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The November Revolution: Income inequality effects of the financial deregulation in Sweden

Hanna Eklööf (23242)

Abstract

The purpose of this thesis is to investigate whether the Swedish financial deregulation caused income inequality to increase in Sweden. In investigating this relationship, the synthetic control method and data over the years 1975 to 1995 are used. The deregulation was implemented in a number of steps beginning in 1982 and ending in 1985 with the so-called "November revolution". Four different measures of income inequality are studied. Namely, the pre-tax and -transfers and post-tax and -transfers Gini coefficients, respectively, and the pre-tax income shares of the top 10 percentile and the top 1 percentile. No direct conclusions can be inferred for three out of four income inequality measures. For the pre-tax and -transfers Gini coefficient, a considerable positive effect of close to two (2) percentage points can be attributed to the financial deregulation for which the results are overall robust. Part of the rise in the pre-tax and -transfers Gini coefficient can be attributed to the post-deregulatory rise in household debt as well as the expansion of the financial sector. This thesis contributes to the literature by evaluating the income inequality effects of the Swedish financial deregulation in the context of the synthetic control method, which has previously not been done.

Keywords**:** Income inequality, Synthetic control method, Financial deregulation

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Table of contents

1. Introduction **7**
2. The deregulation of the Swedish financial sector **8**
1. The “November revolution” 8
3. Literature review **9**
1. Models 10
2. Financial development and income inequality 11
3. Financial deregulation and income inequality 13
4. Hypotheses **15**
1. Household debt and income inequality 16
2. Financial sector expansion and income inequality 18
5. Data and method **20**
1. Data 20
1. Income inequality measures *22*
2. Control variables *24*
2. The Synthetic Control Method 26
1. Theoretical background *26*
2. Implementation of the synthetic control method *28*
3. Placebo tests *29*
4. Limitations of the synthetic control method *29*
6. Results **30**
1. Descriptive statistics 30
2. Simple regression analysis 32
3. Synthetic control method 34
4. Hypothesis tests 38
1. Household debt *39*
2. Financial sector expansion *40*
7. Robustness tests **42**
1. In-space placebo test 42
2. In-time placebo test 46
3. Constructed p-value 50
8. Discussion **51**
9. Limitations **54**
1. Financial sector deregulations in donor pool countries 54
2. Limitations of the synthetic control method 55
3. Scandinavian legal origin 56
4. Trade-off between time-span and number of countries 56
5. Interpolations 57
6. Income inequality measures 57
10. Conclusion **58**
11. References **60**
1. Written references 60
2. Other references 64

A. Appendix **66**
1. Data availability of dependent variables per country 66
2. Data availability of independent variables per country 67
3. Interpolated time series per country and variable: dependent variables 68
4. Interpolated time series per country and variable: independent variables 69
5. Synthetic control method outcomes using non-interpolated data 70
6. Descriptive statistics for countries in the synthetic control groups 74
7. Time lines of dependent variables per country 79
8. Time lines of independent variables per country 83

Abbreviations overview

GDP: Gross Domestic Product
GMM: Generalised Method of Moments
OECD: Organisation for Economic Co-Operation and Development
OLS: Ordinary Least Squares
RMSPE: Root Mean-Squared Percentage Error
SCG: Synthetic Control Group
SCM: Synthetic Control Method
SWIID: Standardized World Income Inequality Database
WDI: World Development Indicators
WID: World Inequality Database

Figures overview

Figure 1. Household and private debt (% of GDP) over time
Figure 2. Domestic credit provided by the financial sector (% of GDP) over time
Figure 3. The Lorenz curve contrasted with perfect equality
Figure 4. The estimated effect of the financial deregulation in Sweden for each of the four income inequality measures
Figure 5. Outcomes of the in-space placebo test using the pre-tax and -transfers Gini coefficient as dependent variable
Figure 6. Outcomes of the in-space placebo test using the post-tax and -transfers Gini coefficient as dependent variable
Figure 7. Outcomes of the in-space placebo test using the pre-tax income share of the top 10 percentile as dependent variable
Figure 8. Outcomes of the in-space placebo test using the pre-tax income share of the top 1 percentile as dependent variable
Figure 9. Outcomes of the in-time placebo test using the pre-tax and -transfers Gini coefficient as dependent variable
Figure 10. Outcomes of the in-time placebo test using the post-tax and -transfers Gini coefficient as dependent variable
Figure 11. Outcomes of the in-time placebo test using the pre-tax income share of the top 10 percentile as dependent variable
Figure 12. Outcomes of the in-time placebo test using the pre-tax income share of the top 1 percentile as dependent variable

Tables overview

Table 1. Overview of income inequality measures (used as dependent variables)
Table 2. Overview of control variables (used as independent variables)
Table 3. Descriptive statistics for Sweden
Table 4. Descriptive statistics for the sample of donor pool countries
Table 5. Simple linear regressions with country dummies

Table 6. Values for the control variables for the treated unit, Sweden, and each synthetic control group
Table 7. Control group unit weights per country and inequality measure
Table 8. Root mean-squared percentage errors (RMSPEs) for each synthetic control group in the pre-treatment period
Table 9. Test of the household debt hypothesis
Table 10. Test of the financial sector expansion hypothesis
Table 11. Constructed p-values for each country acting as the treated unit per inequality measure
Table 12. Table depicting the years of first implemented measures in relation to financial deregulation in synthetic control group countries

Appendix figures

Figure A1. The estimated effect of the financial deregulation in Sweden for each of the four income inequality measures using non-interpolated data
Figure A2. The Gini coefficient (pre-tax and -transfers) over time per country
Figure A3. The Gini coefficient (post-tax and -transfers) over time per country
Figure A4. The pre-tax income share of the top 10 percentile over time per country
Figure A5. The pre-tax income share of the top 1 percentile over time per country
Figure A6. The annual GDP per capita (constant USD2010) over time per country
Figure A7. The annual GDP growth (%) over time per country
Figure A8. The employment tax rate (%) over time per country
Figure A9. The union density (%) over time per country
Figure A10. The exports as % of GDP over time per country

Appendix tables

Table A1. Data availability of dependent variables per country
Table A2. Data availability of independent variables per country
Table A3. Interpolated time series of dependent variables per country
Table A4. Interpolated time series of independent variables per country
Table A5. Values for the control variables for the treated unit, Sweden, and each synthetic control group.
Table A6. Control group unit weights per country and income inequality measure
Table A7. Root mean-squared percentage errors (RMSPEs) for each synthetic control group
Table A8. Descriptive statistics for Denmark
Table A9. Descriptive statistics for Finland
Table A10. Descriptive statistics for France
Table A11. Descriptive statistics for Italy
Table A12. Descriptive statistics for Norway

1. Introduction

In the 2018 government election in Sweden, the topic of income inequality was on the agenda of many of the parties. Solutions for this issue ranged from lowering the marginal taxes on labour income to maintaining the current progressivity of the taxation system. The 1960s were characterised by decreased inequality through the expansion of the welfare state which entailed reforms regarding, for example, the labour market and the taxation system (Buendía, 2015). In the 1980s, on the other hand, income inequality levels started to rapidly increase. The pattern of rising income inequality holds true for more traditional measures of income inequality, such as the Gini coefficient, as well as income inequality as measured by the pre-tax income shares held by the top percentiles.

Beginning in the early 1980s, the Swedish credit market was exposed to a number of decisions that led to its eventual deregulation. The deregulation process is also referred to as the "November revolution" after the decision to abolish the lending ceiling for financial institutions, implemented on 21 November 1985 (Svensson, 1996).

In parts of the literature, it is suggested that the deregulation caused the Swedish financial crisis of the early 1990s. Englund (1999) puts forth that post-deregulation, the inter-competitive forces between financial institutions greatly increased which led to rapid credit expansion. This entailed greater risks in the economy while prices and the investment rate rose. The rise in interest rates in conjunction with the European Exchange Rate Mechanism crisis and a newly implemented tax-reform finally led to the financial crisis. Englund conveys that the per taxpayer-cost of the financial crisis is estimated to two (2) percent of GDP. This view is further supported by Jonung (2000) who states that the Swedish economy became overheated in the end of the 1980s as a consequence of the expansive financial policies following the deregulation. Swedish households and companies started borrowing more than before, for both investments and consumption. The prices of bonds and property rose hand-in-hand with the inflation rate, eventually resulting in the Swedish financial crisis of the early 1990s.

This paper attempts to study whether a causal effect from the Swedish financial deregulation on different measures of income inequality can be found. As income inequality measures, the pre-tax and -transfers and post-tax and -transfers Gini coefficients are used, as well as the pre-tax income shares of the top 10 and top 1 percentiles, respectively. The Gini coefficient is one approach for determining income inequality. The interval for the Gini coefficient is between zero (0) and one (1) where one denotes perfect inequality and zero denotes perfect equality. In order to shed light on this possible relationship, the synthetic control method (SCM) is utilised, thus adding to the relatively scarce literature of income inequality studies with the aforementioned method. Moreover, the Swedish financial deregulation and its impact on income inequality has not been previously studied in the context of the SCM. The SCM, in short, is a method for constructing a synthetic counterfactual in event studies

where there is no real control group (Abadie et al., 2010; 2015). The synthetic control group (SCG) is meant to assume the trajectory of the treated unit in absence of treatment. By comparing the SCG to the treated unit, the outcome of a specific treatment can be evaluated. Some connections between income inequality and financial crises has been found in the literature (see, for example, van Treeck (2013) for an overview). Assessing the causes of income inequality can therefore provide stronger foundations for policymakers and regulators in attempting to alleviate skewed income distributions which is relevant for the stability of the economy, and the society as a whole.

The rest of the thesis is organised as follows. First, the background of the Swedish deregulation will be presented as well as the current state of the literature on income inequality and its relation to financial development and deregulation, respectively. After reviewing the literature, three hypotheses are presented which are followed by a presentation of the data as well as the method and the case-specific application of the SCM. The thesis continues with a presentation of the descriptive statistics and the results, which are followed by placebo tests. The results are analysed in the subsequent section. Lastly, the thesis is concluded with a discussion of the limitations and a summary.

2. The deregulation of the Swedish financial sector

2.1 The "November revolution"

The deregulation of the Swedish financial sector was a gradual process taking place between the years 1982 to 1985 (Svensson, 1996). Jonung (2000) affirms that prior to the deregulation, in the 1970s, Sweden had strict regulations in place for the credit market and exchange rate of the Swedish krona. Following the election won by the Social Democrats in 1982, the Swedish krona was devalued by 16 percent. This was the context in which the series of decisions that led to the financial deregulation were set in motion.

Svensson (1996) describes the deregulatory process as beginning in 1982, when new forms of government securities, the treasury bills, were introduced in order to help decrease the national debt. Banks were only allowed to act as intermediaries in the buying process. This was historically ground-breaking in the sense that non-financial institutions would help in alleviating the national debt. Moreover, for the first time ever the emission rate would be set by the market instead of the Riksbank. The treasury bills were followed by longer-term treasury notes the subsequent year. In 1983, the liquidity requirements for banks and other financial institutions were abolished. As a result, they were no longer required to keep a certain quota in cash and cash equivalents to cover real as well as simulated cash outflows under a stress period of 30 days (Finansinspektionen, 2018). Jonung (2009) remarks that in 1984, a standard

for currency loans was rolled out which entailed a large increase in the private sector holdings of foreign debt.

Svensson (1996) further accounts for the measures implemented in the deregulation. On 13 May, 1985, the lending ceiling on subordinated loans for banks, financial institutions, and housing institutions was lowered from four (4) to two (2) percent. The lending ceiling essentially capped how much the banks could lend to borrowers posting little to no collateral. Moreover, the interest regulation was abolished. It is, however, the final measure to remove the lending ceiling altogether, implemented on 21 November 1985 that has given the deregulation the overarching name of the "November revolution". By Svensson (1996, p. 37) it is described as "the most essential step in the deregulation of the credit market… [author's translation]". The removal of the lending ceiling was matched with an increase of the reserve requirements from one (1) to three (3) percent. For banks and other financial institutions, this implied that they had to keep a fixed percentage of the assets partly corresponding to the lending and borrowing in a separate account at the central bank or within the institution. Furthermore, the regulation of a two (2) percent maximum annual increase in the total amount of outstanding credit was removed. Requirements for the public pension funds and life insurance companies withstood, meaning that they had to buy a certain amount of government bonds. However, they were able to sell the bonds to a second party. Lastly, the interest rate at which the banks could borrow from the Riksbank was changed from a fixed rate to a step-wise interest rate contingent on the loan amount.

In summary, for banks and other financial institutions, the deregulation led to an increased amount of lending, more freedom in setting the interest rates, and weaker liquidity constraints. For households and the private sector, the deregulation was mainly associated with easier access to credit.

3. Literature review

In the following section, the current state of the literature on income inequality and its relation to financial development and financial deregulation, respectively, will be reviewed.

In the oft-cited paper from 1955, Kuznets examines the relationship between income distribution and financial development. According to Kuznets, economic and financial development tend to hurt the poor while benefitting the rich in at least the first and mid stages of a developing economy. The main take-away from Kuznets is the inverted U-shape of income inequality in relation to financial development. For a country in the developing stages of its economy, income inequality rises hand-in-hand with the level of financial development. In the mid-point of developing and developed economies, inequality reaches its peak. As the country becomes more and more financially developed, however, inequality starts to decrease.

Kuznets' finding is tested by Nikoloski (2012) using dynamic multivariate data analysis on a panel dataset of both developed and developing countries over the years 1962-2006. He uses the Gini coefficient as inequality measure, and derives a high-quality measure using an algorithm that provides a Gini coefficient merely based on income. As a robustness check, regressions are run also on the non-transformed Gini coefficient. Taking advantage of both the time and cross-sectional aspects of his panel data, he gets robust results strengthening Kuznets' proposed inverted U-shape curve.

While the effect on different kinds of inequality from financial development has been studied extensively in a number of settings, the relationship between financial deregulations and income inequality has been less so. In Demirgüç-Kunt and Levine (2008), financial development is described as financial intermediaries, markets and instruments improving information gathering and contract enforcement, and reducing transactions cost. This leads to a more efficient exchange of products and services and greater access to credit markets for both borrowers and lenders. Moreover, financial development simplifies the trading, diversification, and management of risk.

Although the connection between financial deregulation and financial development may not be immediately clear, financial deregulation can be interpreted as resulting in the abovementioned consequences of financial development. For example, as can be seen in figure 2 (section 4.2), the Swedish financial deregulation was associated with an expansion of the financial sector as measured by the domestic credit provided by the financial sector as percent of GDP. Therefore, it is of interest to review the literature on the relationship between income inequality and financial development, respectively financial deregulation.

3.1 Models

There have been several attempts to develop theoretical models to ascertain the relationship between financial development and inequality, a few of which will be reviewed below. Greenwood and Jovanovic (1990) present a model to address the connection between economic growth and income distribution as well as the relationship between economic development and financial structure. Their model suggests that income distribution becomes more disproportionate as incomes increase, the financial structure broadens, and the economic growth speeds up. In the long-run, however, the income inequality attains a stable level, thus speaking for the inverted U-shape originally proposed by Kuznets.

Galor and Zeira (1993) develop a model in the attempt to theoretically explain how income distribution and macroeconomic factors are related. The model consists of open economies with overlapping generations of homogenous agents as well as inter-generational transfers. A crucial assumption is that credit markets are imperfect, hence, the borrowing interest rate exceeds the lending rate. A second important assumption is indivisibility of human capital investments, which leads to the long-term

propagation of income distribution within the model society. One of the main takeaways is that cross-country differences in income equality arise due to differences in human capital investments because of the aforementioned imperfections in the credit market. Furthermore, Galor and Zeira's model suggests that different starting points of income has both short- and long-run consequences for aggregate economy measures.

Whereas Galor and Zeira focus on explaining why cross-country differences in the income distribution arise, Ghossoub and Reed (2017) instead attempt to model how financial systems and monetary policies should be constructed in order to alleviate income inequality. Thus, inflation plays a big role in their framework. Ghossoub and Reed take a similar approach as Greenwood and Jovanovic in that their model proposes a pathway where income inequality is increasing in the extent of financial development. The gist of Ghossoub and Reed's model is that optimal monetary policy need to evaluate how a particular policy affects capital owners versus liquid assets owners. Noteworthy is that income inequality seems to be less affected by monetary policy than financial development.

3.2 Financial development and income inequality

Clarke et al. (2006) evaluate the relationship between financial development and income inequality by using data for 83 countries over the years 1960 to 1995. To control for the possible endogeneity in financial development, the authors use control variables such as the inflation rate, government consumption, ethnolinguistic fractionalisation, a measure for the risk of expropriation, and different variants of the log of initial real GDP per capita. Income inequality is measured using the log of a modified Gini coefficient. The results in Clarke et al. suggest a negative long-term relationship between financial development and income inequality, i.e. that financial development is beneficial in reducing income equality. As a limitation to the results, the authors put forth the drawbacks of using the Gini coefficient as a dependent variable. One example is that there is no information on specific income groups, suggesting that it is difficult to track why changes in the Gini coefficient arise over time.

Beck et al. (2007) offer supporting evidence when studying if financial development affects income distribution and poverty levels from a cross-sectional perspective. In line with many other papers, Beck et al. use the Gini coefficient as a measure for income distribution. In addition, they use the income share of low-income individuals and the share of the population subsisting on less than 1 USD per day. The latter measure reflects absolute poverty levels. The amount of credit provided by financial intermediaries to the private sector divided by GDP is used as a measure for financial development. By utilising standard ordinary least squares (OLS) regressions and dynamic panel instrumental variables regressions, Beck et al. present three main findings. Firstly, more extensive financial development is correlated to a lower Gini coefficient, meaning less income inequality. Secondly, the income share of low-income individuals grows disproportionally quicker than the income share of high-income

individuals. Thirdly, the results suggest a negative correlation between financial development and the share of the population living on less than $1 per day. A caveat for the analysis on poverty levels is, however, lack of data over a long time span. The overall conclusion is that financial development benefit low-income individuals disproportionally, thus alleviating income inequality.

