	.0008611
cm_labor	-.0008357	.0029683	-0.28	0.778	-.0066534	.0049819
w_labor	-.0069233	.00184	-3.76	0.000	-.0105296	-.003317
cm_ext	-.0026757	.0239269	-0.11	0.911	-.0495715	.0442201
w_ext	.0261798	.0090022	2.91	0.004	.0085359	.0438238
w_tax						
L1.	-.0005781	.0002313	-2.50	0.012	-.0010314	-.0001248
L2.	-.0004824	.0002257	-2.14	0.033	-.0009247	-.0000402
L3.	-.0004324	.0002044	-2.12	0.034	-.000833	-.0000319
c.cm_tax# c.w_tax	.0001107	.0000444	2.49	0.013	.0000237	.0001977
c.cm_imp# c.w_labor	.0001137	.0000545	2.09	0.037	6.84e-06	.0002205
_cons	.7635445	2.08583	0.37	0.714	-3.324607	4.851696

Random-effects Parameters		Estimate	Std. Err.	[95% Conf.	Interval]
id: Identity					
	var(_cons)	.0020919	.0032497	.0000996	.0439396
Residual: AR(1), by CN					
Australia:	rho	.6138273	.2287866	-.0044756	.8925962
	var(e)	.0017171	.001019	.0005366	.0054944
Canada:	rho	.9972262	.0050999	.9024674	.9999248
	var(e)	.02113	.0385289	.0005927	.7533523
Denmark:	rho	.9367517	.1615687	-.7035428	.9996289
	var(e)	.0012901	.0032745	8.91e-06	.1867139
Finland:	rho	.7599085	.3330336	-.4996133	.9876564
	var(e)	.0014825	.0020549	.000098	.0224333
France:	rho	.9918005	.0169934	.6087867	.9998606
	var(e)	.0038533	.0080306	.0000648	.228984
Germany:	rho	.6420566	.2907972	-.2050816	.9392166
	var(e)	.0011738	.000817	.0003	.0045927
Ireland:	rho	.8157869	.1572888	.2188539	.9683887
	var(e)	.0019033	.0016313	.0003548	.010211
Italy:	rho	.9943326	.0180022	-.1877768	.999989
	var(e)	.0074797	.0238436	.0000145	3.866449
Japan:	rho	.9985759	.0027928	.9354246	.9999696
	var(e)	.0782801	.1523749	.0017249	3.552583
Korea:	rho	.5927801	.4198645	-.5275888	.9603723
	var(e)	.0022199	.0023175	.0002869	.0171763
Netherlands:	rho	.9354272	.1358232	-.4052662	.9990583
	var(e)	.0023446	.0048672	.0000401	.1371253
New Zealand:	rho	.7845174	.1705145	.1857179	.958419
	var(e)	.0065426	.0051039	.0014182	.0301835
Norway:	rho	.6624302	.1610838	.2303323	.8763288
	var(e)	.0082106	.0040165	.0031476	.0214176
Portugal:	rho	.9556472	.0942582	-.2324078	.9993595
	var(e)	.0065575	.0137284	.0001083	.3969794
Spain:	rho	.9961668	.0079682	.7956392	.9999352
	var(e)	.0205688	.0428922	.0003453	1.225235
Sweden:	rho	.9924871	.0162685	.578492	.9998935
	var(e)	.0160093	.0343917	.0002376	1.078815
Switzerland:	rho	.9413746	.1255141	-.3897123	.9991994
	var(e)	.001161	.0024768	.0000177	.0759755
United Kingdom:	rho	.5748035	.1820993	.1210545	.829859
	var(e)	.0009234	.0004049	.000391	.002181
United States:	rho	.9921865	.0156812	.6618474	.9998488
	var(e)	.0124635	.0249238	.0002474	.6277967

LR test vs. linear regression: chi2(38) = 1084.09 Prob > chi2 = 0.0000

Diagnostics

Hausman fixed effects and random effects:

	(b) fixed	(B) random	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
	Coefficients			
occ	.0018892	.00189	-7.99e-07	.0000143
w_tax	-.0073187	-.0072922	-.0000265	.0000212
w_GDPgr	.0035828	.0035774	5.47e-06	.000012
w_unem	.0050482	.0050549	-6.61e-06	.0000137
w_imp	.0017212	.0016926	.0000287	.0000157
w_exp	-.0003468	-.0003179	-.0000289	.0000162
w_popgr	-.0105364	-.0104681	-.0000683	.0000677
w_labor	-.0088618	-.0088595	-2.34e-06	.0000244
w_ext	.065441	.0653137	.0001273	.0001825
w_tax				
L1.	-.0003892	-.0003926	3.38e-06	3.11e-06
L2.	-.0008548	-.0008579	3.11e-06	4.36e-06
L3.	-.0023989	-.0023893	-9.65e-06	6.18e-06
c.cm_tax#				
c.w_tax	.0001413	.0001407	6.87e-07	4.61e-07
c.cm_imp#				
c.w_labor	.0000775	.000078	-4.25e-07	3.74e-07

```
                     b = consistent under Ho and Ha; obtained from mixed
      B = inconsistent under Ha, efficient under Ho; obtained from mixed

Test:  Ho:  difference in coefficients not systematic

            chi2(13) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                     =        7.64
          Prob>chi2 =      0.8663
```

Alternative models

The plots above show the evolution of the change of the variables.

The tables below are: to the left, “Mixed (no outliers)” to the right “Fixed (ML)

Mixed-effects REML regression — Number of obs = 447
Group variable: id — Number of groups = 19

Obs per group: min = 8; avg = 23.5; max = 28

Wald chi2(24) = 739.19
Log restricted-likelihood = 1015.3993 — Prob > chi2 = 0.0000

log10	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
occ	.0034643	.0006856	5.05	0.000	.0021205	.0048081
cm_tax	-.0090701	.0029303	-3.10	0.002	-.0148134	-.0033269
w_tax	-.007846	.0023753	-3.30	0.001	-.0125015	-.0031906
cm_logGDP	.9806193	.2807897	3.49	0.000	.4302816	1.530957
cm_GDPgr	.2177735	.0579709	3.76	0.000	.1041525	.3313944
w_GDPgr	.0009845	.0003661	2.69	0.007	.0002669	.0017022
cm_unem	.0221265	.0058428	3.79	0.000	.0106748	.0335782
w_unem	.0003624	.0007914	0.46	0.647	-.0011888	.0019136
cm_imp	.0427789	.0088863	4.81	0.000	.0253622	.0601957
w_imp	.0005743	.000746	0.77	0.441	-.0008879	.0020364
cm_exp	-.036903	.0085891	-4.30	0.000	-.0537373	-.0200687
w_exp	.0001592	.000684	0.23	0.816	-.0011813	.0014998
cm_logpop	.029853	.0358137	0.83	0.405	-.0403406	.1000466
cm_popgr	-.5064368	.1343624	-3.77	0.000	-.7697823	-.2430914
w_popgr	-.004673	.0029372	-1.59	0.112	-.0104299	.0010838
cm_labor	-.0002856	.0021045	-0.14	0.892	-.0044104	.0038392
w_labor	-.0074177	.0018335	-4.05	0.000	-.0110113	-.003824
cm_ext	.0463821	.0158563	2.93	0.003	.0153042	.0774599
w_ext	.0200617	.008572	2.34	0.019	.0032608	.0368625
w_tax						
L1.	-.0005375	.0002134	-2.52	0.012	-.0009558	-.0001192
L2.	-.0006749	.0002138	-3.16	0.002	-.0010939	-.0002559
L3.	-.0001255	.0002176	-0.58	0.564	-.0005521	.0003011
c.cm_tax#						
c.w_tax	.0001324	.0000432	3.07	0.002	.0000478	.0002171
c.cm_imp#						
c.w_labor	.0001335	.0000536	2.49	0.013	.0000285	.0002385
_cons	-6.9855	2.671456	-2.61	0.009	-12.22146	-1.749543