Hamori and Hashiguchi (2012) use an unbalanced panel dataset covering the years 1963 to 2002 in 126 countries and estimated household income inequality (EHII) as inequality measure. Their method of choice is panel data analysis using the absolute values and the natural logarithm of the EHII, respectively, as dependent variables. Apart from financial deepening measures, also financial openness is included as a control variable. Financial deepening is defined as the scalar growth of financial transactions vis-á-vis the real economy. As a robustness test, the possible endogeneity problem is addressed using dynamic models in which first-lagged values of the EHII and the natural logarithm are added as control variables. The results in Hamori and Hashiguchi's paper, in likeness with, for example, Clarke et al. (2006), suggest that financial deepening reduces income inequality. Moreover, they offer a possible explanation in the form of financial deepening leading to greater access to credit for low-income individuals, thus making them able to borrow more capital. This in turn leads to a larger mass of individuals being able to invest in physical and human capital.

In Jauch and Watzka (2015), a positive relationship between financial development and income inequality is found using a long-span dataset of 138, both developed and developing, countries. As in other papers, the Gini coefficient and the ratio of private credit to GDP are used as proxies for income inequality and financial development. Their stated goal is to test the conclusions that financial development is negatively correlated with income inequality from, for example, Galor and Zeira (1993). Furthermore, they test Greenwood and Jovanovic's (1990) model which suggests that income inequality follows an inverted U-shape with respect to financial development. Endogeneity problems are controlled for by using fixed effects panel estimation with yearly dummies. Jauch and Watzka propose that this is the main econometric difference from earlier research efforts. Although it is not ruled out that financial development may be beneficial for society as a whole, high-income groups benefit more than low-income groups. Therefore, Jauch and Watzka draw the conclusion that the hypothesis proposing that financial development has an income inequality reducing effect should be rejected. However, using a dynamic panel approach, the results suggest an inverted U-curve as proposed by Kuznets (1955).

Compared to many other papers reviewed, Ben Naceur and Zhang (2016) include several different measures of financial development related to financial access, efficiency, stability, and liberalisation. Moreover, each measure is divided into two separate indicators, related to financial institutions and financial markets, correspondingly. Ben Naceur and Zhang use a panel data set of 143 countries over the years 1961 to 2011 and the Gini coefficient and the poverty gap index to reflect

income distribution as well as the welfare distribution of low-income individuals. The methodology consists of a basic OLS regression with multiple independent variables. Furthermore, the authors utilise the instrumental variable approach to control for endogeneity and reverse causality issues. Finally, Ben Naceur and Zhang have a third regression specification with dummies for country-income groups, with the high-income countries acting as the baseline. The main findings reported are that greater financial development overall may reduce income inequality and poverty levels whereas financial liberalisation show a tendency to widen the income distribution.

In a more recent paper by de Haan and Sturm (2017), the authors use cross-sectional data for 121 countries in the period 1975 to 2005 and a panel fixed effects model in order to investigate the correlation between income inequality and financial development, financial liberalisation, and banking crises. Income inequality is measured in a similar manner as in other papers, with the Gini coefficient. Interestingly, the results in de Haan and Sturm contradict what was uncovered in e.g. Clarke et al. (2006). de Haan and Sturm find instead that for all financial measures, income inequality increases. They further put forth that their results are robust for using legal origin as instrument for financial development, as well as using random effects and cross-country regressions. De Haan and Sturm suggest that their results can be interpreted in accordance with the model developed by Greenwood and Jovanovic (1990).

3.3 Financial deregulation and income inequality

The events of the US financial deregulation are described in Kroszner and Strahan (1999). The deregulation consisted mainly of the lifting of intra- and interstate banking regulations, of which the former was restricted in many states and the latter prohibited in all states. Starting in the 1970s, some states began the process by allowing for full intrastate branching whereas other states were more restrictive and allowed it only through mergers and acquisitions. Furthermore, multibank holding companies were gradually permitted to convert subsidiary offices to single-bank branches. Interstate banking regulations were lifted later, with the states of Alaska and New York as forerunners. The deregulatory process culminated in 1994 when the Riegle-Neal Interstate and Branching Efficiency Act was passed and national branching restrictions were completely removed. Xu et al. (2018) point to the main result of the banking deregulation as being a decrease in the banks' local monopoly power coupled with an increase in the quality of the financial intermediation of the banks.

Beck et al. (2010) study the effect of the US deregulation on income inequality with a focus on the lifting of intra-state branching regulations. The income distribution is measured using the Current Population Survey data between the years 1976 and 2005. Four measures of income distribution are used, namely, the natural logarithm of the Gini coefficient, the coefficient of variation of income, and the difference between the natural logarithm of incomes of the 90^{th} and the 10^{th} percentile as well as the 75^{th}

and 25th percentile. The authors estimate the relationship between income distribution and the branch deregulation by utilising a differences-in-differences approach in which the measures of income distribution act as dependent variables. Beck et al. find that the branching regulation led to a decrease of 2.6 percentage points in the Gini coefficient. When using alternative measures of income inequality, Beck et al. uncover the same pattern. That is, the branching deregulation decreases income inequality. They present two theories for why these results may occur, the first of which is that access to credit increase post-deregulation for low-income households which gives them greater possibilities to attain more education as well as becoming entrepreneurs. However, this is not supported empirically. Instead, Beck et al. propose that the decrease in income inequality arose mainly due to changes in labour market conditions such as a lower wage difference between high- and low-skilled workers and between men and women, respectively. In other words, financial deregulation helps low-income individuals without hurting high-income individuals.

Xu et al. (2018) investigate the effects of the US deregulation on inequality measured in terms of the Gini coefficient and Frank's (2014) Theil index by using a panel dataset. The Theil index is similar to the Gini coefficient in that lower values signify low inequality levels, and vice versa. However, they differ in that the Theil index can be decomposed into within-group (e.g. a specific geographical area) and across-group (e.g. a certain ethnicity) inequality. The method consists of an OLS model with fixed effects, as well as system Generalised Method of Moments analysis (GMM). In brief, as described by Zsohar (2012), GMM uses several distribution moments of the data, in addition to the mean and variance, which tends to provide more accurate parameters than standard regression models. The general finding of Xu et al. (2018) is that the US financial deregulation is correlated with a statistically significant increase in the Gini coefficient, thus meaning an increase in inequality. Xu et al. therefore put forth contradicting evidence to Beck et al. (2010). The results point in a similar direction when the Theil index is used as the dependent variable. The authors conclude that a possible explanation for their results is that access to credit was shifted from smaller and lower-income borrowers to higher-income borrowers, hence leading to greater inequality.

In Tanndal and Waldenström (2018), the so-called "Big Bang" financial deregulations in Japan and the United Kingdom are studied. The authors focus on differences in pre-tax top incomes shares before and after the financial deregulations that took place in 1986 (the United Kingdom) and 1997-1999 (Japan). By utilising the synthetic control method, Tanndal and Waldenström attempt to find causal estimates of the income inequality effects from financial deregulation. The results suggest a substantial increase in the pre-tax top decile income shares five years post-deregulation, with the United Kingdom and Japan experiencing increases of 20 percent and 15 percent, respectively. For the pre-tax top percentile income shares, the increase was close to 30 percent for the United Kingdom and 10 percent in Japan five years post-deregulation. The results are robust with respect to synthetic control placebo tests.

Two possible explanations for the observed pattern are put forth, concerning the extensive margin and the intensive margin. The former is related to the returns to wealth in the financial sector and whether the access to credit markets changes with the deregulation. The latter is connected to whether the incomes of individuals already employed in the financial sector increases. Tanndal and Waldenström propose that the observed results are mainly explained by changes in the intensive margin, that is, that the earnings of financial sector employees increased.

Also Casti (2018) employs the synthetic control method to evaluate the effects of financial deregulation, focusing on Italy and Canada. The Italian financial deregulation took place in the years 1990-1993 and the Canadian one in 1987. In similarity with Tanndal and Waldenström, she uses top income shares as a measure of income inequality. Casti points out the commonality between the reforms in Italy and Canady as being the re-establishment of quasi-universal banks, that is, banks that perform a wide range of services from underwriting loans to asset management and financial advisory. In addition to the changes in extensive and the intensive margin, another possible pathway from financial deregulation to income inequality is consolidation of financial intermediaries. Casti puts forth that banking sector consolidation may affect both the intensive and the extensive margin, depending on for example how concentrated the banking sector is and what options are available to borrowers. The results in Casti's paper tell a similar story as Tanndal and Waldenström, namely that income inequality increased post-deregulation as a consequence of the top income shares benefitting disproportionally. Furthermore, Casti empirically tested applicability of the previously mentioned paths for Italy. She found the higher level of financial intermediary consolidation, the increase in financial sector wealth and income, and the banking sector privatisation process to be important factors for the observed relationship.

4. Hypotheses

It is possible to imagine different scenarios for if, and how, the financial deregulation in Sweden has affected income inequality. As put forth in section 3, previous literature is inconsistent with respect to the relationship between financial deregulation and financial development. Much of the research efforts have had cross-sectional approaches, which makes hard-cut comparisons difficult. The SCM has been previously utilised to evaluate the connection between financial deregulation and income inequality. Sweden has, as far as revealed by an extensive review of previous literature, not been hitherto studied in this context. Furthermore, it is not entirely certain that financial deregulations in other countries share enough similarities with Sweden so that the results are externally valid.

Considering the poor external validity of the previous income inequality studies in conjunction with SCM, the first hypothesis has the purpose of testing whether a causal

effect of the financial deregulation on income inequality can be found (see section 6.3). In short:

H_0^1: *The financial deregulation entailed no impact on income inequality.*

H_1^1: *The financial deregulation entailed increased income inequality.*

Assuming that H_0^1 can be rejected, two hypotheses for the channels through which the financial deregulation would partially cause an increase in income inequality are presented in sections 4.1 and 4.2 below.

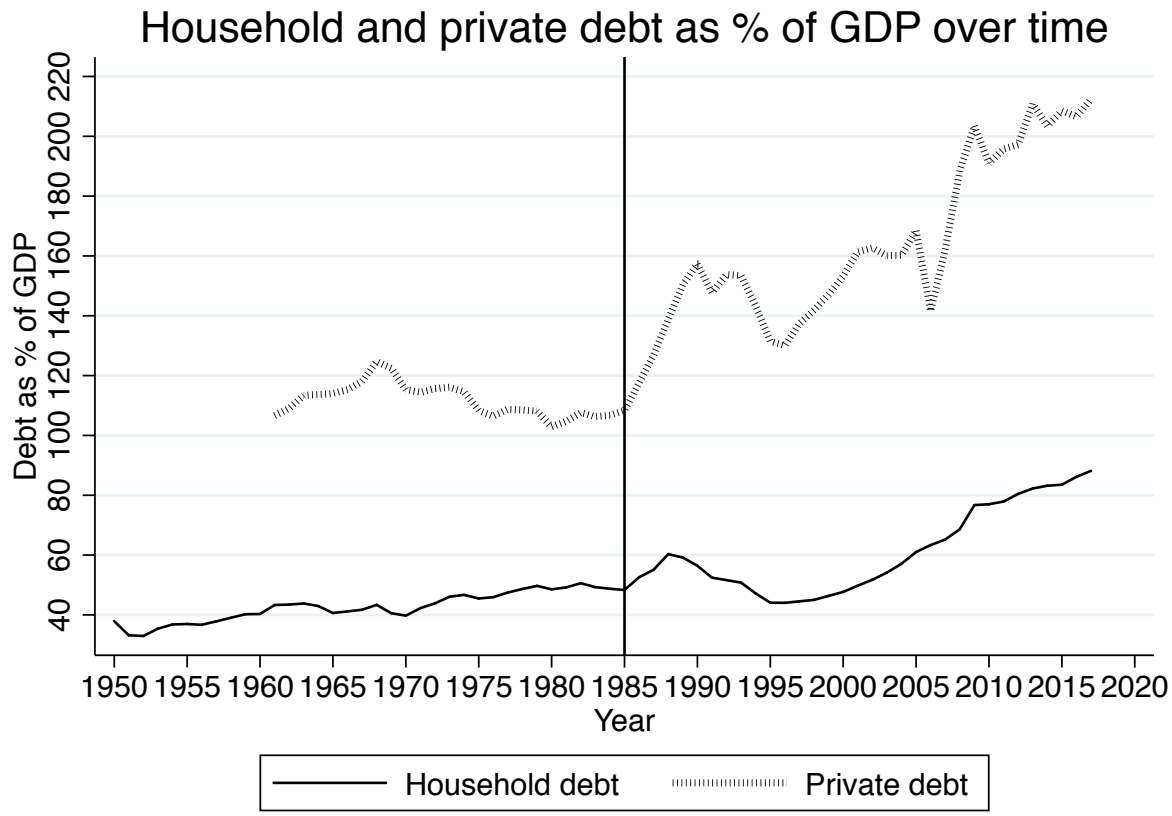
4.1 Household debt and income inequality

If the financial deregulation is viewed as a kind of financial development (see section 3 above), then the deregulation may indirectly, through household indebtedness, affect income inequality. Financial development typically leads to greater financial access, for example in terms of loan and credit availability. In Sweden, the time trend of household and private debt is strongly positive, especially in the period under study (see figure 1 below). Household debt is defined as the stocks of outstanding debt for households whereas private debt is defined as the gross outstanding stock of all liabilities classified as debt instruments (Chae, Mbaye, and Moreno Badia, 2018).

In the influential Iacoviello paper from 2008, the aim is to systematically explain the relationship between micro- and macro-volatility in household debt over time. Iacoviello presents a dynamic general equilibrium model in which agents are heterogeneous. In addition, he shows that the long-run tendencies of household debt and income inequality move parallel over time. To make the model more realistic, some households are assumed to experience binding constraints on the collateral they are able to post. Iacoviello's model suggests that disproportional income distribution is the main cause for households accumulating large amounts of debt.

In an attempt to determine whether rising debt levels may have caused the Great Recession in 2008-2009, Perugini et al. (2015) use a logit model with random effects to estimate the probability of a financial crisis. The amount of credit to GDP ratio is used as control variable. Moreover, a dynamic model is utilised to evaluate the effect on credit expansion of financial deregulation and income inequality, for which strongly positive and, mostly, statistically significant effects are found for the income inequality. In Berisha et al. (2017), the link between household debt, the stock market, and income distribution is studied. The authors use long-spanning US data from the 20th century in order to shed light on this relationship. A significant and positive effect of household debt on income inequality is uncovered. Berisha et al. suggest that their results are a consequence of high-income households making money by lending to low-income households, thus widening the income distribution.

Figure 1
Household and private debt (% of GDP) over time



Notes: The year in which the financial deregulation was finalised, 1985, is marked by the vertical line in the figure. Data are gathered from the Global Debt Database, International Monetary Fund (2018, accessed on 2 April 2019).

In the “November revolution”, lending ceilings for banks and other financial institutions were abolished in conjunction with more freedom in setting the lending interest rate. In addition, regulations for the annual increase in outstanding credit were removed and banks could to a larger extent lend to borrowers posting little to no collateral. Therefore, households were able to accumulate more debt. In line with Berisha et al. (2017), income inequality would rise as richer households are, due to the financial deregulation, able to further their income by lending to poorer households at some interest rate. Because of the subordinated lending, the poorer households would also be able to take on more debt than economically rational which could cause payment issues in the event of, for example, interest rate increases. The proposition is that the financial deregulation, through household indebtedness, consequently was associated with a rise in income inequality. The second hypothesis is tested with a simple OLS-regression (see section 6.4.1) where the percentage point deviation between Sweden and the synthetic Sweden is used as a dependent variable and the household debt is used as a control variable. The SCM provides a causal estimate of the rise in income inequality due to the financial deregulation. Hence, the estimated coefficient should be interpreted as a causal measure of household indebtedness on income inequality.