Random-effects Parameters		Estimate	Std. Err.	[95% Conf.	Interval]
id: Identity					
	var(_cons)	5.69e-22	.	.	.
Residual: AR(1), by CN					
Australia:	rho	.7003567	.2318854	-.0240199	.9425058
	var(e)	.0016236	.0012472	.0003603	.007317
Canada:	rho	.9993907	.0009022	.9889492	.9999666
	var(e)	.0875569	.1271445	.0050843	1.507825
Denmark:	rho	.9647165	.0612967	.2699261	.9988786
	var(e)	.0011921	.0020571	.0000405	.0350857
Finland:	rho	.7226957	.2152232	.0302329	.9464202
	var(e)	.0012762	.0009907	.0002787	.0058437
France:	rho	.9899709	.0211357	.5150122	.9998413
	var(e)	.0032754	.0069154	.0000523	.2053093
Germany:	rho	.5966461	.2848793	-.1771771	.9145925
	var(e)	.0010444	.0006232	.0003243	.0033635
Ireland:	rho	.8200311	.1520425	.2422205	.9684487
	var(e)	.0019856	.0016955	.0003724	.0105861
Italy:	rho	.9947948	.0103832	.7675646	.9998964
	var(e)	.0079997	.0158689	.0001639	.3904737
Japan:	rho	.9990837	.0014092	.9814722	.9999551
	var(e)	.1217631	.1841506	.0062833	2.35964
Korea:	rho	.5562347	.4192479	-.5098159	.9485595
	var(e)	.0020203	.0019379	.0003083	.0132402
Netherlands:	rho	.9393342	.0916591	.2025607	.997053
	var(e)	.0017407	.0025765	.0000957	.0316701
New Zealand:	rho	.9932816	.0100363	.8803818	.9996429
	var(e)	.1192029	.1751827	.0066888	2.124359
Norway:	rho	.7707192	.1222942	.4067496	.9235262
	var(e)	.0050319	.0027146	.001748	.0144853
Portugal:	rho	.9311835	.1032019	.1441929	.9966104
	var(e)	.0041093	.006013	.0002335	.0723258
Spain:	rho	.9939359	.0117873	.7561096	.9998668
	var(e)	.0140912	.0273607	.0003135	.6334559
Sweden:	rho	.9916331	.0158452	.7026607	.9997979
	var(e)	.0094886	.0178146	.0002394	.3761056
Switzerland:	rho	.9213511	.1175547	.0730497	.9961281
	var(e)	.0009565	.0014076	.0000535	.0171131
United Kingdom:	rho	.5873331	.1774116	.1417847	.8349989
	var(e)	.0008998	.000395	.0003806	.0021272
United States:	rho	.9841209	.0246906	.7054049	.9992587
	var(e)	.0062796	.0096452	.0003094	.1274528

LR test vs. linear regression: chi2(38) = 1130.25 Prob > chi2 = 0.0000

Mixed-effects ML regression — Number of obs = 447
Group variable: id — Number of groups = 19

Obs per group: min = 8; avg = 23.5; max = 28

Wald chi2(32) = 1556.24
Log likelihood = 1173.7934 — Prob > chi2 = 0.0000

log10	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
id						
2	.2424141	.0229746	10.55	0.000	.1973846	.2874435
3	-.1391474	.0209179	-6.65	0.000	-.1801458	-.098149
4	.0134248	.0177166	0.76	0.449	-.0212991	.0481488
5	.0889356	.036752	2.42	0.016	.016903	.1609682
6	.1625109	.0157411	10.32	0.000	.1316589	.1933629
7	.1493295	.0196294	7.61	0.000	.1108566	.1878024
8	.0495177	.0237161	2.09	0.037	.0030349	.0960004
9	.2086998	.0271784	7.68	0.000	.155431	.2619685
10	.2898264	.0212562	13.63	0.000	.2481651	.3314877
11	.0018727	.023181	0.08	0.936	-.0435612	.0473067
12	.0393393	.0367731	1.07	0.285	-.0327345	.1114132
13	-.1080546	.0304876	-3.54	0.000	-.1678092	-.0483
14	.1408344	.0278408	5.06	0.000	.0862673	.1954014
15	.1148592	.076946	1.49	0.136	-.0359522	.2656705
16	-.1508978	.0317323	-4.76	0.000	-.2130921	-.0887036
17	.066469	.0185681	3.58	0.000	.0300762	.1028617
18	.2475991	.0149597	16.55	0.000	.2182786	.2769196
19	.3220909	.0437565	7.36	0.000	.2363299	.407852
occ	.0035426	.0006032	5.87	0.000	.0023603	.0047248
cm_tax	0	(omitted)				
w_tax	-.0078015	.0022099	-3.53	0.000	-.0121327	-.0034702
cm_logGDP	0	(omitted)				
cm_GDPgr	0	(omitted)				
w_GDPgr	.0009253	.0003593	2.58	0.010	.0002211	.0016295
cm_unem	0	(omitted)				
w_unem	.0006094	.0007677	0.79	0.427	-.0008952	.002114
cm_imp	0	(omitted)				
w_imp	.0008666	.0007249	1.20	0.232	-.0005541	.0022872
cm_exp	0	(omitted)				
w_exp	.0000851	.0006605	0.13	0.898	-.0012096	.0013797
cm_logpop	0	(omitted)				
cm_popgr	0	(omitted)				
w_popgr	-.004825	.0028826	-1.67	0.094	-.0104749	.0008248
cm_labor	0	(omitted)				
w_labor	-.0070351	.0015088	-4.66	0.000	-.0099922	-.004078
cm_ext	0	(omitted)				
w_ext	.0228688	.0080487	2.84	0.004	.0070936	.038644
w_tax						
L1.	-.0006007	.0002037	-2.95	0.003	-.0009999	-.0002015
L2.	-.0007696	.0002049	-3.76	0.000	-.0011712	-.000368
L3.	-.0002244	.0002111	-1.06	0.288	-.0006381	.0001893
c.cm_tax#						
c.w_tax	.000131	.0000401	3.27	0.001	.0000524	.0002096
c.cm_imp#						
c.w_labor	.0001259	.0000436	2.88	0.004	.0000403	.0002114
_cons	3.315389	.0158873	208.68	0.000	3.284251	3.346528