To summarise,

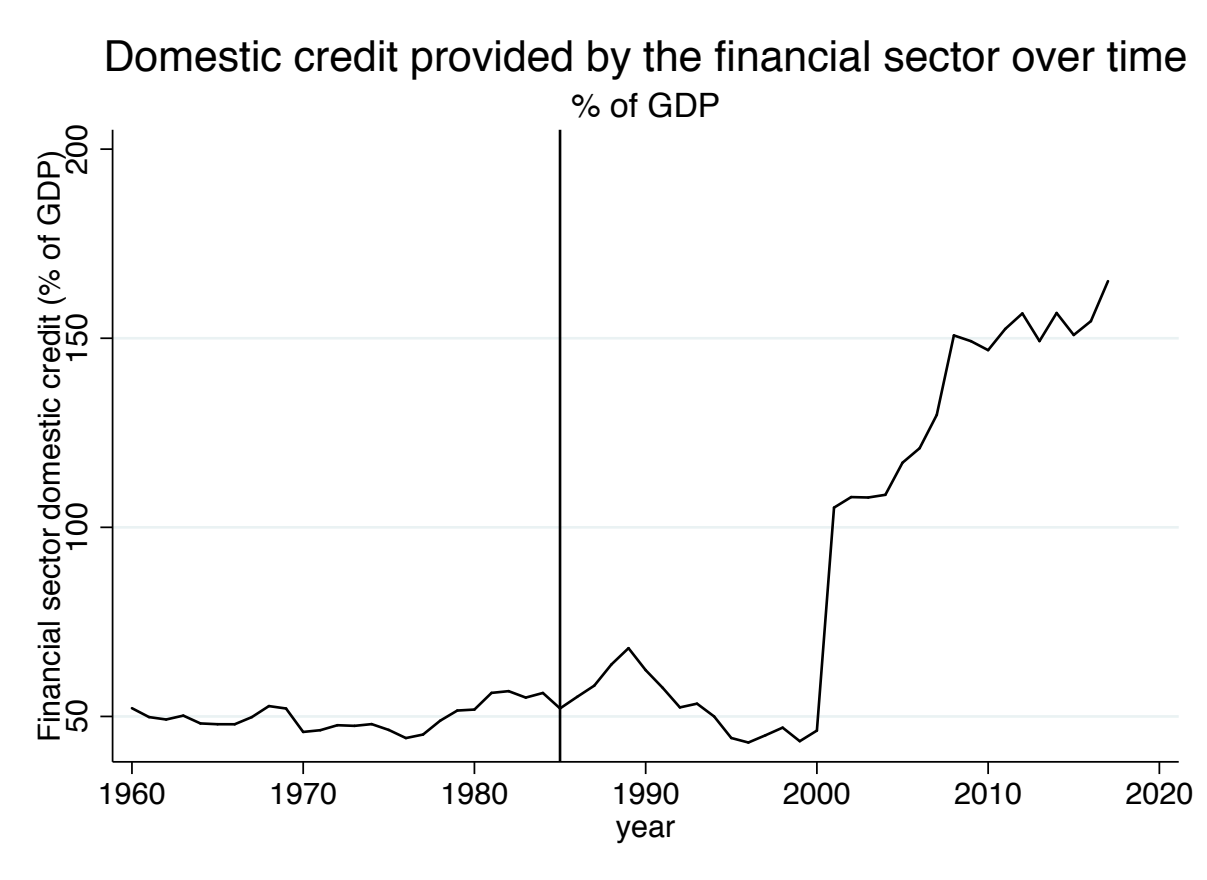
H_0^2: *Household indebtedness had a negative impact or no impact on income inequality.*

H_1^2: *Household indebtedness caused an increase in income inequality.*

4.2 Financial sector expansion and income inequality

The expansion of the financial sector resulting from the financial deregulation is shown graphically in figure 2 below, in which the domestic credit provided by the financial sector as a percentage of GDP in Sweden is plotted over time.

Figure 2
Domestic credit provided by the financial sector (% of GDP) over time



Notes: The year in which the financial deregulation was finalised, 1985, is marked by the vertical line in the figure. Data are gathered from the International Monetary Fund, International Financial Statistics and data files, and World Bank and OECD GDP estimates (2019, accessed on 25 April 2019).

The domestic credit provided by the financial sector as percent of GDP, starts to rise immediately after the deregulation. Shortly before 1990, the financial sector domestic credit starts to fall, most likely as a pre-stage to the financial crisis of the early 1990s. The financial sector domestic credit starts to rapidly increase from the year 2000 onwards. The latest data point to record-high levels, where the financial sector

provides around 160 percent of the domestic credit in terms of the GDP. This is a clear indication of the expansion of the financial sector. Had it not been for the financial crisis of the early 1990s, the dot-com bubble in the end of the 1990s and beginning of the 2000s, and the Great Recession in the late 2000s, it is not implausible that the levels would have been consistently higher since the deregulation.

For the hypothesis that the financial sector expansion led to rising inequality levels, two main aspects can be considered. These are changes in the extensive and the intensive margins, respectively. The first regards the returns to wealth and the number of employees within the sector. The latter concerns the compensation to financial sector employees already working within the sector.

Denk (2015a) studies the correlation between the financial sector and income inequality. By looking at a large dataset of in total 18 European countries, he finds that, overall, 19 percent of the top 1 percent income earners are financial sector employees. Data are presented for Sweden, showing that the share of financial sector employees among the top 10 and 1 percent earners in 2010 amounted to around 8 and 15 percent, respectively. While these are not large shares in absolute levels, they should be considered in conjunction with the fact that the financial sectors across Europe tend to be small in relation to the rest of the economy, as put forth by Denk. Moreover, the percentages exclude the effect of working time on salaries and earnings. As a third point, the financial sector employees tend to receive sizeable bonuses in proportion to their salaries and compared to other sectors of the economy. Denk argues that this holds true for the majority of the top income earners. Denk (2015b) suggests that capital income tends to be more focused to the top income shares than labour income, which may further the disproportion in the total income distribution. Albeit only focusing on the top earners of the United Kingdom, also Kaplan and Rauh (2010) find results consistent with Denk, advocating that many top income earners are employed within the financial sector.

In a Sweden-specific setting, Roine and Waldenström (2010) claim that capital gains and asset price increases have been important factors in the rising inequality levels, whereas labour income has been less so. Asset prices in this context refer mostly to the prices of stocks. Comparing income shares of the top 10 and top 1 percent earners with and without capital gains included, the top income shares increase when accounting for capital income. Connecting the findings to Denk, this suggests that capital gains, the financial sector, and income shares are connected.

A third hypothesis, supported by the findings in Denk (2015a, 2015b), Kaplan and Rauh (2010), and Roine and Waldenström (2010) is that the income inequality rose due to the expansion of the financial sector. The expansion of the financial sector can be interpreted in light of the increased lending and new government assets introduced. With the financial deregulation causing the financial sector to expand and given that the financial sector tends to have a large amount of high net worth individuals, income

inequality would increase hand-in-hand with financial sector employment thus entailing the financial sector employees to hold a larger share of the top income shares. In addition, if banks and other financial institutions through the deregulation increase their profit margins, higher compensation to financial sector employees is made possible. This would analogously to above, also create a wider income distribution. Both channels proposed above entailed an overall increase, albeit not one-to-one, in the top income shares. It is, however, not likely that the income inequality increase can be fully attributed to the financial sector compensation given the relatively small size of the financial sector compared to the rest of the economy. Also the third hypothesis is tested with a simple OLS-regression, in which the percentage point deviation between the synthetic Sweden and Sweden is the dependent variable (see section 6.4.2). The domestic credit provided by the financial sector as percent of GDP is used as a control, implying that the estimated coefficient should be interpreted as the financial sector associated increase in income inequality. In summary,

H_0^3: *Financial sector expansion had a negative or no impact on income inequality.*

H_1^3: *Financial sector expansion caused an increase in income inequality.*

5. Data and method

5.1 Data

Data are gathered from different sources, described in further detail below. In tables A1 and A2 in the Appendix, the data availability in terms of years for each variable and country is presented. Given the lack of data for some countries and variables in certain years, linear interpolations of the time series have been performed where intermediate data are missing. Thorough information regarding which variables have been interpolated for which countries and years is available in tables A3 and A4 in the Appendix. As a robustness test, the same analyses have been executed without the interpolated variables. The results are presented in section 5 in the Appendix. To note is that interpolations have only been made for intermediate years of data, and not for years before or after the time series in question begin.

The linear interpolation essentially fills in missing values of a given variable, y, on the basis of the year variable, x. The interpolated values uses the closest pairs of observations (x_i, y_i) and (x_{i+1}, y_{i+1}) such that the missing value lies in-between. The linear interpolation uses the formula:

(1) $$y = \frac{y_{i+1} - y_i}{x_{i+1} - x_i}(x - x_i) + y_i.$$

For linear interpolation to be performed, y_i and y_{i+1} must be observable (Meijering, 2002).

As can be seen in section 6.3, the synthetic controls in majority do not give weight to the countries most exposed to interpolations. Furthermore, many of the interpolations are performed on year(-s) prior to the synthetic control "window" which is set to ± 10 years counting from the treatment period. The interpolations should therefore not have a major impact on the result. Finally, the results are very similar between the interpolated synthetic control groups (SCGs) and the non-interpolated SCGs (see section 5 in the Appendix). However, the main reason for interpolating data in order to be able to include more countries in the donor pool is that the author should not "pre-select" which countries are included in the groups but rather let it be decided by the algorithm.

A relatively large number of countries is included in the donor pool in order to avoid researcher bias in selecting donor countries. In total the donor pool amounts to 16 OECD countries: Australia, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, The Netherlands, New Zealand, Norway, Spain, Switzerland, the United Kingdom, and the United States. The country sample is inspired by Casti (2018) and Tanndal and Waldenström (2018). Due to lack of data mainly in the dependent variables, some countries have had to be excluded from the process in which the synthetic counterfactual is estimated. For the pre-tax and -transfers Gini coefficient as well as the post-tax and -transfers Gini coefficient, Denmark, the Netherlands, New Zealand, Spain, Switzerland, and the United States are excluded. For the pre-tax income share of the top 10 percentile, Finland, Spain, Switzerland, the United Kingdom, and the United States are excluded. The same countries are excluded for the pre-tax income share of the top 1 percentile, with the exception of Finland. This information is also provided in table 7 in section 6.3, where excluded countries are clearly marked.

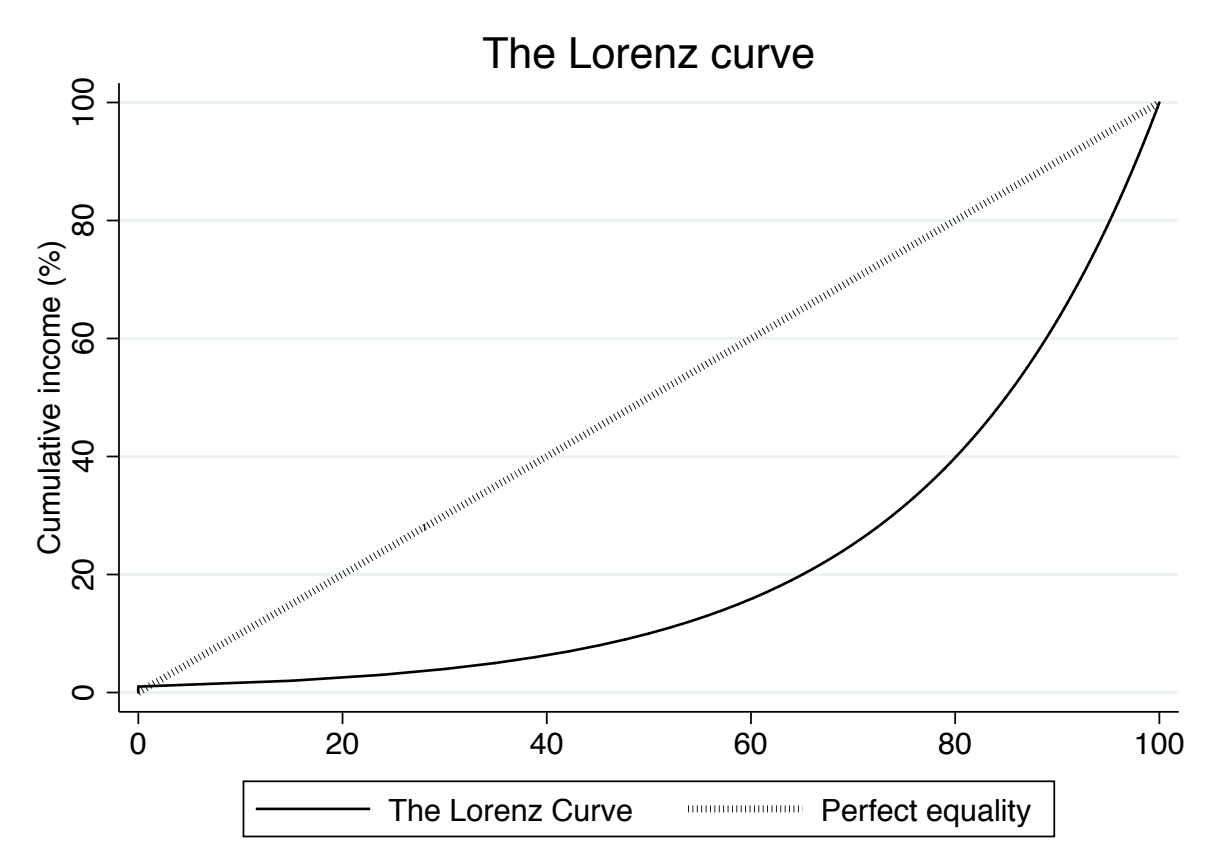
The time range for which the algorithm determines the synthetic control group is limited to the years 1970 to 1984. This can be considered a relatively small range but can be motivated by the fact that the majority of the control variables exhibit clear time trends. If not taken into account, part of the effect would possibly be ascribed to unmeasured factors which would make the results harder to interpret. The pattern of the dependent and the independent variables over time per country are available in figures A2-A10 in sections 7 and 8 the Appendix. Note that the time patterns of the dummy-variables are not shown. Moreover, there is a trade-off between deciding the pre-treatment time range and the number of countries included in the analysis. The earlier the first period is set, the fewer countries can be included in the donor pool. To not pre-select the sample and, as a consequence, the unit weights given, more countries and a smaller time frame is chosen. The true outcome and the synthesised outcome for independent variables are displayed over the range 1975 to 1995 (see figure 4 in section 6.3). Although data for most variables are available up until at least the early 2010s, it is likely that other events have taken place in the later half of the 1990s, such as the dot com bubble and the Great Recession, that have also had an effect on income inequality

in Sweden. Therefore, the results period in which the effect of the treatment is assessed, is limited to 1986 to 1995.

5.1.1 Income inequality measures

For the purpose of this study, four different measures are used to define income inequality. Traditionally, income inequality is measured with the Gini coefficient, also known as the Gini Index. The Gini coefficient ranges between 0 and 1, where 0 signifies perfect income equality and 1 perfect income inequality. The lower part of the range therefore suggests a more equal society in terms of income. The derivation of the Gini coefficient builds upon the Lorenz curve, which is obtained by plotting the income percentile of the population on the x-axis and the cumulative income on the y-axis. For example, if a society is very unequal, then the top percentiles will hold a larger share of the cumulative income. Perfect equality is represented by the 45-degree line, depicted by the dashed line in figure 3 below, implying that the first percentile should own one percent of the cumulative income, and so on. The Gini coefficient is then calculated as twice the area between the perfect equality line and the Lorenz curve for any given society. (Cowell, 2011)

Figure 3
The Lorenz curve contrasted with perfect equality



Notes: The author's own generated data was used in portraying the Lorenz curve and perfect equality.

Two kinds of Gini coefficients are utilised, using market income and disposable income, respectively, as inputs. The market income is the income of a household pre-tax and -transfers, whereas the disposable income is post-tax and -transfers. It is worthwhile to consider both measures since Sweden has a relatively extensive system of redistribution with respect to both transfers and taxes. Thus, it should be expected that the disposable income Gini coefficient display relatively lower income inequality vis-á-vis the market income Gini coefficient. One obvious caveat of using the Gini coefficients as sole measures of income inequality is that there is no information obtained regarding the income share of specific percentiles. Data on the Gini coefficients are provided by the Standardized World Income Inequality Database (Solt, 2019). To note is that in compiling and estimating the Gini coefficients, Solt has primarily used the Luxemburg Income Study as source. Other sources include the OECD Income Distribution Database, the Socio-Economic Database for Latin America and the Caribbean, the World Bank's PovcalNet, and the UN Economic Commission for Latin America and the Caribbean. Given the uncertainty in the data, Solt has compiled estimates of the Gini coefficients, together with a series of associated "uncertainty values". For the purpose of this thesis, a per-country and -year average of the different Gini coefficients is calculated and used as independent variables in the subsequent analysis.

To complement the analysis of income inequality, also the pre-tax national income shares of the top 10 and 1 percentile groups, respectively, are used as measures of income inequality. The trajectory of the income shares over time are depicted in figures A4 and A5 in the Appendix. Data are gathered from the World Inequality Database. The top income shares are derived from tax data with consistent methodologies across countries, making them comparable both over time and over units. The income inequality measures are summarised in table 1 below.

Table 1

Overview of income inequality measures (used as dependent variables)

Variable	Description	Source
Gini coefficient (market income)	The market income is defined as pre-tax and -transfers income on the household level.	SWIID*
Gini coefficient (disposable income)	The disposable income is defined as post-tax and -transfers income on the household level.	SWIID*
Top 10 percentile income share	The pre-tax national income share of the top 10 percentile group.	WID**
Top 1 percentile income share	The pre-tax national income share of the top 1 percentile group.	WID**

Notes: *The Standardized World Income Inequality Database

**The World Inequality Database

5.1.2 Control variables

This thesis closely mimics the control variables selected by Tanndal and Waldenström (2018) given the similarity in method and research question. There are mainly two selection criteria for choosing control variables. Firstly, control variables that best determine the relationship between financial deregulation and income inequality, based on what has previously been found in the literature. Secondly, as also mentioned by Tanndal and Waldenström, it is necessary to include variables that seem likely to impact whether a financial deregulation takes place or not since it cannot be considered an exogenous event. As a third point, it is important not to include too many control variables since in the SCM, each average value of the treated unit in the pre-treatment period is matched to the weighted average values of the control group. If more control variables are added, each weighted average may exhibit a poor fit between the treated unit and the counterfactual. The control variables are summarised in table 2.

Starting with the first selection criterion, one measure that seems to be important in explaining inequality patterns are aggregate economy measures. To name an example, Roine et al. (2009) study inequality determinants from a cross-country perspective. By dividing the income earners into three separate units, they find that the top income shares benefit disproportionally in periods of high economic growth. Although the measure used in Roine et al. is the per-capita GDP, it is relevant also to include the annual percentage change in the GDP, since that is more comparable across countries and focuses less on the GDP in levels. This belief is further strengthened by Galor and Zeira (1993), whose open-economy equilibrium model suggests a positive correlation between aggregate economic activity and the within- and cross-country differences in incomes and how it is distributed.

To control for the institutional setting in which the deregulation took place, variables for trade union density (OECD) and employment tax rates (Nickell, 2006), respectively, are included. In a semi-recent paper by Jaumotte and Buitron (2015), the connection between labour market institutions and income inequality is reviewed. From a cross-country perspective, they consistently find that decreases in the union density is coupled with increased inequality.

In the literature, it is common to use the top tax rate, that is, the marginal tax paid by the highest paid employees, normally the tax rates compiled by Piketty (2014). However, the data are insufficient for the countries in question, so instead the employment tax rate as provided by Nickell (2006) is used. Furthermore, a legal origin dummy is included, taking on the value 1 if the country has a Scandinavian legal origin, and 0 otherwise. Scandinavian law is considered to be a subset of the civil law family, and is, for example, signified by lower creditor rights compared to common law countries, and a high rule of law (La Porta et al., 1997, 1998). Since the dataset at

hand is in panel form, and legal origin by definition is static over time, countries have constant values for all years in the sample.

Addressing the second selection criterion, a measure of financial openness is relevant to include because that may affect the likelihood of a financial deregulation. Differently from Tanndal and Waldenström (2018) who use the Quinn index, the share of exports of goods and services as a percentage of GDP is used to control for how open an economy is to cross-border trade. This is mainly because of lack of data for the countries of interest. Although the share of exports over GDP does not capture the concentration of capital controls in the same manner as the Quinn index, financial openness and exports are dimensions in determining the per-country Quinn index (Quinn, 1997). Therefore, it can be considered a proxy to the Quinn index.

Moreover, although the Swedish central bank is supposed to act as a separate entity vis-á-vis the government (Svensson, 1996), it is relevant to control for the political orientation of the chief executive. This is done using a dummy-variable taking on the value 1 for a chief executive with right-wing political orientation, and 0 for left-wing and centre political orientations (Cruz et al., 2015; Database of Political Institutions 2015).

Table 2
Overview of control variables (used as independent variables)

Variable	Description	Source
GDP growth (%)	The annual percentage change in the GDP (gross domestic product) per country.	WDI*
GDP per capita	Gross domestic product per capita in constant USD2010 per country.	WDI*
Scandinavian legal origin	A dummy variable taking on the value 1 if the country has Scandinavian legal origin, and 0 otherwise.	La Porta et al. (2008)
Political orientation of chief executive	A dummy variable taking on the value 1 if the chief executive in a given year has a right-wing political orientation, and 0 otherwise.	DPI2015**
Exports as % of GDP	The measure is calculated as the value of goods and market services exports provided to the rest of the world over GDP.	WDI*
Trade union density (%)	Trade union density is defined as the percentage of wage and salary earners that are trade union members compared to the total number of wage and salary earners.	OECD***
Employment tax rate (%)	The employment tax rate is calculated as: $Tax\ rate = \frac{ESS}{IE-ESS}$ where ESS is the employer's social security contribution, and ESS equals total employee compensation.	Nickell (2006)

Notes: *World Development Indicators
**Database of Political Institutions 2015
***Organisation for Economic Co-Operation and Development

5.2 The Synthetic Control Method

The synthetic control method (SCM) is a relatively novel econometric method first put forth in Abadie and Gardeazabal (2003) in which the authors use the SCM to research the economic effects of the terrorist conflict in the Basque Country. It was further developed in Abadie et al (2010; 2015). The SCM is useful for comparative case studies in instances where the researcher lacks a counterfactual, that is, a control group. The rationale for the SCM is that pre-treatment characteristics of the treatment group can be better approximated by a combination of untreated units (thus forming the counterfactual) than any single, untreated unit. Abadie et al. have made the SCM publicly available through open-source code for programs such as STATA, Matlab, and R. An advantage of using this algorithm to select which units should make up the synthetic control is that researcher bias is reduced. The SCM is described below, adapted from Abadie et al. (2010; 2015).

5.2.1 Theoretical background

A total of $J = 17$ countries are observed, indexed by j. The first unit, $j = 1$, is the treated unit, in this setting, Sweden. Countries $j = 2$ to $j = 17$ act as a pool of potential donors. The outcome of the dependent variable in Sweden in the period of interest, $t = 1985$, and in absence of financial deregulation is denoted by Y_{jt}^{N} for all countries $j = 1, 2, \dots, 17$ and time periods $t = 1975, 1976, \dots, 1984 = T_0$. The N superscript denotes "not treated". T_0 hence denotes the number of pre-treatment periods. The number of pre- and post-treatment periods, respectively, together sum to the full number of periods, T, where $1 \leq T_0 < T$. The observed outcome for a country exposed to the treatment in periods $T + 1 = 1985$ to $T = 1995$ is denoted by Y_{jt}^{S} where j and t are defined as before and the S superscript denotes Sweden. Three assumptions need to be fulfilled in order for the synthetic control method to be utilised. Firstly, the dataset should be a balanced panel, which implies that all countries are observed in the same time periods. The intervals between sample periods are allowed to vary, however. Secondly, the number of pre- and post-treatment periods exceed zero. That is, $T_0 > 0$ and $T_1 > 0$ where T_0 and T_1 sum to the full number of periods, T. Thirdly, it is assumed for simplicity that the treatment has no effect on the outcome in any of the periods prior to its implementation. Hence, for the years 1975 to 1984, $Y_{jt}^{N} = Y_{jt}^{S}$ for all countries in the sample. In cases where a treatment can be assumed to have anticipation effects, so that the treatment affects the outcome prior to the implementation, the number of pre-treatment periods can be redefined to fit the data better. As described in section 2, the financial deregulation in Sweden was rolled out in a number of steps, beginning in 1982, which may cause such "anticipation effects".

In this specific application of the SCM, the first and second assumptions are clearly fulfilled. In part thanks to due the interpolations of the data, the panels for the countries and variables are balanced and collected at annual intervals. Moreover, the time range

is set to have a positive number of pre- and post-treatment periods, namely ± 10 years counting from the treatment period. The third assumption is tested by the in-time placebo test, described in further detail below.

The effect of the treatment in any post-treatment period t is calculated as $\alpha_{jt} = Y_{jt}^{S} - Y_{jt}^{N}$. D_{jt} is a dummy variable taking on the value 1 if country j is exposed to the treatment in time t and zero otherwise. As in standard differences-in-differences techniques, it is presumed that only the unit of interest, Sweden in this case, is treated and only in the years post-treatment. Therefore,

(2) $$D_{jt} = \begin{cases} 1 \; if \; j = Sweden \; and \; t > 1985 \\ 0 \; otherwise \end{cases}.$$

In the next step, $(\alpha_{1T_{0+1}}, \dots, \alpha_{1T})$ is estimated. In periods after 1985, α_{1t} can be calculated as $\alpha_{1t} = Y_{1t}^{S} - Y_{1t}^{N} = Y_{1t} - Y_{1t}^{N}$ since Y_{1t} is observable. Using the assumption that Y_{jt}^{N} is produced by a factor model, it can be written as:

(3) $$Y_{jt}^{N} = \delta_t + \boldsymbol{\theta_t Z_j} + \boldsymbol{\lambda_t \mu_j} + \varepsilon_{jt}$$

where δ_t captures time fixed effects, $\boldsymbol{Z_j}$ is a $(r \; x \; 1)$ vector that is observed and country-varying, $\boldsymbol{\theta_t}$ is a $(1 \; x \; r)$ year-varying vector with unobserved parameters, $\boldsymbol{\lambda_t}$ is a $(1 \; x \; F)$ year-varying vector with observed parameters, and $\boldsymbol{\mu_j}$ is a $(F \; x \; 1)$ vector with unobserved, country-varying parameters. The error terms ε_{jt} varies both at country- and year-level with a zero mean.

W is a $(J \; x \; 1)$ vector of weights, $\boldsymbol{W} = (w_2, \dots w_{J+1})'$ where $w_j \geq 0$ for all $j = 2, \dots, J+1$ and $\sum_{j=2}^{J+1} w_j = 1$. The value of the outcome variable for any particular synthetic control, indexed by $\boldsymbol{W}$, is given by:

(4) $$\sum_{j=2}^{J+1} w_j Y_{jt} = \delta_t + \boldsymbol{\theta}_t \sum_{j=2}^{J+1} w_j \boldsymbol{Z}_j + \boldsymbol{\lambda}_t \sum_{j=2}^{J+1} w_j \, \boldsymbol{\mu_j} + \sum_{j=2}^{J+1} w_j \, \varepsilon_{jt}.$$

The optimal control vector, W^*, is given by $W^* = \left(w_2^*, \dots w_{J+1}^*\right)'$ where:

(5) $$\sum_{j=2}^{J+1} w_j^* Y_{j1} = Y_{11},$$

(6) $$\sum_{j=2}^{J+1} w_j^* Y_{j2} = Y_{12},$$

(7) $$\sum_{j=2}^{J+1} w_j^* Y_{jT_0} = Y_{1T_0},$$

(8) $$\text{and } \sum_{j=2}^{J+1} w_j^* \boldsymbol{Z}_j = \boldsymbol{Z}_1.$$

Since it often is the case that it is not possible to choose weights so that the equations 5 to 8 hold, the synthetic control is instead chosen so they approximately hold.

5.2.2 Implementation of the synthetic control method

The synthetic control is the weighted average of selected countries from the pool of potential donors. Thus, the synthetic control, W, takes the form of a $(J\ x\ 1)$ vector consisting of weights $W = (w_2, w_3, \dots, w_{J+1})'$ where $0 \leq w_j \leq 1$ for all units j excluding Sweden, and $\sum_{j=2}^{J+1} w_j = 1$. Assigning specific values for W then corresponds to choosing a particular synthetic control.

By adjusting the values in the vector W, different synthetic controls can be obtained. Abadie et al. (2015) put forth that the weights on specific countries should be selected so as to obtain pre-treatment characteristics of the weighted donor pool, i.e. the synthetic control, such that it accurately resembles the pre-treatment characteristics of the treated unit.

X_1 is a $(k\ x\ 1)$ vector containing values for pre-treatment characteristics for Sweden. X_0 is a $(k\ x\ J)$ matrix containing values for the same pre-treatment characteristics of countries belonging to the donor pool where k is the number of control variables utilised. Note that it is possible to include pre-treatment values of the outcome variable in X_1 and X_0. Since the goal is to obtain a synthetic control that matches the pre-treatment characteristics of Sweden as closely as possible, a difference vector $X_1 - X_0W$ is created. Minimising this difference provides the optimal synthetic control, W^*.

Letting $m = 1, \dots, k$, X_{1m} consists of the value of the m^{th} variable for Sweden. X_{0m} is a $(1\ x\ J)$ vector consisting of the values of the m^{th} variable for the donor countries. W^* is selected as the value of the vector W that minimises the sum $\sum_{m=1}^{k} v_m(X_{1m} - X_{0m}W)^2$ where v_m is a weighting variable displaying the relative importance assigned to the m^{th} variable when measuring the difference between X_1 and X_0W. Variables with significant predictive power on the outcome of interest and the values taken on by Sweden should be closely reproduced by the synthetic control. Therefore, these variables should be assigned larger weights v_m, relative to variables with non-significant predictive power.

Y_{jt} denotes the outcome of country j in time t. Y_1 denotes a $(T_1 x 1)$ vector consisting of the post-treatment values of the outcome for Sweden $(j = 1)$, the country exposed to the treatment. $Y_1 = (Y_{1T_0+1}, \dots, Y_{1T})$. Y_0 denotes a $(T_1 x\ J)$ matrix in which the last column J consists of the post-treatment values of the outcome for the last country $j = 17$. The effect of the treatment is then estimated as the difference between the post-treatment outcomes of the treated and the un-treated unit(-s), respectively. That is, $Y_1 - Y_0W^*$. For any given post-treatment period, $t \geq T_0$, the synthetic control estimator of the treatment's effect can be estimated as: $Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}$. The vector X_0 and matrix X_1, respectively, contains the predicted values for the post-treatment outcomes and are not themselves exposed to the treatment.

5.2.3 Placebo tests

Since the SCM is constructed such that standard statistical inference methods are inapplicable, there are a number of so-called placebo tests that the researcher can utilise in order to test the case-specific application of the SCM. These will be reviewed below.

The *in-space placebo test* analyses the outcome of the SCM by reassigning the treatment to a country from the donor pool, rather than the actually treated country. In this instance, if the reassignment of the treatment to countries in the donor pool also produces sizeable estimated effects, the synthetic control estimate does not reflect the effect of the treatment in a plausible manner.

The *in-time placebo test* is meant to test the validity of the SCM and the effect estimated. This is done by evaluating the estimated effect when the method is applied to a time period in which the treatment did not take place. If the SCM estimated a sizeable effect also when the time period is shifted, the researcher should be aware that the estimated post-treatment effect probably measures other factors than intended. The in-time placebo test is feasible if there are data for a large number of pre-treatment time periods available in which there were no structural shifts in the outcome variable.

By applying the in-space placebo test to all member units of the donor pool, the researcher can create a *constructed p-value*. Calculating the fraction of in-space placebo effects that are equal to, or greater than, the estimated effect for the treated unit provides this specific p-value. As in standard inference, the constructed p-value can be understood as the "…probability of obtaining an estimate at least as large as the one obtained for the unit representing the case of interest when the intervention is reassigned at random in the data set" (Abadie et al., 2015 p. 500). However, the constructed p-value cannot be used to calculate confidence intervals or posterior distributions.

5.2.4. Limitations of the synthetic control method

One obvious limitation of the SCM is that countries in the donor pool should not have been affected by the treatment of interest or treatments of similar nature, which can be investigated manually or with the help of the placebo tests. Such countries should be eliminated from the donor pool. Furthermore, the donor pool in terms of number of countries should be limited, since there otherwise might be a problem of over-fitting (see section 9.2). The donor pool should also be limited to countries that share traits with the treated unit. Moreover, any member countries of the donor pool exposed to large idiosyncratic shocks to the outcome variable during the time period studied should be excluded, in cases where the shock would only have affected the Sweden in the presence of treatment.

Abadie et al. (2015) also mentions that the SCM may be problematic if unmeasured or unobserved variables affect the outcome variable or if there is heterogeneity in how the unobserved and observed variables, respectively, affect the outcome variable. Nevertheless, they argue that if there is a sufficiently large number of pre-treatment time periods, the researcher is partially able to control for these unobserved variables and the possible heterogeneity. Their rationale for this is that only units, the treated unit as well as the donor units, that share resemblance in observed and unobserved variables affecting the outcome variable produce similar paths for the outcome variable over time. If the researcher can make sure that the trajectories over a number of time periods pre-treatment match, the difference in the outcome variable between the treated unit and the synthetic control can be seen as the effect of the treatment. This connects to what is partly mentioned earlier, the number of pre-treatment periods needs to be positive and also relatively large since the over-time likeness in trajectories is one determinant of how reliant the researcher can be in the choice of synthetic control. Abadie et al. (2010) point out that it may be beneficial to have such a sizeable number of pre-treatment periods that the the sample can be divided into a training period and a validation period, respectively.

6. Results

6.1 Descriptive statistics

In tables 3 and 4, descriptive statistics are presented. The descriptive statistics are divided into two groups where the treated unit, Sweden, constitutes the first, and the countries belonging to the donor pool make up the second. Country-wise descriptive statistics for the countries that are given weights in the synthetic controls are available in section 6 in the Appendix to conserve space.

In its extremes, the data ranges from 1940 to 2018. However, for some of the countries in the donor pool, intermediate years of data are missing. Furthermore, starting and ending periods differ between countries. As previously mentioned in section 5.1, interpolations have been run on the intermediate missing years in the sample to provide as long panels as possible. The descriptive statistics presented above depict the interpolated data. For transparency, the country-year-variable interpolations are presented in tables A3 and A4 in the Appendix following the data availability for each country and variable (see tables A1 and A2).

Table 3
Descriptive statistics for Sweden

		Statistic					
	Variable	Min	Mean	P50	Max	Sd	N
Sweden	Top 10 percentile	0.224	0.284	0.293	0.356	0.0326	72
	Top 1 percentile	0.041	0.070	0.069	0.111	0.018	72
	Gini (post-tax and -transfers)	0.208	0.258	0.245	0.365	0.045	57
	Gini (pre-tax and -transfers)	0.405	0.456	0.464	0.510	0.028	57
	GDP growth (%)	-5.185	2.290	2.559	6.042	2.175	49
	GDP per capita	25,190.520	39,860.060	37,513.080	56,935.190	9,744.445	49
	Employment tax rate (%)	1.700	19.837	26.400	30.000	9.955	43
	Exports as share of GDP (%)	22.601	35.772	34.491	49.813	8.518	49
	Scandinavian legal origin	0.000	0.987	1.000	1.000	0.113	79
	Right-wing chief executive	0.000	0.237	0.000	1.000	0.431	38
	Union density (%)	64.555	75.354	76.230	87.427	6.898	54

Note: Descriptive statistics are provided on full-sample basis in terms of years.

Since the legal origin dummy is assumed to be static over time, it is the only variable with a value for each country and each consecutive year. The full sample hence amounts to 1343 observations dispersed over 17 countries in total, that is, the donor pool countries and Sweden.