Random-effects Parameters		Estimate	Std. Err.	[95% Conf.	Interval]
id:	(empty)				
Residual: AR(1), by CN					
Australia:	rho	.5817734	.2183481	.0182305	.8647922
	var(e)	.0011755	.0006177	.0004197	.0032924
Canada:	rho	.9309481	.0654209	.6067743	.9896035
	var(e)	.0007267	.0006935	.000112	.0047165
Denmark:	rho	.9279214	.0728275	.5483633	.9904617
	var(e)	.0005642	.0005622	.00008	.0039782
Finland:	rho	.6065729	.1805627	.1426016	.851994
	var(e)	.0008892	.0004183	.0003536	.0022356
France:	rho	.9777011	.0298171	.7246719	.9984086
	var(e)	.0015367	.0020621	.0001108	.02132
Germany:	rho	.4348072	.3401604	-.3419709	.8585865
	var(e)	.0007763	.0003712	.0003041	.0019815
Ireland:	rho	.7117618	.1356088	.3381948	.8915514
	var(e)	.0012234	.0005877	.0004772	.0031365
Italy:	rho	.9443762	.0746606	.4003285	.9961851
	var(e)	.0007031	.0009389	.0000513	.0096322
Japan:	rho	.9154449	.0673568	.632177	.9828542
	var(e)	.0012584	.001025	.000255	.0062106
Korea:	rho	.317392	.3425006	-.3950282	.7914245
	var(e)	.0012735	.0007099	.0004271	.0037974
Netherlands:	rho	.8896365	.1104289	.3647446	.9854502
	var(e)	.0009637	.0009339	.0001442	.0064387
New Zealand:	rho	.8199515	.1260311	.3823713	.9571278
	var(e)	.0044066	.0029434	.00119	.0163177
Norway:	rho	.7238324	.1248646	.3813014	.8916084
	var(e)	.0041389	.001906	.0016784	.0102062
Portugal:	rho	.8222425	.1632181	.1743006	.973295
	var(e)	.0015528	.0013594	.0002792	.0086356
Spain:	rho	.986937	.0175777	.8290027	.9990758
	var(e)	.0067531	.0090151	.0004934	.0924309
Sweden:	rho	.95105	.0509798	.6620405	.9938279
	var(e)	.001433	.0014924	.0001861	.0110336
Switzerland:	rho	.8654091	.1157733	.3890753	.976604
	var(e)	.000542	.0004603	.0001026	.002864
United Kingdom:	rho	.501721	.1715686	.1018584	.7620113
	var(e)	.0007257	.0002604	.0003592	.0014662
United States:	rho	.96278	.0456453	.6399159	.99673
	var(e)	.0026605	.0032302	.0002463	.0287355

LR test vs. linear regression: chi2(37) = 608.57 Prob > chi2 = 0.0000

Fixed FD model:

Mixed-effects REML regression — Number of obs = 409
Group variable: id — Number of groups = 19

Obs per group: min = 7
avg = 21.5
max = 27

Wald chi2(31) = 95.43
Log restricted-likelihood = 941.9449 — Prob > chi2 = 0.0000

D.log10	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
id						
2	.000585	.0059688	0.10	0.922	-.0111136	.0122835
3	-.0039293	.0060056	-0.65	0.513	-.0157001	.0078414
4	.0020879	.0083133	0.25	0.802	-.0142059	.0183818
5	-.0038432	.0060983	-0.63	0.529	-.0157957	.0081092
6	.0040743	.0099192	0.41	0.681	-.015367	.0235156
7	-.0005312	.0108393	-0.05	0.961	-.0217757	.0207134
8	.0018662	.0063071	0.30	0.767	-.0104954	.0142279
9	.0021708	.0079867	0.27	0.786	-.0134827	.0178244
10	.0069967	.013434	0.52	0.602	-.0193336	.0333269
11	-.0058911	.0061672	-0.96	0.339	-.0179785	.0061963
12	-.0022515	.0119369	-0.19	0.850	-.0256474	.0211444
13	.0048036	.0097868	0.49	0.624	-.0143782	.0239855
14	.0076852	.007417	1.04	0.300	-.0068519	.0222223
15	-.0076494	.0065867	-1.16	0.245	-.0205591	.0052602
16	-.0000108	.0060585	-0.00	0.999	-.0118852	.0118636
17	-.000447	.007544	-0.06	0.953	-.0152329	.0143389
18	.0008773	.0076336	0.11	0.909	-.0140843	.0158389
19	.0039714	.0062967	0.63	0.528	-.0083698	.0163127
occ						
D1.	0	(omitted)				
cm_tax						
D1.	0	(omitted)				
w_tax						
D1.	-.0074365	.0023192	-3.21	0.001	-.0119821	-.0028908
cm_logGDP						
D1.	0	(omitted)				
cm_GDPgr						
D1.	0	(omitted)				
w_GDPgr						
D1.	.0007549	.0003239	2.33	0.020	.00012	.0013897
cm_unem						
D1.	0	(omitted)				
w_unem						
D1.	-.0003588	.0007593	-0.47	0.637	-.001847	.0011294
cm_imp						
D1.	0	(omitted)				
w_imp						
D1.	.0005166	.0006705	0.77	0.441	-.0007976	.0018308
cm_exp						
D1.	0	(omitted)				
w_exp						
D1.	.0005697	.0006238	0.91	0.361	-.000653	.0017924
cm_logpop						
D1.	0	(omitted)				
cm_popgr						
D1.	0	(omitted)				
w_popgr						
D1.	-.0057228	.0024797	-2.31	0.021	-.0105829	-.0008626
cm_labor						
D1.	0	(omitted)				
w_labor						
D1.	-.005822	.003202	-1.82	0.069	-.0120978	.0004538
cm_ext						
D1.	0	(omitted)				
w_ext						
D1.	.0150633	.0080853	1.86	0.062	-.0007835	.0309101
w_tax						
LD.	-.000278	.000196	-1.42	0.156	-.0006621	.000106
L2D.	-.000352	.0002033	-1.73	0.083	-.0007506	.0000465
L3D.	-.0000713	.0001918	-0.37	0.710	-.0004473	.0003047
c.cm_tax# cD.w_tax	.0001292	.0000419	3.09	0.002	.0000471	.0002112
c.cm_imp# cD.w_labor	.0001173	.0000946	1.24	0.215	-.0000682	.0003028
_cons	.0051434	.0057886	0.89	0.374	-.006202	.0164888

Random-effects Parameters		Estimate	Std. Err.	[95% Conf.	Interval]
id:	(empty)				
Residual: AR(1), by CN					
Australia:	rho	-.1537347	.214277	-.5263657	.2684364
	var(e)	.0009789	.0002942	.0005431	.0017644
Canada:	rho	-.1599759	.2120789	-.5284169	.2591737
	var(e)	.0000931	.0000284	.0000512	.0001692
Denmark:	rho	-.0774559	.2354635	-.4944223	.3684894
	var(e)	.0000629	.0000209	.0000329	.0001205
Finland:	rho	-.0431722	.2370019	-.4688393	.3987683
	var(e)	.000735	.000246	.0003815	.0014163
France:	rho	.3081289	.2223681	-.1616468	.6640539
	var(e)	.0000618	.0000215	.0000312	.0001224
Germany:	rho	-.0707078	.4373777	-.7317007	.6588201
	var(e)	.0005166	.0003009	.000165	.0016177
Ireland:	rho	.3749135	.200058	-.062027	.691259
	var(e)	.0008446	.0002985	.0004225	.0016883
Italy:	rho	.4106167	.2190552	-.079887	.7410314
	var(e)	.0000764	.000029	.0000363	.0001608
Japan:	rho	.5671482	.1826601	.11503	.8246168
	var(e)	.0002498	.0001077	.0001073	.0005814
Korea:	rho	-.3151835	.3559421	-.8008118	.420493
	var(e)	.0018308	.0010837	.0005738	.0058408
Netherlands:	rho	-.3488806	.217121	-.6903861	.119778
	var(e)	.0001289	.0000462	.0000638	.0002603
New Zealand:	rho	.309009	.2195832	-.1550973	.6613774
	var(e)	.0015491	.000523	.0007993	.0030022
Norway:	rho	-.1640562	.1990614	-.5127817	.2311387
	var(e)	.0021128	.0006217	.0011868	.0037613
Portugal:	rho	-.231037	.2562022	-.6444495	.2868931
	var(e)	.0005253	.0001991	.00025	.0011041
Spain:	rho	.2460653	.2271092	-.2189893	.6200181
	var(e)	.0001427	.0000475	.0000744	.000274
Sweden:	rho	-.0713203	.2150088	-.4581803	.3382564
	var(e)	.0000991	.0000308	.000054	.0001821
Switzerland:	rho	.3776125	.2712493	-.2191668	.7687748
	var(e)	.0001671	.0000808	.0000648	.0004311
United Kingdom:	rho	-.1039523	.2607978	-.5518707	.3905161
	var(e)	.0007942	.0002339	.0004459	.0014147
United States:	rho	.0584317	.20091	-.3244629	.4248731
	var(e)	.0001805	.0000573	.0000969	.0003361

LR test vs. linear regression: chi2(37) = 273.07 Prob > chi2 = 0.0000

Mixed-effects REML regression
Group variable: id

Number of obs = 409
Number of groups = 19

Obs per group: min = 7
avg = 21.5
max = 27

Wald chi2(13) = 66.24
Log restricted-likelihood = 1011.4443
Prob > chi2 = 0.0000

D.log10	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
occ D1.	0	(omitted)				
cm_tax D1.	0	(omitted)				
w_tax D1.	-.0077666	.0023103	-3.36	0.001	-.0122948	-.0032385
cm_logGDP D1.	0	(omitted)				
cm_GDPgr D1.	0	(omitted)				
w_GDPgr D1.	.0007783	.0003234	2.41	0.016	.0001444	.0014122
cm_unem D1.	0	(omitted)				
w_unem D1.	-.0001098	.000764	-0.14	0.886	-.0016071	.0013875
cm_imp D1.	0	(omitted)				
w_imp D1.	.0005296	.0006707	0.79	0.430	-.0007848	.0018441
cm_exp D1.	0	(omitted)				
w_exp D1.	.0005113	.0006204	0.82	0.410	-.0007047	.0017273
cm_logpop D1.	0	(omitted)				
cm_popgr D1.	0	(omitted)				
w_popgr D1.	-.0058038	.0025191	-2.30	0.021	-.0107411	-.0008664
cm_labor D1.	0	(omitted)				
w_labor D1.	-.0078994	.0028767	-2.75	0.006	-.0135377	-.0022611
cm_ext D1.	0	(omitted)				
w_ext D1.	.0162444	.0079999	2.03	0.042	.0005649	.031924
w_tax LD.	-.0002807	.0001938	-1.45	0.148	-.0006605	.0000992
L2D.	-.0003498	.0002014	-1.74	0.082	-.0007444	.0000449
L3D.	-.0000925	.0001919	-0.48	0.630	-.0004687	.0002837
c.cm_tax# cD.w_tax	.0001354	.0000417	3.25	0.001	.0000537	.0002171
c.cm_imp# cD.w_labor	.0001687	.000085	1.98	0.047	2.11e-06	.0003353
_cons	.0040879	.0010877	3.76	0.000	.0019561	.0062197

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
id: Identity var(_cons)	5.69e-06	5.49e-06	8.61e-07	.0000377
Residual: AR(1), by CN				
Australia: rho	-.1851657	.2057637	-.5405514	.2262952
var(e)	.0009431	.0002826	.0005242	.0016966
Canada: rho	-.1611827	.2085801	-.5243455	.2515931
var(e)	.0000957	.0000291	.0000527	.0001738
Denmark: rho	-.0821491	.2341436	-.4962855	.3624437
var(e)	.0000626	.0000207	.0000328	.0001197
Finland: rho	-.0788872	.225737	-.48098	.3506244
var(e)	.0007064	.0002316	.0003715	.0013433
France: rho	.3010521	.2183917	-.1586722	.6534961
var(e)	.0000602	.0000205	.0000309	.0001175
Germany: rho	-.1404522	.3811026	-.7179328	.5515401
var(e)	.0004777	.0002609	.0001638	.0013933
Ireland: rho	.326075	.1873184	-.0722612	.6346997
var(e)	.0007847	.000252	.0004182	.0014724
Italy: rho	.3621697	.2128438	-.1004249	.6960135
var(e)	.0000753	.0000267	.0000376	.000151
Japan: rho	.5166893	.170087	.1165067	.772536
var(e)	.0002316	.0000861	.0001117	.0004801
Korea: rho	-.3578072	.3217957	-.799664	.3354366
var(e)	.0017398	.0010116	.0005566	.0054379
Netherlands: rho	-.327178	.2246354	-.6819346	.1522003
var(e)	.0001278	.0000456	.0000635	.0002573
New Zealand: rho	.2536644	.2066887	-.171912	.5994491
var(e)	.0014572	.0004504	.0007951	.0026704
Norway: rho	-.1846315	.1934866	-.5222175	.2029784
var(e)	.0020794	.0006088	.0011714	.0036911
Portugal: rho	-.1707256	.2636322	-.6073024	.3450454
var(e)	.0005612	.0002099	.0002696	.0011682
Spain: rho	.3131907	.2358178	-.1861843	.6839721
var(e)	.0001558	.0000564	.0000766	.0003169
Sweden: rho	-.0819346	.2103709	-.4599317	.3212025
var(e)	.0000961	.0000294	.0000527	.0001751
Switzerland: rho	.3091358	.2459124	-.2101392	.6923713
var(e)	.0001515	.0000628	.0000672	.0003413
United Kingdom: rho	-.1386016	.2508839	-.5654808	.3468471
var(e)	.0007718	.000227	.0004336	.0013736
United States: rho	.0850718	.20346	-.3062512	.4517996
var(e)	.0001825	.0000583	.0000975	.0003414

LR test vs. linear regression: chi2(38) = 269.92 Prob > chi2 = 0.0000

Mixed-effects REML regression
Group variable: id

Number of obs = 453
Number of groups = 19

Obs per group: min = 8
avg = 23.8
max = 28

Wald chi2(22) = 690.04
Log restricted-likelihood = 1001.0311
Prob > chi2 = 0.0000

log10	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
occ	.0036649	.0007312	5.01	0.000	.0022317	.0050981
cm_tax	.0014753	.0018215	0.81	0.418	-.0020947	.0050453
w_tax	-.0063819	.0023921	-2.67	0.008	-.0110704	-.0016934
cm_logGDP	-.482416	.1099791	-4.39	0.000	-.6979711	-.266861
cm_GDPgr	-.0258107	.022362	-1.15	0.248	-.0696395	.0180181
w_GDPgr	.0015087	.0003925	3.84	0.000	.0007394	.0022781
cm_unem	.0121739	.0057011	2.14	0.033	.0010001	.0233478
w_unem	-.0001829	.0007562	-0.24	0.809	-.001665	.0012991
cm_trade	.0009661	.0007953	1.21	0.224	-.0005926	.0025248
w_trade	.0002711	.0002036	1.33	0.183	-.000128	.0006702
cm_logpop	.0829268	.0275798	3.01	0.003	.0288714	.1369823
cm_popgr	.1184186	.0706552	1.68	0.094	-.020063	.2569002
w_popgr	-.0051424	.0030152	-1.71	0.088	-.0110521	.0007672
cm_labor	.0018403	.0015899	1.16	0.247	-.0012758	.0049564
w_labor	-.0066218	.0017095	-3.87	0.000	-.0099723	-.0032712
cm_ext	-.0704292	.0104098	-6.77	0.000	-.0908319	-.0500264
w_ext	.0275275	.0090051	3.06	0.002	.0098779	.0451771
w_tax L1.	-.0005893	.0002291	-2.57	0.010	-.0010383	-.0001402
L2.	-.0004843	.0002245	-2.16	0.031	-.0009243	-.0000443
L3.	-.0004366	.0002031	-2.15	0.032	-.0008347	-.0000385
c.cm_tax#c.w_tax	.0001043	.0000436	2.39	0.017	.0000189	.0001897
c.cm_trade# c.w_labor	.000052	.0000241	2.16	0.031	4.84e-06	.0000992
_cons	6.611103	.857097	7.71	0.000	4.931223	8.290982