Due to the descriptive statistics being presented on donor-sample basis, the standard deviations in relation to the mean and median of the variables are rather large. This is easily explainable by the large difference in levels between countries, as can be seen in figures A2-A10 in the Appendix. For Sweden, on the other hand, the standard deviations are smaller in general. Since many of the variables have clear trend patterns over time, the standard deviations are still quite large relative to the minimum, mean, and maximum values. Compared to the donor pool, the mean union density is high for Sweden. Sweden has a long tradition of strong labour movements and pro-union governments which accounts for these high numbers. While it is not surprising that Sweden has had a relatively larger number of centre- or left-wing politically orientated chief executives over the years 1975 to 2012, the donor pool countries have all-in-all had a majority of centre- or left-wing politically orientated chief executives, too. The mean values for Sweden and the donor pool are 0.237 and 0.488, respectively.

Table 4
Descriptive statistics for the sample of donor pool countries

		Statistic					
	Variable	Min	Mean	P50	Max	Sd	N
Donor pool	Top 10 percentile	0.218	0.323	0.321	0.471	0.046	818
	Top 1 percentile	0.035	0.090	0.088	0.208	0.028	875
	Gini (post-tax and -transfers)	0.205	0.290	0.291	0.383	0.038	768
	Gini (pre-tax and -transfers)	0.349	0.443	0.442	0.538	0.043	768
	GDP growth (%)	-8.269	2.648	2.671	25.557	2.518	766
	GDP per capita	12,430.710	38,004.590	35,115.630	91,617.280	15,361.490	770
	Employment tax rate (%)	0.000	10.386	6.800	29.800	8.176	639
	Exports as share of GDP (%)	5.089	31.516	27.151	124.643	18.384	769
	Scandinavian legal origin	0.000	0.119	0.000	1.000	0.324	1264
	Right-wing chief executive	0.000	0.488	0.000	1.000	0.500	562
	Union density (%)	7.794	37.960	34.200	81.224	17.864	833

Note: Descriptive statistics are provided on full-sample basis in terms of years.

For the income inequality measures, displayed in the first four rows for each group in the table, Sweden lies quite on-par with the donor pool sample. The same pattern holds true for the GDP per capita, where Sweden has minimum, mean, and maximum values of 25 190, 39 860, and 56 935 in constant USD2010, respectively. The corresponding values for the donor pool are 12 430, 38 004, and 91 617. There is therefore a larger span in the donor pool, in which both less income-rich countries such as Spain and Italy are included, as well as the more income-rich countries such as the United States, the United Kingdom, and Switzerland.

6.2 Simple regression analysis

As a first step in determining whether there is a connection between the financial deregulation in Sweden and rising inequality levels, four separate regressions are run using each of the inequality measures as dependent variables. The independent variables are an interaction dummy taking on the value 1 for Sweden in the years after the deregulation as well as country dummies. Sweden is used as the baseline with respect to the country dummies. Moreover, for each inequality measure, one regression is run with the controls for the SCM analysis included. Although this is a very crude way of determining whether a relationship between the deregulation and

income inequality can be found, it serves as a basis for the continued analysis with the help of the SCM. The regressions are restricted to a window of 10 years prior to and after the deregulation, respectively.

Table 5
Simple linear regressions with country dummies

	Gini (pre-tax and -transfers)		Gini (post-tax and -transfers)		Share top 10 percentile		Share top 1 percentile	
Dummy	0.029***	0.021**	0.008	0.011*	0.009	0.014**	0.011***	0.007**
	(0.009)	(0.008)	(0.006)	(0.006)	(0.007)	(0.007)	(0.004)	(0.004)
Cons.	0.411***	0.400***	0.216***	0.330***	0.235***	0.380***	0.0442***	0.956***
	(0.007)	(0.015)	(0.004)	(0.011)	(0.005)	(0.013)	(0.003)	(0.007)
N	312	257	312	257	299	242	313	256
Country dummies	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

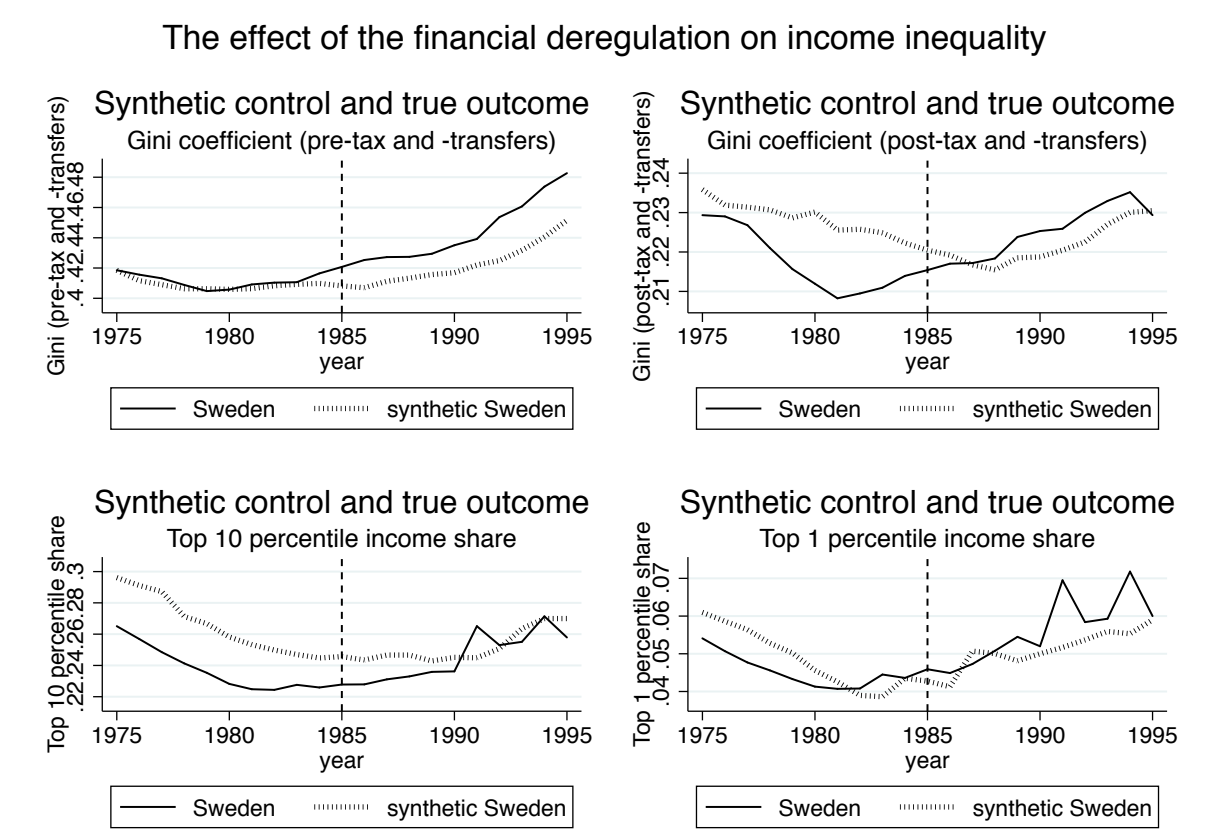
Notes: “N” denotes the number of observations, “Y” denotes “yes”, and “N” denotes “no”. Dummy is a variable taking on the value 1 for Sweden, post-deregulation, and 0 otherwise. Note that the p-values correspond to double-sided hypotheses. Country specific coefficients are not shown to conserve space. Sweden is used as the baseline.

Table 5 above shows that a positive relationship between income inequality and the financial deregulation in Sweden can be found, both with and without controls added. The coefficients for the pre-tax and -transfers Gini coefficient, as well as the share of the top 1 percentile, are significant on less than 1 percent significance level without controls and at less than percent 5 level with controls. Moreover, they are also economically significant given the range of the variables. The Swedish deregulation is associated with an average increase of 2.9 and 2.1 percentage points, respectively, in the pre-tax and -transfers Gini. For the pre-tax top 1 percentile share, the corresponding average increases are 1.1 percentage points and 0.7 percentage points. For the post-tax and -transfers Gini coefficient as well as the pre-tax income share of the top 10 percentile, the results are less economically and statistically significant. However, they convey the same positive relationship between the financial deregulation and income inequality. Since this regression approach fails to account for the dynamic patterns of income inequality, it is not of value to go into the results in depth. However, it serves its purpose by presenting evidence for some kind of positive relationship between the financial deregulation and income inequality.

6.3 Synthetic control method

In figure 4 the true paths of the separate income inequality measures as well as the estimated paths of the four synthetic control groups (SCGs) are plotted.

Figure 4
The estimated effect of the financial deregulation in Sweden for each of the four income inequality measures



Notes: The solid lines represent the actual outcome in Sweden per year, pre- and post-treatment. The dashed lines represent the estimated outcome in Sweden in the absence of financial deregulation. The year in which the financial deregulation was finalised is represented by the vertical dashed line. The pre- and post-treatment period are restricted to a $\pm$ 10-year window from 1985, hence ranging from 1975 to 1995.

In estimating the synthetic controls, pre- and post-treatment periods of $\pm$ 10 years from the treatment year have been used. There is of course a trade-off between being able to include as many countries as possible in the donor pool and allowing the algorithm to have enough observations to credibly estimate the synthetic control. Although the country-year data availability differs between the different inequality measures, the most restrictive time frame is chosen for all of them for consistency.

The goodness-of-fit of the SCG for the pre-tax and -transfers Gini coefficient is the best out of the four, with the outcome for the SCG closely tracking the true outcome up until circa 1984. After 1984, a clear deviation between the control and the treated unit can

be seen, in which the income inequality reaches higher levels than the synthetic control. In 1990, an increase of close to two (2) percentage points in the pre-tax and -transfers Gini coefficient from the deregulation is estimated. Since the effect seems to emerge prior to the deregulation, there might have been some kind of anticipation effect in the final stages of the deregulation. As explained in section 2.1, the Swedish financial deregulation did not take place in one single step, but gradually over the course of a few years. It might therefore be the case that it was not the final decision and its consecutive implementation that has led to an increase in the income inequality, but rather earlier decisions.

Considering the pre-tax and -transfers Gini coefficient, the H_0^1 null hypothesis that the financial deregulation did cause an increase in income inequality can be rejected.

Also the SCG for the pre-tax income share of the top 10 percentile behaves relatively well in mimicking the pattern of the true outcome prior to the implementation. Although the dashed and the solid lines do not follow the same level, it is easy to see that they follow the same trend over time. Both the synthetic control and Sweden experience gradually decreasing levels in the income shares of the top 10 percentile. After the deregulation, the income shares seem to level out. Moreover, the difference between the synthetic control and the treated unit seem to decrease after the deregulation, suggesting a higher relative income inequality in Sweden.

The SCGs for the pre-tax income share of the top 1 percentile and the post-tax and -transfers Gini coefficient, respectively, do a worse job than the aforementioned income inequality measures. These patterns imply that the control variables and/or the donor pool countries are unable to explain the paths of the income inequality variables. For example, it might be the case that Sweden has a very specific tax and transfers regime compared to the countries in the donor pool, thus making it difficult to match.

In summary, the H_0^1 null hypothesis for the post-tax and -transfers Gini coefficient and the pre-tax income share of the top 10 and top 1 percentiles, cannot be rejected.

Moreover, as can be seen in tables 3 and 4 with descriptive statistics, the range for the top 1 percentile share is relatively smaller than the range for the donor pool countries which may affect how well the synthetic control fits the pre-treatment trend of Sweden. As is put forth in section 5.2.1 and 5.2.2, the SCG should match the pre-treatment characteristics of Sweden. If this is not possible due to lack of data or a poor choice of donor countries, the fit between the SCG and Sweden will be insufficient to draw any definitive conclusions.

Both of the top percentile income shares display several spikes in the first half of the 1990s. In those years, Sweden experienced a big financial crisis, as mentioned in section 1, which likely caused this behaviour.

Table 6
Values for the control variables for the treated unit, Sweden, and each synthetic control group

		Inequality measure				
Variables	Sweden	Gini (pre-tax and -transfers)	Gini (post-tax and -transfers)	Top 10 percentile	Top 1 percentile	Mean
GDP growth (%)	1.755	2.810	3.250	3.303	2.795	3.040
GDP per capita	31,112.910	26,968.080	32,318.660	39,600.110	27,518.670	31,601.380
Employment tax rate (%)	24.564	12.071	10.789	13.718	5.056	10.409
Exports as % of GDP	29.360	27.008	31.164	33.606	28.828	30.151
Scandinavian legal origin	1.000	0.748	0.942	0.514	0.791	0.749
Political orientation of chief executive	0.000	0.142	0.183	0.361	0.078	0.191
Union density (%)	77.793	54.682	61.329	60.141	69.805	61.489

Notes: Weighted values of the control variables that are utilised to find the optimal synthetic control group for each separate income inequality measure. A good synthetic control should display control variable values that closely resembles the control variable values for the treated unit. The control variables are further described in section 5.1.2.

Table 6 describes the weighted averages of the control variables for Sweden and each respective synthetic control. Interestingly enough, the pattern between which inequality measure control group lies the closest to the true values differ between the control variables. For the GDP growth, the exports as percent of GDP, the political orientation of the chief executive, and the union density, respectively, the synthetic control values of the top 1 percentile share most closely match the treated unit's values. For the GDP per capita and the Scandinavian legal origin-dummy the post-tax and -transfers Gini coefficient lies most on-par. For the employment tax rate, the pre-tax and -transfers Gini coefficient stands out, and for the employment tax rate the top 10 percentile share performs best. It is however not surprising that the weighted average values for the top 10 percentile share are not very similar to the values for the treated unit, given that they only follow the same pre-treatment trend but differ in levels.

Table 7
Control group unit weights per country and inequality measure

	Unit weights			
Country	Gini (pre-tax and -transfers)	Gini (post-tax and -transfers)	Top 10	Top 1
Australia	0	0	0	0
Canada	0	0	0	0
Denmark	0*	0*	0.278	0.209
Finland	0.681	0.625	0*	0.791
France	0.253	0.058	0	0
Germany	0	0	0	0
Ireland	0	0	0	0
Italy	0	0	0.208	0
Japan	0	0	0	0
Netherlands	0*	0*	0	0
New Zealand	0*	0*	0	0
Norway	0.067	0.317	0.514	0
Spain	0*	0*	0*	0*
Switzerland	0*	0*	0*	0*
United Kingdom	0	0	0*	0*
United States	0*	0*	0*	0*

Note: Unit weights denoted by * were excluded in the analysis due to lack of data.

As can be seen in table 7, the countries with the largest weights are the Scandinavian countries in the donor pool, namely, Denmark, Finland, and Norway. Also France and Italy are assigned weights in the synthetic controls for the two Gini coefficients and for the top 10 percentile income share, respectively. The Scandinavian countries tend to be relatively similar overall, and it is not surprising that they constitute the more part of the control groups. One cause for concern may be the relatively high weight assigned to a single country in each of the SCGs, rather than a larger number of small-weighted countries. However, this is not uncommon and the same pattern arises in, for example, Tanndal and Waldenström (2017).

Table 8 presents the root mean-squared percentage error (RMSPE) for each synthetic control group in the pre-treatment period.

Table 8
Root mean-squared percentage errors (RMSPEs) for each synthetic control group in the pre-treatment period

	Inequality measure				
	Gini (pre-tax and -transfers)	Gini (post-tax and -transfers)	Top 10	Top 1	Mean
RMSPE	0.005	0.012	0.032	.006	0.013

Note: The RMSPEs are presented in decimal form, and not in percentages.

The RMSPE is calculated as:

$$RMSPE = \sqrt{(\frac{1}{T_0}\sum_{t=1}^{T_0}(Y_{1t} - \sum_{j=2}^{J} w_j Y_{jt})^2)}.$$

T_0 is the number of pre-treatment periods, Y_{1t} is the outcome of the inequality measure for Sweden in period t, w_j is the country-specific weight $(0 \leq w_j \leq 1)$ and Y_{jt} is the outcome of a country from the donor pool in time t.

The RMSPE acts as measure of the pre-treatment fit of the control, where a lower value is favoured since it behaves as an estimation of the average deviation. Note that the RMSPEs should be interpreted with respect to the values of the dependent variables. Noteworthy is also that even if the post-deregulation RMSPE is large, if the pre-treatment fit of the synthetic control is not close to the true trend, this does not suggest that there is a large effect from the treatment (Abadie et al., 2015).

Although the synthetic control outcome for all the income inequality measures have very low RMSPEs, the pre-tax and -transfers Gini coefficient is the lowest at 0.005, or 0.5 percent. The post-tax and -transfers Gini coefficient, the top 10 percentile share, and the top 1 percentile share have RMSPEs of 0.012, 0.032, and 0.006, respectively, which can also be considered low. In context of the values of the dependent variables, the pre- and post-tax and -transfers Gini coefficients display value ranges of around 0.20 - 0.25 and 0.40 - 0.50, respectively. The top 10 and 1 percentile income shares exhibit value ranges of around 0.20 - 0.30 and 0.04 - 0.07, respectively. For the pre-tax and -transfers Gini coefficient to display such a low RMSPE is therefore a sign the synthetic control being relatively well-behaved, which what can be deduced from the first graph in figure 4.

6.4 Hypothesis tests

In testing the hypotheses presented in sections 4.1 and 4.2, the percentage point deviation (PPD) between Sweden and synthetic Sweden per inequality measure is used as the dependent variable since all variables are measured in percentages. That is:

(9) $$Y_{PPD} = Y_{Sweden} - Y_{synthetic\ Sweden}.$$

The hypothesis testing consists of simple OLS-regressions of the form:

(10) $$Y_{PPD} = \beta_0 + \beta_1 X_1 + \varepsilon.$$

The independent variables are the household debt as percentage of GDP, and the domestic credit provided by the financial sector as percentage of GDP. The constant,

i.e. the intercept, is included in the regressions for the post-tax and -transfers Gini coefficient, and the pre-tax income shares of the top 10 and top 1 percentile, respectively. This is motivated by the fact that, as seen in figure 4, the synthetic controls consequently lie higher than the true outcome pre-treatment and this consistent difference in levels should therefore be taken into account. For the pre-tax and -transfers Gini coefficient, however, the constant is excluded from the regressions due to the close pre-treatment fit of the synthetic control to the true outcome.