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
id: Identity var(_cons)	1.36e-21	.	.	.
Residual: AR(1), by CN				
Australia: rho	.6375756	.2107705	.057965	.8957178
var(e)	.0018352	.0010662	.0005877	.0057308
Canada: rho	.9691394	.0422435	.6140923	.9979475
var(e)	.0018281	.0025101	.000124	.0269621
Denmark: rho	.998512	.002167	.9744212	.9999144
var(e)	.0537826	.0768772	.0032653	.8858394
Finland: rho	.6882944	.2138179	.0483283	.927619
var(e)	.0011297	.0007724	.0002957	.004315
France: rho	.9929256	.0126658	.7855396	.9997902
var(e)	.0046412	.0082615	.0001417	.1519813
Germany: rho	.5627398	.2908996	-.1950174	.899809
var(e)	.0009783	.0005364	.000334	.0028654
Ireland: rho	.8001981	.147756	.2858298	.9566046
var(e)	.0017675	.0013168	.0004104	.0076122
Italy: rho	.9777863	.0359351	.5658475	.9990905
var(e)	.0018639	.0029829	.0000809	.0429175
Japan: rho	.9570402	.0635776	.4030777	.9977373
var(e)	.0025563	.0038067	.0001381	.0473342
Korea: rho	.5639026	.4024396	-.4761469	.9462924
var(e)	.0020481	.0019215	.0003257	.0128809
Netherlands: rho	.9376142	.0909198	.2390328	.9966298
var(e)	.0024536	.0034919	.0001508	.039923
New Zealand: rho	.7718462	.1472257	.3014161	.9400735
var(e)	.0062766	.0039682	.0018179	.0216708
Norway: rho	.6342345	.1547524	.2364851	.8499269
var(e)	.0075435	.0032849	.003213	.0177107
Portugal: rho	.9423701	.0970663	.0591816	.9980199
var(e)	.0050465	.0083342	.0001983	.1284475
Spain: rho	.996042	.006935	.8834138	.999873
var(e)	.0206853	.0357741	.0006975	.6134372
Sweden: rho	.9986458	.002015	.975228	.9999268
var(e)	.0879832	.12824	.0050551	1.531331
Switzerland: rho	.9994492	.0008159	.9899974	.9999698
var(e)	.1237715	.1788822	.0072847	2.102954
United Kingdom: rho	.5594867	.1767299	.1271765	.8131653
var(e)	.0008922	.0003679	.0003977	.0020019
United States: rho	.9956881	.0062349	.9286644	.9997476
var(e)	.0223371	.0317445	.0013783	.3620054

LR test vs. linear regression: chi2(38) = 1112.91 Prob > chi2 = 0.0000

The model above to the left is the mixed FD model. The model above to the right is the mixed model using trade

Models below are estimated without outliers and series breaks in UK and Netherlands.

Mixed-effects REML regression — Number of obs = 430
Group variable: id — Number of groups = 19

Obs per group: min = 8, avg = 22.6, max = 28

Wald chi2(24) = 971.60
Log restricted-likelihood = 977.82617 — Prob > chi2 = 0.0000

log10	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
occ	.0028708	.0006465	4.44	0.000	.0016038	.0041379
cm_tax	-.0073085	.0022762	-3.21	0.001	-.0117697	-.0028473
w_tax	-.0091964	.0024224	-3.80	0.000	-.0139442	-.0044486
cm_logGDP	.1046936	.166761	0.63	0.530	-.2221519	.4315391
cm_GDPgr	.0232097	.0378256	0.61	0.539	-.0509271	.0973465
w_GDPgr	.0009939	.0003672	2.71	0.007	.0002743	.0017135
cm_unem	.0061046	.0071708	0.85	0.395	-.0079498	.0201591
w_unem	.0005395	.0007819	0.69	0.490	-.000993	.002072
cm_imp	.0187167	.0062344	3.00	0.003	.0064976	.0309358
w_imp	.0008258	.0007422	1.11	0.266	-.000629	.0022805
cm_exp	-.0142123	.0056498	-2.52	0.012	-.0252857	-.0031389
w_exp	.000016	.0006966	0.02	0.982	-.0013492	.0013813
cm_logpop	.0348089	.0308982	1.13	0.260	-.0257504	.0953682
cm_popgr	-.0734083	.099129	-0.74	0.459	-.2676974	.1208809
w_popgr	-.0044778	.002966	-1.51	0.131	-.010291	.0013354
cm_labor	-.0037788	.0018498	-2.04	0.041	-.0074043	-.0001532
w_labor	-.0108198	.0021623	-5.00	0.000	-.0150578	-.0065818
cm_ext	-.0435505	.0182733	-2.38	0.017	-.0793655	-.0077356
w_ext	.0225576	.0084833	2.66	0.008	.0059307	.0391846
w_tax						
L1.	-.0004551	.0002105	-2.16	0.031	-.0008676	-.0000426
L2.	-.0004805	.0002126	-2.26	0.024	-.0008973	-.0000637
L3.	-.0000299	.0002118	-0.14	0.888	-.000445	.0003851
c.cm_tax# c.w_tax	.0001586	.0000436	3.64	0.000	.0000732	.000244
c.cm_imp# c.w_labor	.0002492	.0000647	3.85	0.000	.0001224	.000376
_cons	2.165601	1.50641	1.44	0.151	-.7869093	5.118111

Random-effects Parameters		Estimate	Std. Err.	[95% Conf.	Interval]
id: Identity					
	var(_cons)	1.78e-20	.	.	.
Residual: AR(1), by CN					
Australia:	rho	.7531746	.2871671	-.3098873	.9793303
	var(e)	.0019745	.0022969	.0002019	.0193048
Canada:	rho	.9936462	.0231894	-.6129906	.9999951
	var(e)	.008477	.0311332	6.34e-06	11.33491
Denmark:	rho	.9021579	.1408412	.0004745	.9947174
	var(e)	.0004177	.000592	.000026	.0067181
Finland:	rho	.9932055	.0104292	.8695761	.9996669
	var(e)	.0529997	.0796453	.002787	1.007896
France:	rho	.9819925	.0322898	.5207251	.9994763
	var(e)	.0016509	.0029298	.0000509	.0534975
Germany:	rho	.6785466	.2566377	-.1054088	.9423501
	var(e)	.001291	.0008715	.0003438	.0048476
Ireland:	rho	.9690931	.2133941	-.9998633	1
	var(e)	.0125848	.0879331	1.42e-08	11153.08
Italy:	rho	.99164	.0170983	.619323	.9998501
	var(e)	.0052341	.0106032	.0000987	.277464
Japan:	rho	.995702	.0145841	-.2563374	.9999945
	var(e)	.0269707	.0917684	.0000342	21.23865
Korea:	rho	.579151	.4170046	-.5143512	.95546
	var(e)	.0021387	.0021326	.0003029	.0150988
Netherlands:	rho	.9974022	.0099359	-.4057834	.9999986
	var(e)	.0103275	.0418729	3.65e-06	29.18737
New Zealand:	rho	.8817162	.1470268	.0885055	.990607
	var(e)	.0070159	.0085257	.0006482	.0759388
Norway:	rho	.7948692	.1176872	.4284776	.9367712
	var(e)	.0056204	.0032518	.0018083	.0174684
Portugal:	rho	.9544779	.0670318	.3826812	.9975728
	var(e)	.0064646	.0092652	.0003896	.1072777
Spain:	rho	.9902487	.0161087	.7749069	.9996215
	var(e)	.0081906	.0134252	.0003297	.2034754
Sweden:	rho	.9857563	.0255261	.6043015	.9995829
	var(e)	.0060373	.010588	.0001941	.1877812
Switzerland:	rho	.8712456	.1417232	.1832215	.9863766
	var(e)	.0005836	.0006306	.0000702	.004851
United Kingdom:	rho	.57204	.2057126	.051208	.8482407
	var(e)	.0008709	.0004259	.000334	.0022708
United States:	rho	.983292	.0234465	.7622276	.9989486
	var(e)	.0055993	.0077701	.0003689	.0849846

LR test vs. linear regression: chi2(38) = 1103.86 Prob > chi2 = 0.0000

Mixed-effects REML regression — Number of obs = 430
Group variable: id — Number of groups = 19

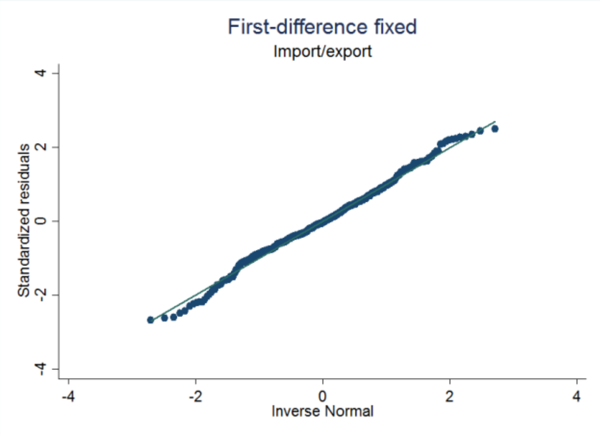
Obs per group: min = 8, avg = 22.6, max = 28

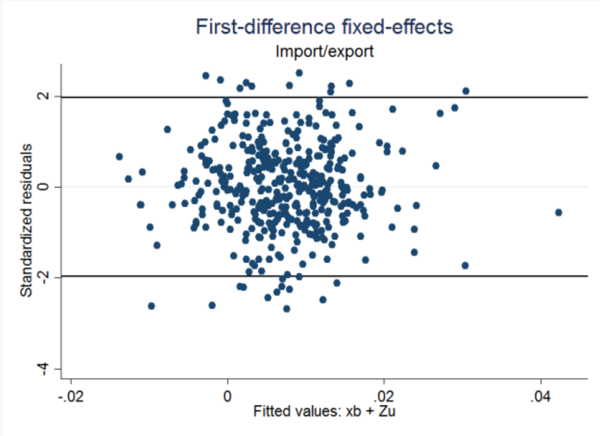
Wald chi2(22) = 440.19
Log restricted-likelihood = 982.48507 — Prob > chi2 = 0.0000

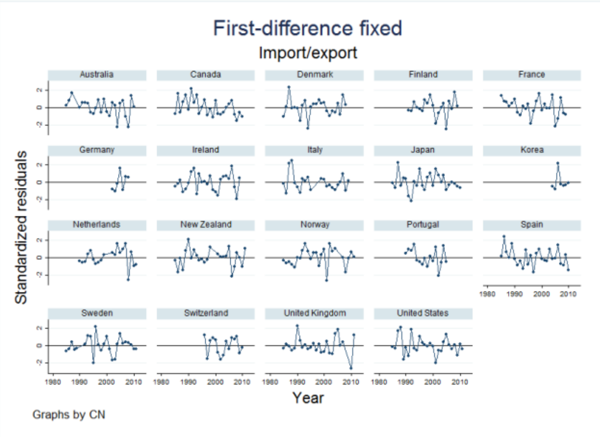
log10	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
occ	.0027874	.0006547	4.26	0.000	.0015043	.0040706
cm_tax	-.0169935	.0029127	-5.83	0.000	-.0227023	-.0112847
w_tax	-.0088932	.0024371	-3.65	0.000	-.0136699	-.0041166
cm_logGDP	-.1483682	.1462953	-1.01	0.311	-.4351017	.1383653
cm_GDPgr	-.0078174	.0356903	-0.22	0.827	-.0777691	.0621342
w_GDPgr	.000956	.0003653	2.62	0.009	.0002401	.0016719
cm_unem	.0084292	.0073552	1.15	0.252	-.0059867	.0228452
w_unem	.0003516	.0007199	0.49	0.625	-.0010594	.0017625
cm_trade	.0023099	.0013442	1.72	0.086	-.0003246	.0049444
w_trade	.0004214	.0001873	2.25	0.024	.0000544	.0007884
cm_logpop	.1054776	.0413826	2.55	0.011	.0243691	.1865861
cm_popgr	-.0199184	.1002516	-0.20	0.843	-.2164078	.176571
w_popgr	-.0042087	.0029598	-1.42	0.155	-.0100097	.0015924
cm_labor	.0037631	.0023858	1.58	0.115	-.000913	.0084391
w_labor	-.0102237	.0020961	-4.88	0.000	-.014332	-.0061155
cm_ext	.0309493	.0192461	1.61	0.108	-.0067725	.068671
w_ext	.0213078	.008418	2.53	0.011	.0048087	.0378068
w_tax						
L1.	-.0004795	.0002103	-2.28	0.023	-.0008917	-.0000674
L2.	-.0004977	.0002129	-2.34	0.019	-.000915	-.0000805
L3.	-.0000276	.0002121	-0.13	0.896	-.0004433	.000388
c.cm_tax# c.w_tax	.0001529	.0000438	3.49	0.000	.000067	.0002388
c.cm_imp# c.w_labor	.0002337	.0000626	3.73	0.000	.000111	.0003564
_cons	3.630423	1.143553	3.17	0.001	1.3891	5.871746

Random-effects Parameters		Estimate	Std. Err.	[95% Conf.	Interval]
id: Identity					
	var(_cons)	.0003586	.001549	7.55e-08	1.703202
Residual: AR(1), by CN					
Australia:	rho	.7261234	.2630474	-.168475	.9648002
	var(e)	.0017838	.0017121	.0002718	.0117043
Canada:	rho	.9979712	.0030637	.9614575	.9998951
	var(e)	.0260398	.0386723	.0014174	.4783837
Denmark:	rho	.918011	.1324968	-.0750082	.9968603
	var(e)	.0004747	.000762	.0000204	.0110348
Finland:	rho	.8092406	.2753051	-.4124928	.9907948
	var(e)	.0018894	.0027068	.000114	.031316
France:	rho	.9870587	.0246214	.5651647	.9996947
	var(e)	.002262	.0043066	.0000542	.0944297
Germany:	rho	.7632027	.4710324	-.8358728	.9967803
	var(e)	.0016585	.0028588	.0000566	.0486362
Ireland:	rho	.9407704	.1059661	-.0619784	.998356
	var(e)	.0065617	.0119366	.0001856	.2319843
Italy:	rho	.9989149	.001782	.9731808	.9999566
	var(e)	.0409825	.0664156	.0017106	.9818437
Japan:	rho	.99906	.0014619	.9803464	.9999554
	var(e)	.1237978	.1890933	.0062024	2.470979
Korea:	rho	.5959121	.4243161	-.5390455	.9623201
	var(e)	.0022182	.0023425	.00028	.017575
Netherlands:	rho	.9923282	.01535	.6703681	.9998497
	var(e)	.003679	.0072128	.0000789	.1716076
New Zealand:	rho	.8675845	.140337	.2079052	.9847845
	var(e)	.0062898	.0064918	.0008319	.0475531
Norway:	rho	.9095832	.1021042	.3505327	.9907193
	var(e)	.012833	.0144537	.0014113	.1166884
Portugal:	rho	.9584503	.063959	.3678911	.9980538
	var(e)	.0071114	.0107024	.0003723	.1358262
Spain:	rho	.992537	.0134918	.7679554	.9997863
	var(e)	.010794	.0193812	.0003197	.3643888
Sweden:	rho	.9977728	.0034045	.9562226	.9998889
	var(e)	.0385807	.058005	.0020259	.7347304
Switzerland:	rho	.8698714	.1462971	.1529244	.9869028
	var(e)	.0005744	.0006368	.0000654	.0050457
United Kingdom:	rho	.578758	.2128666	.0332332	.8585863
	var(e)	.000883	.0004503	.000325	.0023989
United States:	rho	.9971151	.0044351	.942642	.9998587
	var(e)	.0331161	.0498726	.0017304	.6337862