6.4.1 Household debt

Table 9 displays the outcome for the regression of the PPDs of the four inequality measures on household debt. The "-" denotes that the constant is not included in the regression.

Table 9
Test of the household debt hypothesis

	PPD Gini (pre-tax and -transfers)	PPD Gini (post-tax and -transfers)	PPD Share top 10 percentile	PPD Share top 1 percentile
Household debt	0.000239***	0.000861*	0.000963*	0.000433
	(4.83e-05)	(0.000413)	(0.0256)	(0.000373)
Constant	-	-0.0474**	-0.0691**	-0.0210
		(0.0209)	(0.0256)	(0.0189)
R-squared	0.550	0.186	0.154	0.066
Observations	21	21	21	21

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: PPD denotes Percentage Point Deviation. The "-" denotes that the constant is not included in the regression.

For the percentage point deviation in the pre-tax and -transfers Gini coefficient, the household debt has a small, but statistically significant effect. The 1 percent significance level, despite the relatively few number of observations, further strengthens the conclusions that can be drawn regarding this relationship. Increasing the household debt by one percentage point is associated with an increase in the percentage point deviation between Sweden and synthetic Sweden by 0.000239 percentage points on average. For the other inequality measures, the pattern conveyed is the same. That is, there is a positive relationship between household debt and the percentage point deviations of the inequality measures. It cannot be ruled out, however, that these effects are inexistent given the significance level of 10 percent for the post-tax and -transfers Gini coefficient and the pre-tax income share of the top 10 percentile. The coefficient for household debt for the pre-tax income share of the top 1 percentile is insignificant on conventional significance levels. These results are not surprising, given the relatively bad fit of the synthetic Sweden to Sweden (see figure

4) in terms of fit of the pre-treatment trends. The constants consistently have negative coefficients of -0.0474, -0.0691, and -0.0210, respectively. This captures the stable pre-treatment trend of the synthetic control exceeding the true outcome in levels.

For the test of the hypothesis of a causal effect of household indebtedness on income inequality, the H_0^2 null hypothesis can be rejected on less than 1 percent significance level for the pre-tax and -transfers Gini coefficient. For the post-tax and -transfers Gini coefficient and the pre-tax income share of the top 10 percentile, the null hypothesis can be rejected on less than 10 percent significance level. However, the null hypothesis cannot be rejected for the pre-tax income share of the top 1 percentile.

6.4.2 Financial sector expansion

Table 10 displays the outcome for the regression of the PPDs of the four inequality measures on the domestic credit provided by the financial sector as percent of GDP. The "-" denotes that the constant is not included in the regression.

Table 10
Test of the financial sector expansion hypothesis

	PPD Gini (pre-tax and -transfers)	PPD Gini (post-tax and -transfers)	PPD Share top 10 percentile	PPD Share top 1 percentile
Domestic credit provided by the financial sector (% of GDP)	0.000224***	0.000336	0.000963*	.000448*
	(4.52e-05)	(0.000301)	(0.000473)	(0.000241)
Constant	-	-0.0219	-0.0691**	-0.0232*
		(0.0163)	(0.0256)	(0.0130)
R-squared	0.551	0.062	0.179	0.154
Observations	21	21	21	21

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: PPD denotes Percentage Point Deviation. The "-" denotes that the constant is not included in the regression.

In the first column of table 10, a positive relationship is conveyed where a one percentage point increase in the domestic credit provided by the financial sector is associated with an average 0.000224 percentage point increase in the pre-tax and -transfers Gini coefficient. Although very small in absolute terms, the coefficient is significantly different from 0 at less than 1 percent significance level. In similarity with table 9, where the household debt hypothesis was tested, positive, but significant only at 10 percent level, average effects of the PPDs in the post-tax and -transfers Gini coefficient, and the pre-tax income shares of the top 10 and top 1 percentile, respectively, are displayed. Consequently, it cannot be dismissed that the effects are

zero. Also in the test of the second hypothesis, the constants are negative, at -0.0219, -0.0691, and -0.0232, respectively. Once again, this is explained by the difference in levels of synthetic Sweden and Sweden in the pre-treatment period.

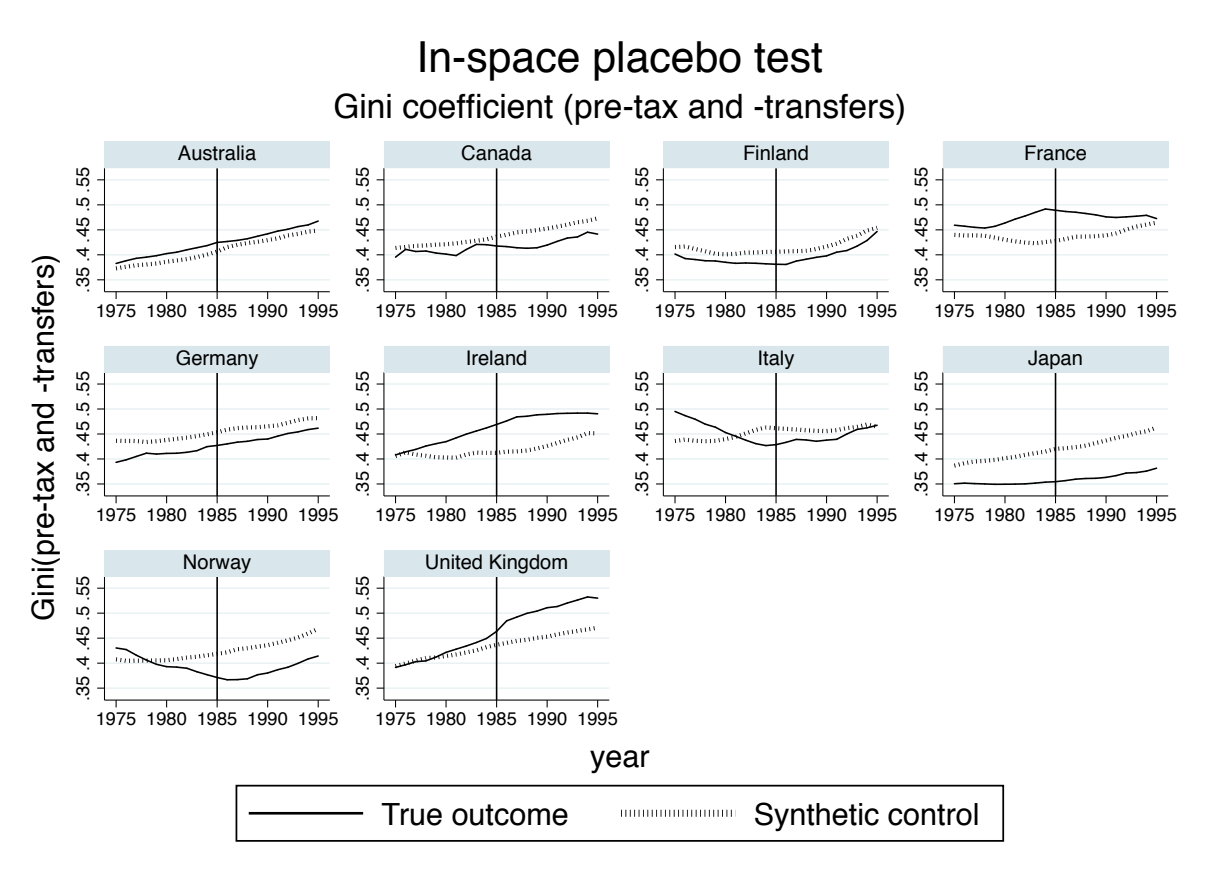
The H_0^3 null hypothesis of a causal impact of the financial sector expansion on income inequality can be rejected on less than 1 percent significance level for the pre-tax and -transfers Gini coefficient. For the pre-tax income shares of the top 10 and top 1 percentile, respectively, the null hypothesis can be rejected on less than 1 percent significance level. For the post-tax and -transfers Gini coefficient, the null hypothesis cannot be rejected on conventional significance levels.

7 Robustness tests

7.1 In-space placebo test

The in-space placebo test, as described earlier in section 5.2.3, evaluates the robustness of the synthetic control(-s) by iteratively changing which unit is acting as the treated unit. Figures 5 to 8 show the results from the in-space placebo test for each inequality measure and each country that data are available for. To conserve space, the reader is referred to figure 4 for the results of Sweden acting as the treated unit. For every sub-graph in the figures, the unit exposed to treatment is described in the headline.

Figure 5
Outcomes of the in-space placebo test using the pre-tax and -transfers Gini coefficient as dependent variable

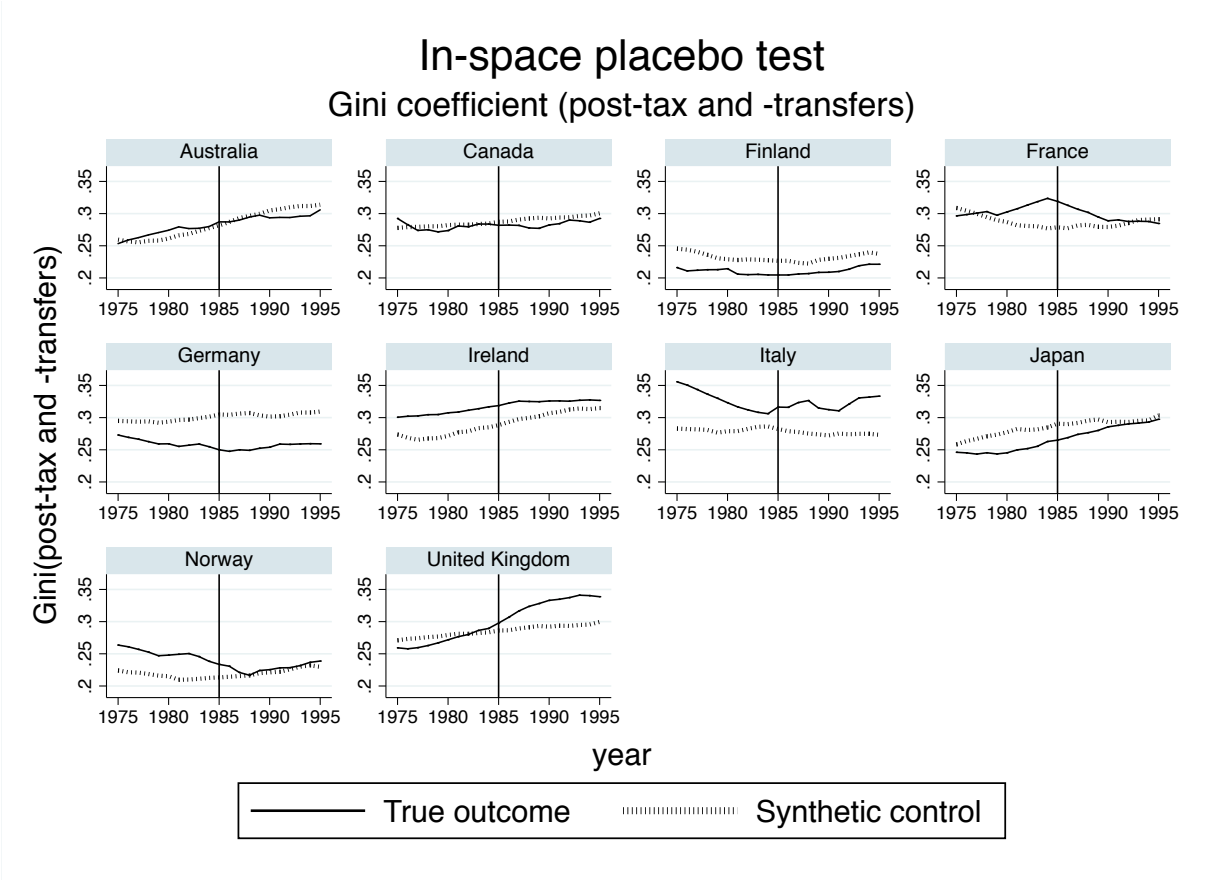


Notes: The country headline describes which country is used as the treated unit. The solid lines represent the actual outcome per year, pre- and post-treatment. The dashed lines represent the estimated outcomes using the synthetic control group. The treatment period, 1985, is represented by the vertical line. The pre- and post-treatment period are restricted to a $\pm$ 10-year window from 1985, hence ranging from 1975 to 1995.

In figure 5, the in-space placebo test results for the pre-tax and -transfers Gini coefficient are shown. The synthetic controls for Australia, Finland, Germany, and Japan behave quite well. However, post-deregulation there does not seem to be a

pattern suggesting a rise in the income inequality. The synthetic control for the United Kingdom seems to start deviating from the true outcome around the years 1978-1979. This does not suggest, however, that the results from the Swedish setting are wrong, but rather that the United Kingdom may also have experienced a rise in income inequality, for which the control variables used do a relatively good job in explaining. Moreover, not much can be concluded for the graphs for Canada, France, Ireland, Italy, and Norway, since the synthetic counterfactuals do not predict the pre-treatment trend very well. Any post-treatment results are therefore hard to argue for.

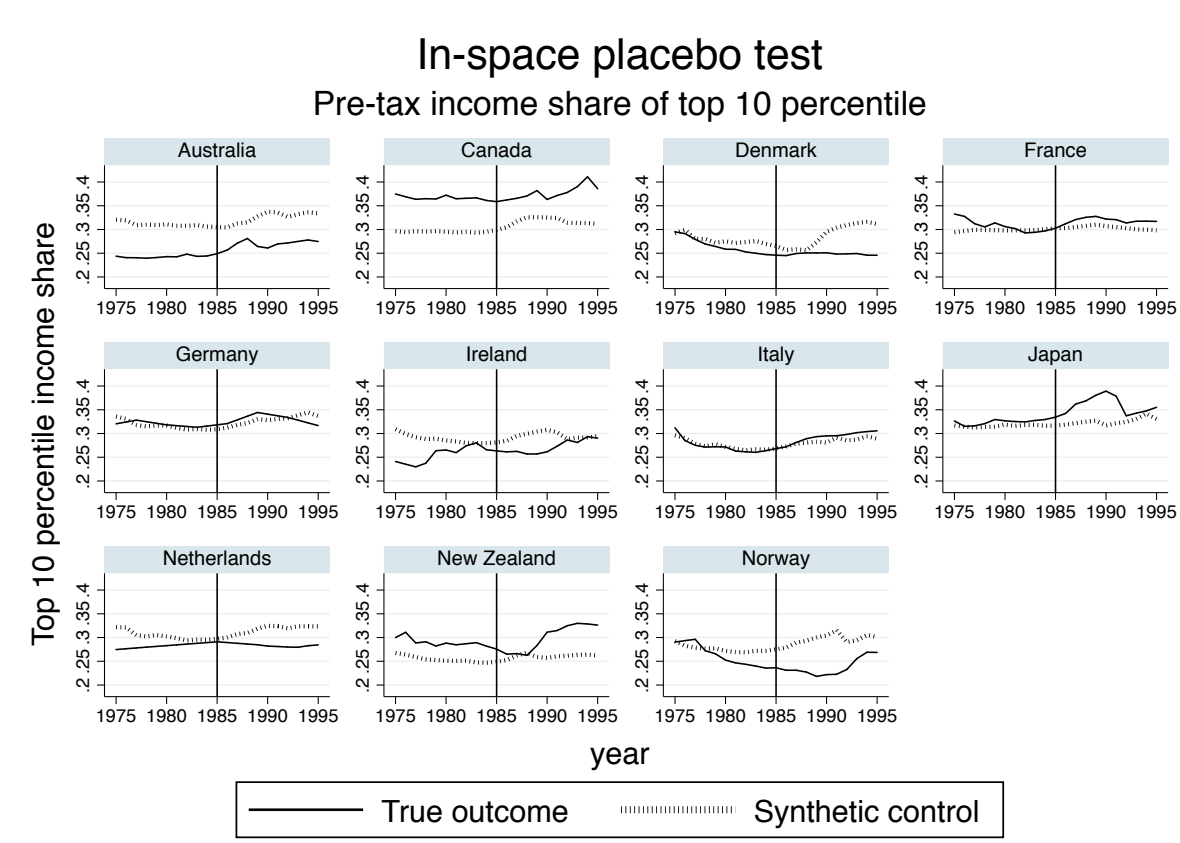
Figure 6
Outcomes of the in-space placebo test using the post-tax and -transfers Gini coefficient as dependent variable



Notes: The country headline describes which country is used as the treated unit. The solid lines represent the actual outcome per year, pre- and post-treatment. The dashed lines represent the estimated outcomes using the synthetic control group. The treatment period, 1985, is represented by the vertical line. The pre- and post-treatment period are restricted to a $\pm$ 10-year window from 1985, hence ranging from 1975 to 1995.

When the post-tax and -transfers Gini coefficient is used as the dependent variable, the synthetic controls for Finland and Ireland are relatively well-behaved. However, for most of the countries, the fit between the SCG and the true outcome path are quite bad which implies either that the deregulatory event in Sweden is not applicable for the other countries or that the control variables chosen are not good enough at predicting this relationship.