LR test vs. linear regression: chi2(38) = 1126.37 Prob > chi2 = 0.0000


First-difference fixed
Import/export
Standardized residuals
Inverse Normal


First-difference fixed-effects
Import/export
Standardized residuals
Fitted values: xb + Zu


First-difference fixed
Import/export
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Denmark
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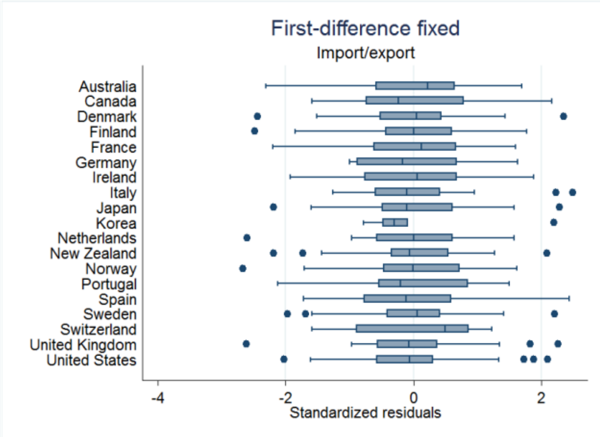
Portugal
Spain
Sweden
Switzerland
United Kingdom
United States
Standardized residuals
Year
Graphs by CN


First-difference fixed
Import/export
Australia
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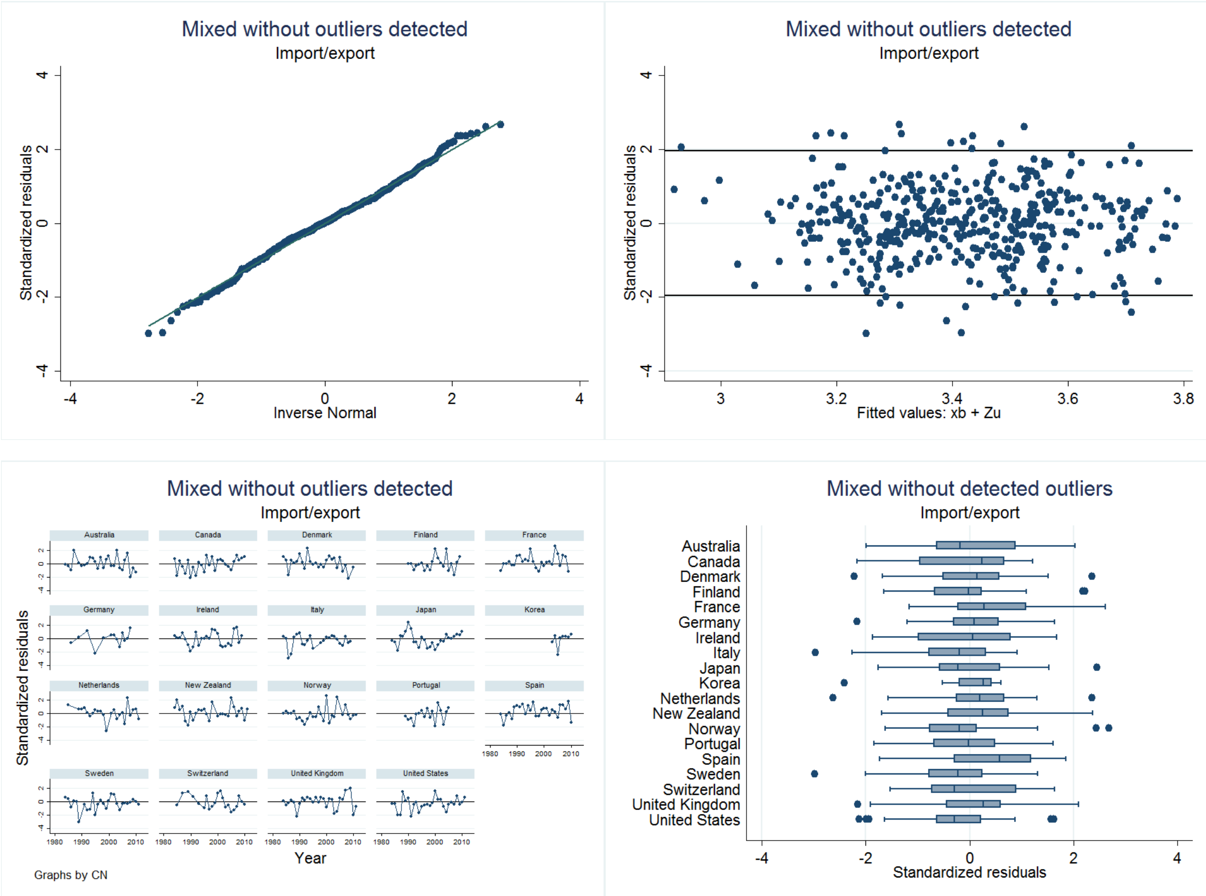
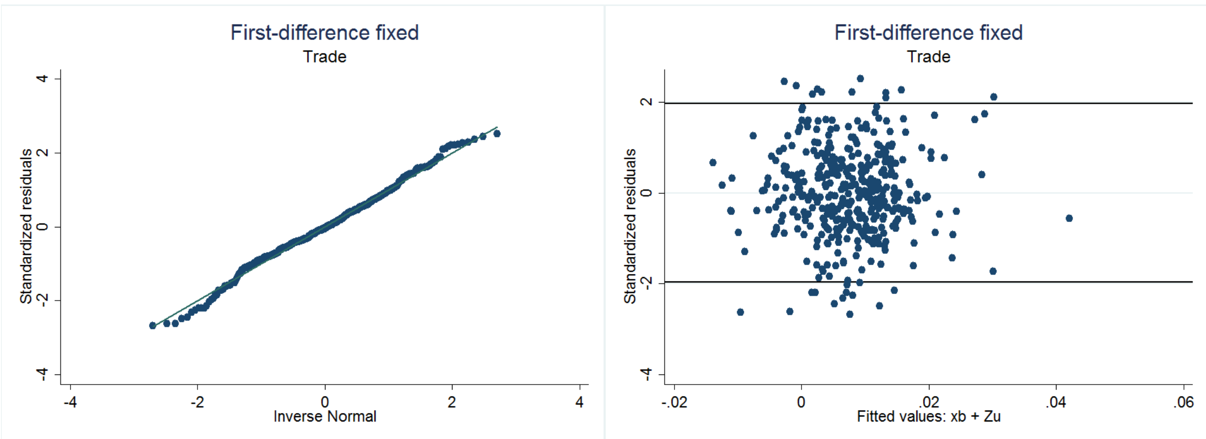
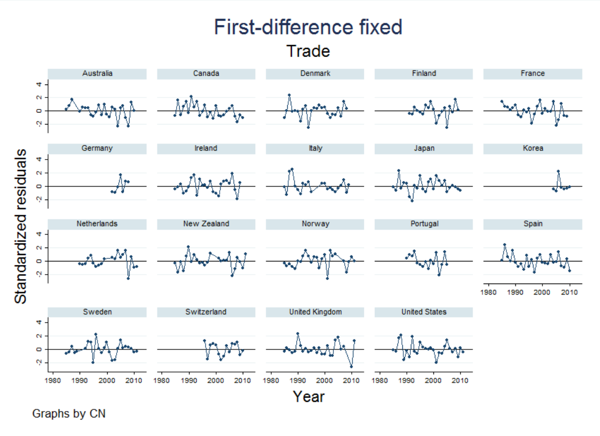
Spain
Sweden
Switzerland
United Kingdom
United States
Standardized residuals