Figure 7
Outcomes of the in-space placebo test using the pre-tax income share of the top 10 percentile as dependent variable

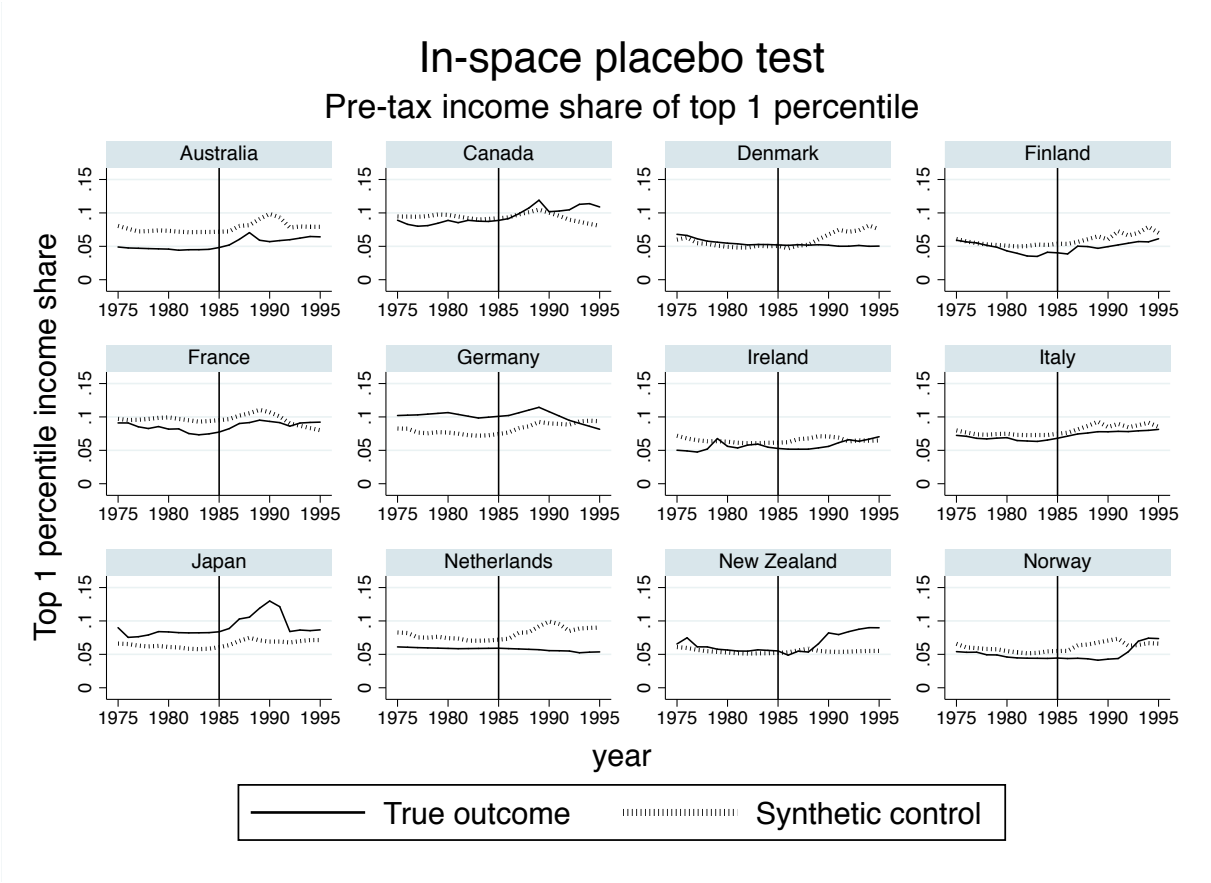


Notes: The country headline describes which country is used as the treated unit. The solid lines represent the actual outcome per year, pre- and post-treatment. The dashed lines represent the estimated outcomes using the synthetic control group. The treatment period, 1985, is represented by the vertical line. The pre- and post-treatment period are restricted to a $\pm$ 10-year window from 1985, hence ranging from 1975 to 1995.

From figure 7 it becomes apparent that the synthetic controls for Germany, France and Italy do particularly well in following the pre-treatment trends of the true outcomes of the pre-tax top 10 percentile income share. There are no clear deviations post-treatment that suggest a rise in income inequality due to the treatment. The pre-treatment parallel trends hold mostly true for Japan and Denmark as well. In these cases, however, there are clear deviations after the deregulation. This is not surprising since Japan deregulated its financial sector in the 1990s which is when the income inequality rises the most. This has been, as mentioned before, studied by Tanndal and Waldenström (2017). Also the controls for Australia and Canada suggest common trends, albeit with differences in levels, of the true outcome and the estimated paths, respectively. For Australia, there is a slight increase in the income inequality, arising a few years after the year 1985. This can be ascribed to many reasons, and does not suggest that the results from the Swedish synthetic control estimation are non-robust. The results for New Zealand, on the other hand, suggest a drop in income inequality post-1985, where the trends were relatively parallel prior. Lastly, the synthetic

counterfactuals for Ireland, The Netherlands, and Norway do not quite fulfil the parallel trends assumption which makes any further conclusions difficult.

Figure 8
Outcomes of the in-space placebo test using the pre-tax income share of the top 1 percentile as dependent variable



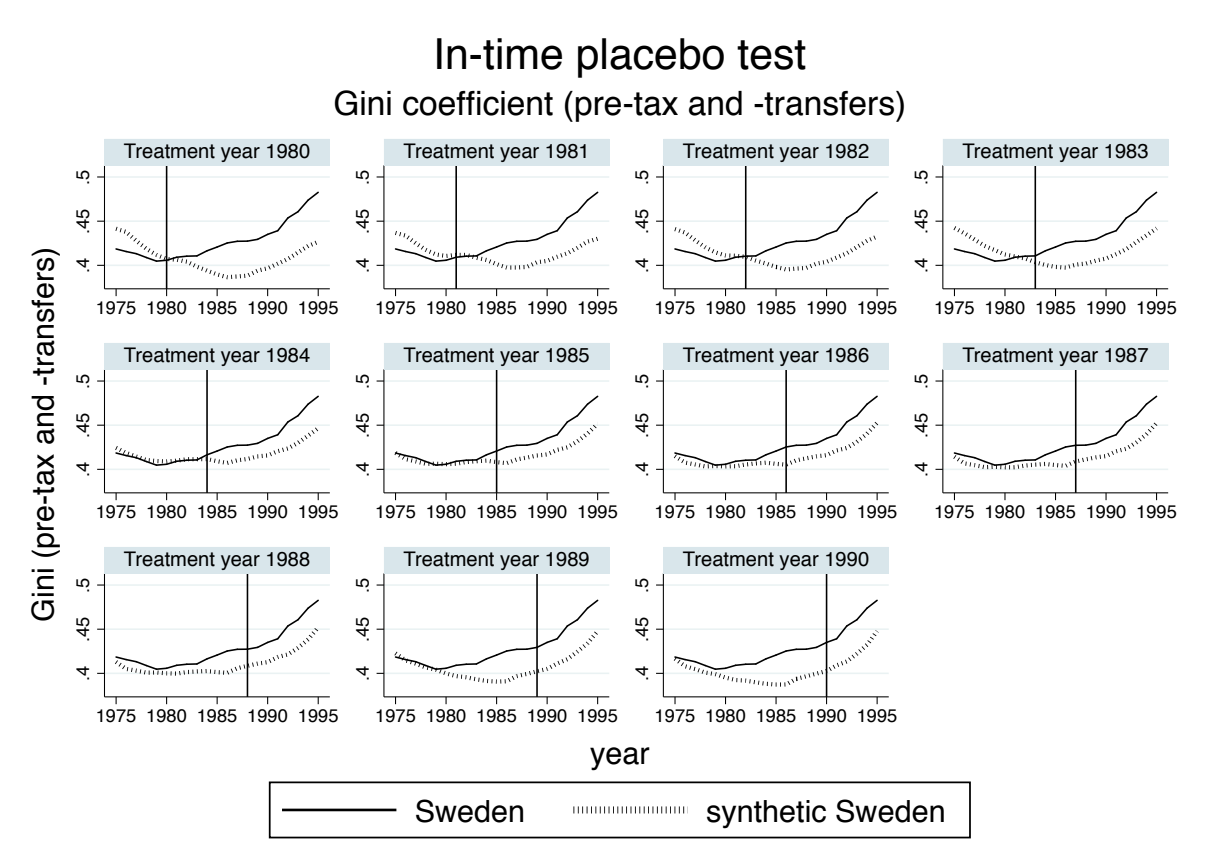
Notes: The country headline describes which country is used as the treated unit. The solid lines represent the actual outcome per year, pre- and post-treatment. The dashed lines represent the estimated outcomes using the synthetic control group. The treatment period, 1985, is represented by the vertical line. The pre- and post-treatment period are restricted to a $\pm$ 10-year window from 1985, hence ranging from 1975 to 1995.

In the final placebo test, the pre-tax income share of the top 1 percentile is used as the dependent variable. Most of the countries exhibit relatively stagnant income share patterns over time. Most noteworthy is perhaps the pattern exhibited by the synthetic control and the true outcome for Japan, in which a clear rise is taking place in the end of the 1980s. As written previously, Japan deregulated its financial sector in the 1990s. This pattern may therefore arise because of some anticipation effects, for example. In general, the synthetic controls tend to display larger increases in the income share of the top 1 percentile than the actual outcomes which may suggest that the synthetic controls are not very adequate or that there are no clear indications of the relationship of interest.

7.2 In-time placebo test

The in-time placebo test is performed by iteratively changing the treatment year. For consistency with the main results, the first year used in the calculations by the algorithm is 1975. The period for which the results are shown is 1975 to 1995. The assigned treatment years range from 1980 to 1990. An obvious caveat is that for the earlier treatment periods assigned, there are fewer years and, consequently, observations used in calculating the synthetic control than for the later treatment periods. However, if the earlier treatment periods would be allowed a, say, $\pm$ 10-year time window as well, then this would heavily influence which countries could be included in the donor pool. The results of the in-time placebo test are presented in figures 9 to 12 below.

Figure 9
Outcomes of the in-time placebo test using the pre-tax and -transfers Gini coefficient as dependent variable

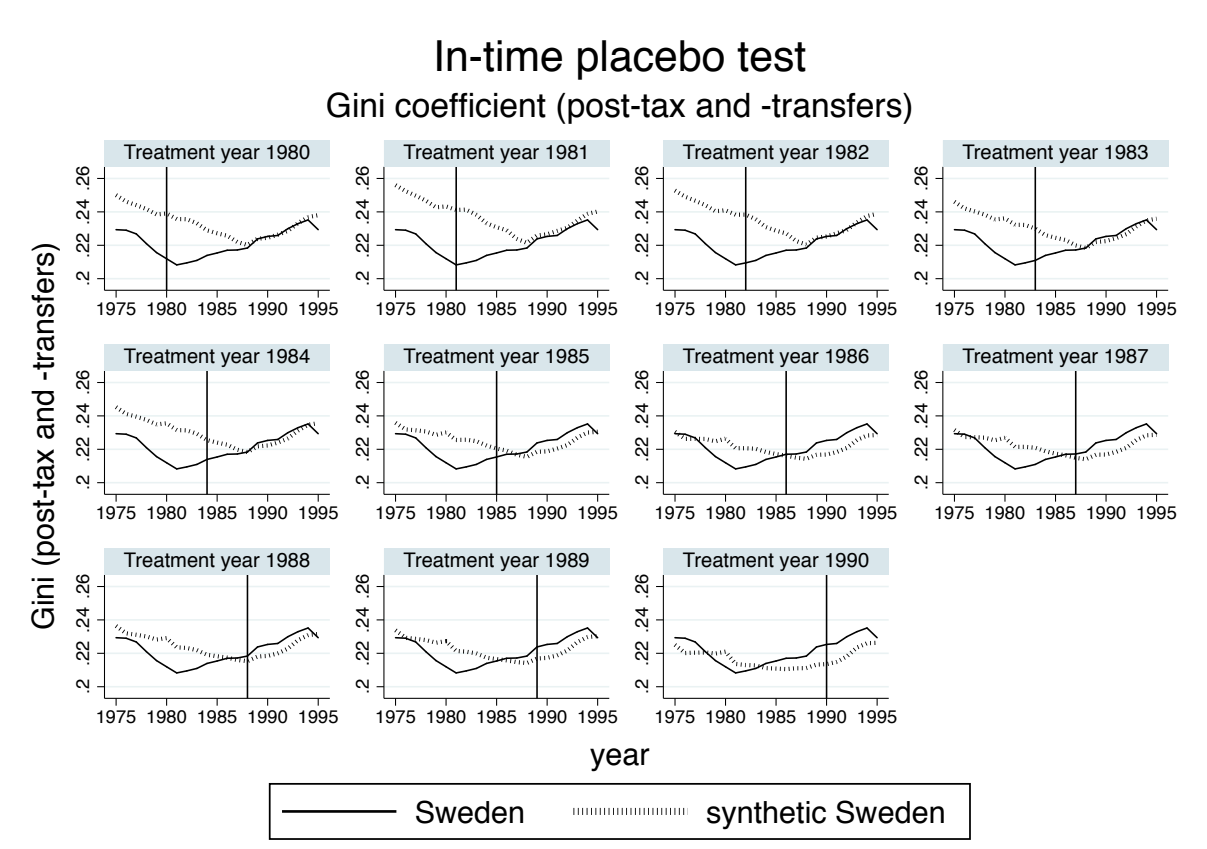


Notes: The headlines of each graph describe which year is used as the treatment period. The results period is 1975 to 1995, and the year from which the synthetic control is estimated is 1975 up to the treatment year. The solid lines represent the true outcome in Sweden and the dashed lines represent the outcome as estimated by the synthetic control method. The vertical lines represent the treatment year.

As expected, given the results presented in figure 4 above, the synthetic control for the pre-tax and -transfers Gini coefficient when the treatment is assigned to the year 1984 produces the most compelling pre-treatment fit and post-treatment deviation out of the

sample. Comparing with the synthetic control and the true outcome paths, respectively, when the treatment period is set to 1985, there seems as if income inequality starts to rise immediately after the treatment period whereas there is a lag for the 1985-graph. This is not necessarily bad, however, since this may just suggest that the treatment period is incorrectly specified in the baseline. As reasoned above, this may be the case since the deregulation was implemented in several steps, of which the steps implemented in 1984 may have been the most important in affecting income inequality. Going further from 1984 and 1985 in either direction, the pre-treatment fit of the synthetic control groups become less accurate. The trajectories do therefore not suggest that the results from the SCM when the pre-tax and -transfers Gini coefficient is used as the independent variable, are non-robust.

Figure 10
Outcomes of the in-time placebo test using the post-tax and -transfers Gini coefficient as dependent variable

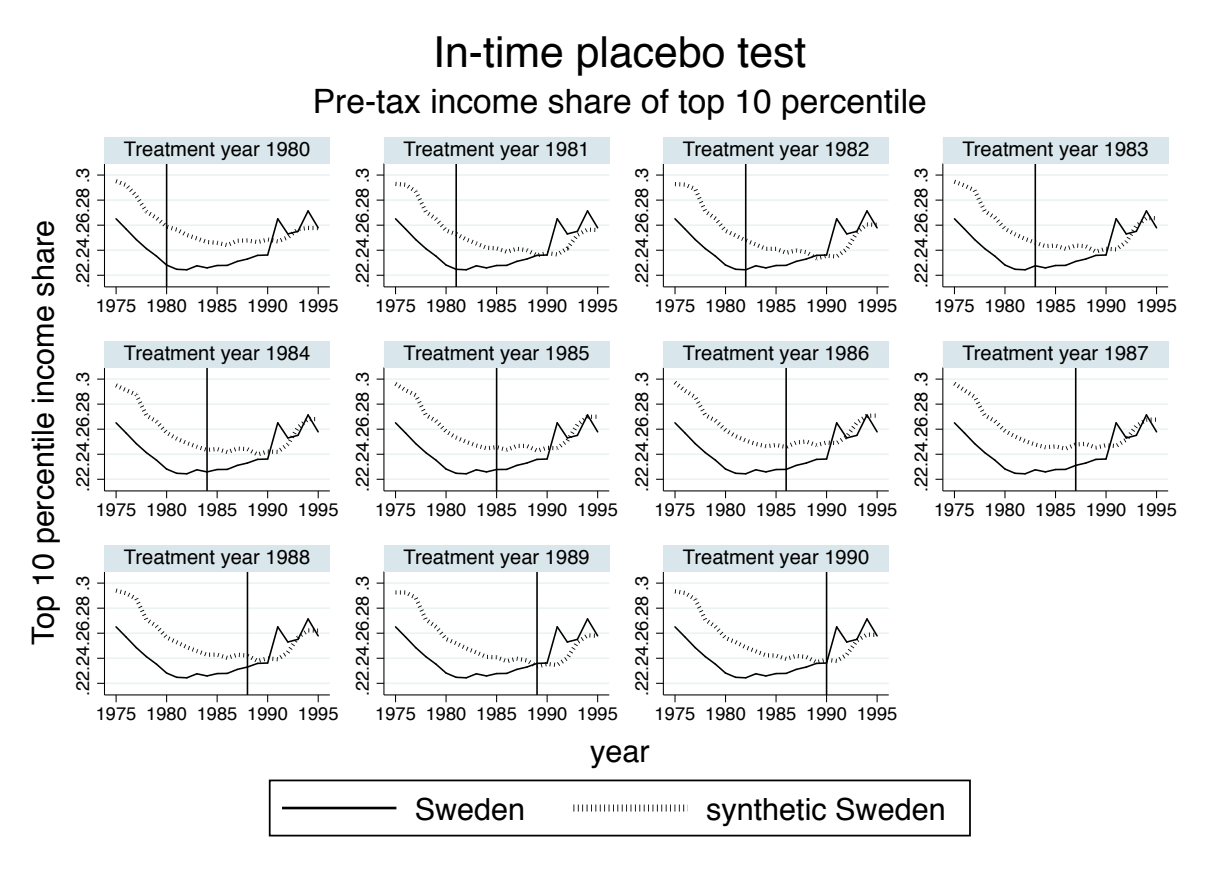


Notes: The headlines of each graph describe which year is used as the treatment period. The results period is 1975 to 1995, and the year from which the synthetic control is estimated is 1975 up to the treatment year. The solid lines represent the true outcome in Sweden and the dashed lines represent the outcome as estimated by the synthetic control method. The vertical lines represent the treatment year.