Mixed without outliers detected
Import/export
Standardized residuals
Inverse Normal
Mixed without outliers detected
Import/export
Standardized residuals
Fitted values: xb + Zu
Mixed without outliers detected
Import/export
Standardized residuals
Year
Graphs by CN
Mixed without detected outliers
Import/export
Australia
Canada
Denmark
Finland
France
Germany
Ireland
Italy
Japan
Korea
Netherlands
New Zealand
Norway
Portugal
Spain
Sweden
Switzerland
United Kingdom
United States
Standardized residuals

Trade


First-difference fixed
Trade
Standardized residuals
Inverse Normal
First-difference fixed
Trade
Standardized residuals
Fitted values: xb + Zu


First-difference fixed
Trade
Standardized residuals
Australia
Canada
Denmark
Finland
France
Germany
Ireland
Italy
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Korea
Netherlands
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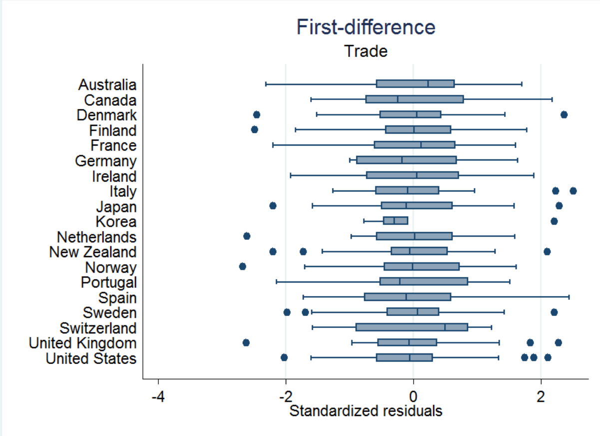
Norway
Portugal
Spain
Sweden
Switzerland
United Kingdom
United States
Year
Graphs by CN


First-difference
Trade
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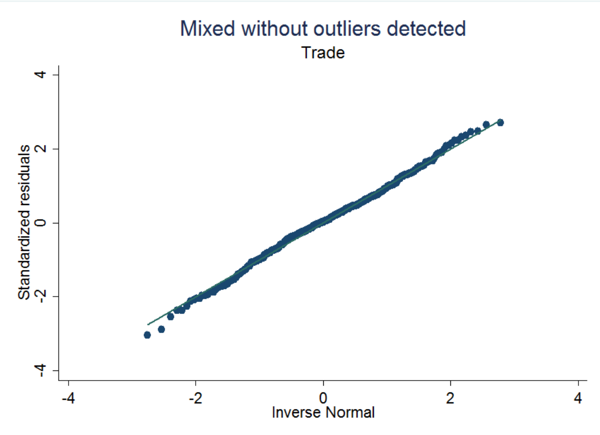
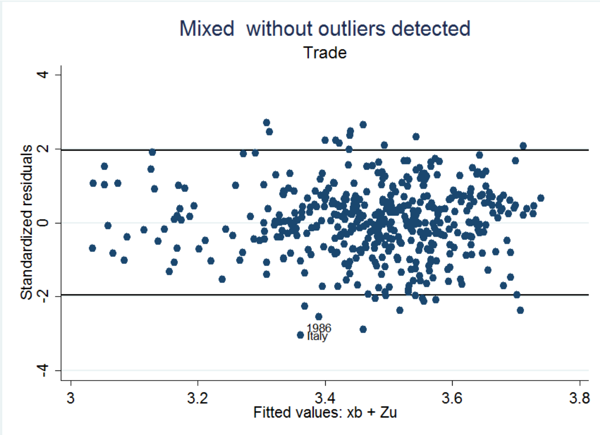
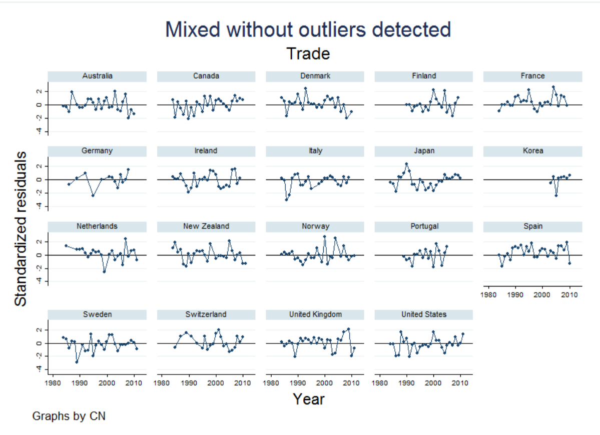
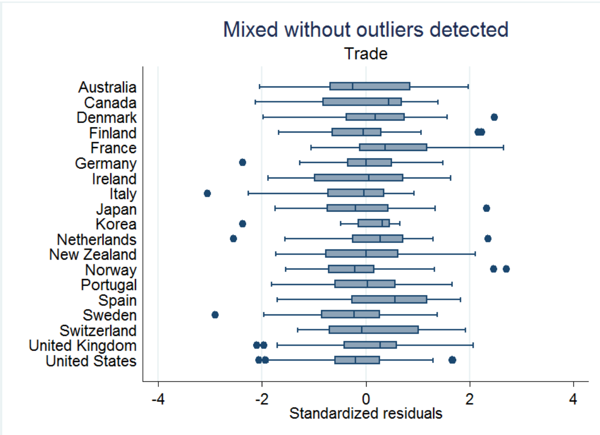
Switzerland
United Kingdom
United States
-4
-2
0
2
Standardized residuals


Mixed without outliers detected
Trade
Standardized residuals
Inverse Normal


Mixed without outliers detected
Trade
Standardized residuals
1986
Italy
Fitted values: xb + Zu


Mixed without outliers detected
Trade
Standardized residuals
Australia
Canada
Denmark
Finland
France
Germany
Ireland
Italy
Japan
Korea
Netherlands
New Zealand
Norway
Portugal
Spain
Sweden
Switzerland
United Kingdom
United States
Year
Graphs by CN


Mixed without outliers detected
Trade
Australia
Canada
Denmark
Finland
France
Germany
Ireland
Italy
Japan
Korea
Netherlands
New Zealand
Norway
Portugal
Spain
Sweden
Switzerland
United Kingdom
United States
-4
-2
0
2
4
Standardized residuals