Neither of the synthetic controls produce a good fit pre-treatment when the post-tax and -transfers Gini coefficient is used as the dependent variable. This is not surprising given that the synthetic control for the baseline, when the treatment year was set to

1985, did not perform well either. None of the synthetic controls suggest that the treatment period of 1985 is incorrectly specified. Moreover, no inference can be drawn that the post-tax and -transfers Gini coefficient rose as a consequence of the financial deregulation.

Figure 11
Outcomes of the in-time placebo test using the pre-tax income share of the top 10 percentile as dependent variable

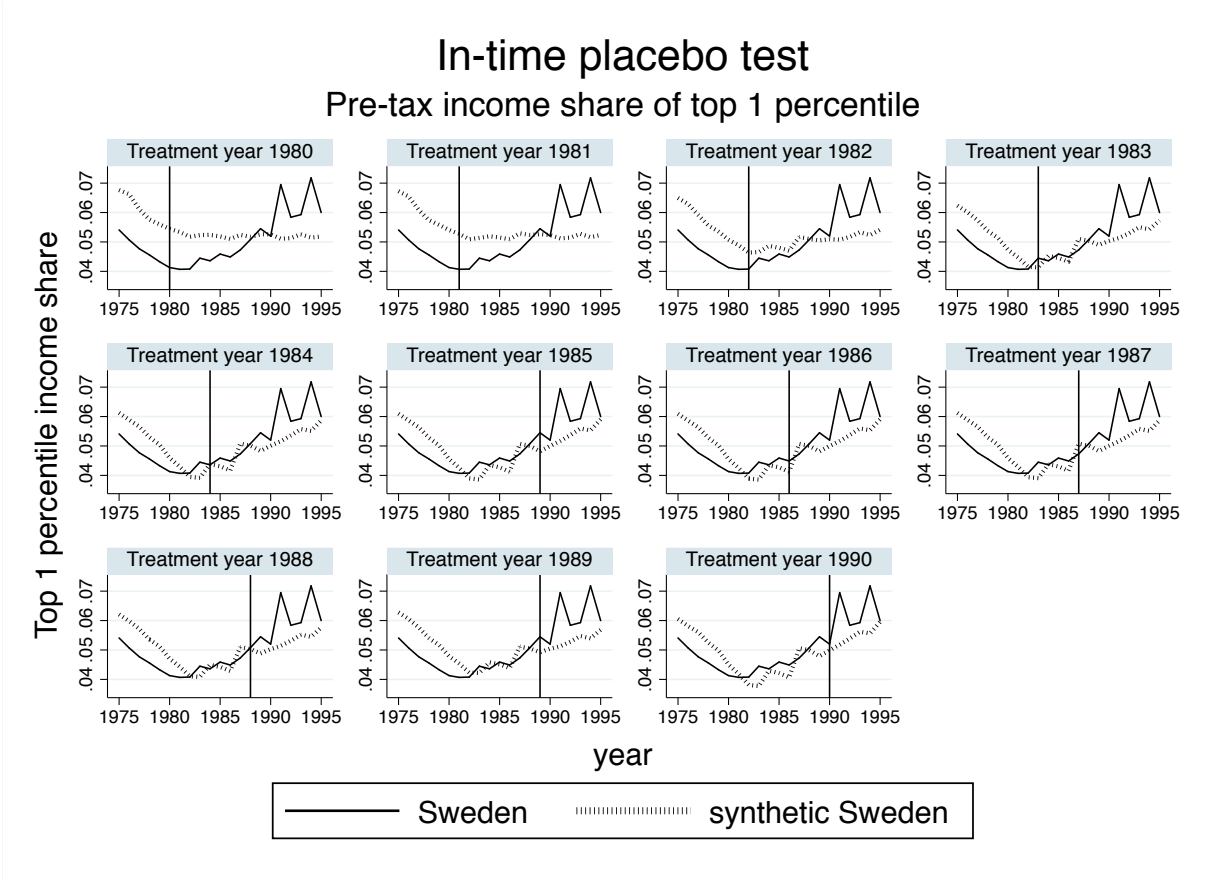


Notes: The headlines of each graph describe which year is used as the treatment period. The results period is 1975 to 1995, and the year from which the synthetic control is estimated is 1975 up to the treatment year. The solid lines represent the true outcome in Sweden and the dashed lines represent the outcome as estimated by the synthetic control method. The vertical lines represent the treatment year.

The synthetic controls for the pre-tax income share of the top 10 percentile in figure 11 convey a relatively similar pattern regardless of which year is set as the treatment period. The synthetic controls seem to follow a very similar trend compared to the true outcome pre-treatment. However, the synthetic controls when the treatment period is set earlier than 1983 and later than 1985 produce quite bad fits in terms of pre- and post-treatment differences between the synthetic control and the true outcome. With respect to income inequality effects of the financial deregulation, it seems as the synthetic control when the treatment period is set to 1983 performs relatively well. The trajectories of the synthetic Sweden compared to the real Sweden, the pre-treatment trends are similar but different in levels. After the treatment, the pre-tax income share

of the top 10 percentile decreases slightly in synthetic Sweden whereas it starts to rise in the real Sweden, which may indicate a slight effect of the financial deregulation. It is difficult to draw any hard-cut conclusions, however.

Figure 12
Outcomes of the in-time placebo test using the pre-tax income share of the top 1 percentile as dependent variable



Notes: The headlines of each graph describe which year is used as the treatment period. The results period is 1975 to 1995, and the year from which the synthetic control is estimated is 1975 up to the treatment year. The solid lines represent the true outcome in Sweden and the dashed lines represent the outcome as estimated by the synthetic control method. The vertical lines represent the treatment year.

To conclude the in-time placebo tests, the results for the pre-tax income share of the top 1 percentile used as dependent variable are shown in figure 12. The synthetic controls for treatment year set to 1980 and 1981, respectively, exhibit quite good pre-treatment parallel trends although it is difficult to conclude anything further regarding the post-treatment outcome of the synthetic control and the true outcome. Neither of the rest of the synthetic controls, compared to the true outcome, display a good fit prior to the treatment period, and suggest no clear patterns of deviations post-treatment. This pattern does not give cause for surprise, though, since the synthetic control vis-á-vis the true outcome did not perform well in the baseline either (see figure 4).

7.3 Constructed p-value

The SCM-specific p-value is constructed as the RMSPE of the post-treatment period over the RMSPE of the pre-treatment period. The constructed p-value is based on the in-space placebo test, where the treatment is iteratively assigned to each of the countries in the donor pool. For each run of the synthetic control method, the pre- and post-treatment RSPEs are calculated. Thereafter, the ratios are constructed. The resulting p-value is calculated as the probability of obtaining as high of a RMSPE-ratio as the one obtained for the true, treated unit, Sweden in this case. Countries denoted by "-" have been excluded due to lack of data.

Table 11
Constructed p-values for each country acting as the treated unit per inequality measure

	Per-variable ratios			
Treated unit	Gini coefficient (pre-tax and -transfers)	Gini coefficient (post-tax and -transfers)	Pre-tax income share of top 10 percentile	Pre-tax income share of top 10 percentile
Australia	0.827	1.165	0.827	0.885
Canada	2.024	1.466	0.869	1.687
Denmark	-	-	3.005	3.609
Finland	1.056	0.790	-	1.578
France	1.036	0.818	0.866	0.808
Germany	0.850	1.464	1.613	0.683
Ireland	1.934	0.638	0.694	0.899
Italy	0.569	0.931	1.623	1.233
Japan	1.498	0.545	4.251	1.636
Netherlands	-	-	1.293	1.985
New Zealand	-	-	1.283	3.611
Norway	2.722	0.252	2.869	2.094
Spain	-	-	-	-
Sweden	4.563	0.394	0.428	1.354
Switzerland	-	-	-	-
United Kingdom	5.871	3.633	-	-
United States	-	-	-	-

Notes: Countries denoted with "-" have been excluded from the estimations due to lack of data. The variables in the top row describe which income inequality measure has been used in running the SCM. Ratios are calculated as $\frac{RMSPE_{post-treatment}}{RMSPE_{pre-treatment}}$.

In the second column of table 11 above, where the independent variable is the pre-tax and -transfers Gini coefficient, only one ratio is higher than Sweden's ratio, namely for the United Kingdom at circa 5.9. Sweden on the other hand has a ratio of about 4.6. In this case, the constructed p-value is 2/11 ≈ 0.18. This is the lowest p-value out of the four, which is not unpredicted given that the pre-tax and -transfers Gini coefficient had the best pre-treatment fit and a significant deviation post-treatment between Sweden and synthetic Sweden. For the post-tax and -transfers Gini coefficient, Sweden has one of the lower ratios, leading to a p-value of 9/11 ≈ 0.82. The p-values for the pre-tax top income shares are 11/12 ≈ 0.92. are and 8/13 ≈ 0.62, respectively. The main

takeaway when assessing the results of the constructed p-values, are that for three of the inequality measures (columns 3-5 in table 11), there is a high chance of obtaining a ratio at least as high as Sweden's. For the pre-tax and -transfers Gini coefficient, the constructed p-value suggests more robust results.

8. Discussion

Figure 4 suggests that there is an income inequality effect of the financial deregulation in terms of the pre-tax and -transfers Gini coefficient. Moreover, the null hypothesis of no causal effect of the financial deregulation on income inequality can be rejected. Although Casti (2018) and Tanndal and Waldenström (2018) have an explicit focus on top income shares as measures of inequality, their results strengthen the relationship found with respect to the pre-tax and -transfers Gini coefficient. Although the pre-treatment fit is good only in terms of parallel trends in levels for the pre-tax top income share of the top 10 percentile, the trajectory of Sweden compared to the synthetic Sweden also suggests a post-deregulatory income inequality increase. In summary, there is some evidence that financial sector deregulations tend to cause income inequality increases. Noteworthy is that Beck et al. (2010) in studying the US financial deregulation find that income inequality was lowered as a result of the deregulation. Contrasting their results, Xu et al. (2018) find similar results in the Gini coefficient in relation to the US financial deregulation as the results in this thesis. Given the very different institutional settings of the US and Sweden as well as the different methods used, it is difficult to state that either result is applicable in a Swedish context.

With respect to the post-tax and -transfers Gini coefficient and the pre-tax income shares of the top 10 and top 1 percentiles, no such strong conclusions can be made as the null hypothesis could not be rejected. This does not imply that there have been no effects of the deregulation on income inequality. Rather it may be indicative of the control variables utilised not being not adequate enough to estimate the trajectories of income inequality over time. It could potentially also be that the donor pool countries are incorrectly chosen and that other countries would have produced a better pre-treatment fit. Finally, another possible reason is that the synthetic control method is not suitable for investigating the impact of the financial deregulation in Sweden on income inequality. As further reasoned in section 9.6, the Gini coefficient is somewhat lacking as an inequality measure due to its incapability in capturing within-distributional changes over time. That is one reason for why the top income shares act as a complementary analysis. However, the relatively poor outcomes of the synthetic control method with regards to the income shares of the top percentiles make it difficult to use those results to further add dimension to the pre-tax and -transfers Gini coefficient. Moreover, the robustness tests presented in section 7 exert restricting pressure on the conclusions that can be drawn from the analysis, especially with respect to the income shares of the top percentiles and the post-tax and -transfers Gini coefficient.

One reason for why the big differences in fit between the Gini coefficients arose can be the relatively unique taxation and transfer systems Sweden has. The expansion of the welfare state entailed several reforms with respect to, for example, the re-distributional system. Therefore, even the other Scandinavian countries composing the lion share of the synthetic controls may not hold up in comparison. An implication of this is that none of the countries belonging to the donor pool share similar enough characteristics, either pre- or post-treatment. That is, that the extensive distributional system in Sweden makes it hard to compose a synthetic control such that the pre-treatment trajectories are identical, or as close to identical as possible. Noteworthy, however, is the stable difference in levels between the synthetic control and Sweden in the pre-tax income top 10 percentile. Since the taxation system in Sweden should not be influencing the differences in pre-tax income, other factors must be relevant in creating this systematical difference. One such factor could be the institutional setting in Sweden compared to the donor pool countries, where Sweden in the period of study had relatively regulated sectors of the industry.

The financial deregulation in Sweden was not implemented at once, but rather rolled out during the course of a few years. As the in-time placebo test for the pre-tax and -transfers Gini coefficient conveys, there is a structural break in 1984 rather than 1985 suggesting an anticipation effect for the final measures of the deregulation. Not directly connected to the financial deregulation, the external debt levels of the private sector increased massively with the introduction of the standard for currency loans in 1984. This could be related to the financial deregulation in that the institutional settings of Sweden changed from heavily regulated to more liberalised overall. At one level, it also connects to the household debt hypothesis discussed below.

Two hypotheses were presented for the possible channels through which the income inequality could increase. They were subsequently tested. Statistically significant, but small, effects and the null hypotheses could be rejected especially with respect to the pre-tax and -transfers Gini coefficient. This suggests that a rise in household debt as well as expansion of the financial sector partially caused the increase in income inequality. Although the SCM did not produce convincing evidence for the same pattern with regards to the other inequality measures, the coefficients had the expected signs albeit insignificant. One important caveat in the hypothesis test of the financial sector expansion is the lack of data on the extensive and intensive margins, respectively.

The financial sector expansion connects to the model by Greenwood and Jovanovic (1990), of which one implication is that the income distribution widens as the financial sector deepens. They moreover suggest that in the long-run, income inequality should take the form of the Kuznets-curve. The inverted U-curve is something not observable in the data which could be because of several reasons. For example, Sweden became a developed country relatively early, at least in comparison to the developing and recently developed countries today. Since the compiled data start in the 1940s at the earliest, and the analysis is performed on the years 1975 to 1995, Sweden could

already have reached the latter stages of the inverted U-curve. Due to the income inequality increasing in Sweden, this is probably not a very likely scenario. In addition, Sweden may not have reached its long-run phase yet, implying that the income inequality is still increasing as a result from the financial sector development. The results from the hypothesis test is also relevant to be assessed in relation to Ghossoub and Reed's (2017) model. In their model, financial development and income inequality are positively related in part because of the difference between capital and liquid assets owners. Reverting back to Denk (2015b), top income earners tend to be more involved with the stock market which is intimately connected to the financial sector. Therefore, if financial development disproportionally favours capital owners and the top income earners hold more capital, it is not surprising that the hypothesis finds support in the data.

In testing the household debt hypothesis, it would be beneficial to separate different income groups and their associated levels of household debt. Furthermore, given the structural break in 1984 in income inequality, the external debt levels in the private sector can possibly be ascribed some of the increase in income inequality if assuming that the household debt and external debt have similar effects but not necessarily through the same channels. External debt leaves the borrower exposed to currency shifts and devaluations, whereas the household debt is more sensitive to changes in the inflation and monetary policy rates. Since currency rates are subject to domestic and international inflation rates, threatening to devalue the currency of interest, it is not completely unlikely that there is some connection. In connection to the Iacoviello model (2008), income inequality has a debt accumulating impact on households. Moreover, the hypothesis results are supported by the results reported in Berisha et al. (2017). Albeit in an US setting, household debt exerts a positive impact on income inequality. Although the institutional contexts between the US and Sweden differ greatly, there may be similar transmission channels from household debt on income inequality.

To conclude, this thesis contributes to the current state of the literature by using the SCM to investigate whether the financial deregulation can be part of the explanation for why inequality has markedly increased in Sweden since the last decades of the 20th century. With respect to the limitations discussed in above as well as in section 9, the results are internally valid, especially with respect to the pre-tax and -transfers Gini coefficient. It is unlikely that the results are externally valid, however. Sweden has a relatively unique institutional setting in conjunction with the generous re-distributional system. Therefore, no direct inference should be possible between Sweden and another country. As shown by the poor pre-treatment fits of three out of the four income inequality measures, it is difficult to properly match the contextual setting of Sweden post-tax and -transfers. If a goal for policymakers and regulators is to alleviate income inequality, it is necessary to correctly discern how it arises. In this thesis, two suggestions in the form of the level of household debt and the degree of financial sector expansion are put forth. Although there is still much left to uncover, this analysis of

income inequality in Sweden and the channels through which it is caused at least lays some of the groundwork for further research efforts.

9. Limitations

9.1 Financial sector deregulations in donor pool countries

In their research paper, Tanndal and Waldenström (2018) put forth that some of the countries in the donor pool have also deregulated their financial sector. Their rationale for why these countries can still be included in the donor pool is that although the counterfactual does not represent a static financial sector, the deregulation analysis instead is performed vis-á-vis a dynamic financial sector. Some of the countries in the donor pool deregulated their financial sectors if not fully outside the scope of the full sample period, at least after the treatment period (see e.g. de Brouwer, 1999; Casti, 2018; Tanndal and Waldenström, 2018). This implies that there is no effect of these deregulations in determining the country weights, which is based on pre-treatment data. In addition, for example the United Kingdom, Japan, and Canada, are not assigned weights in any of the SCGs, suggesting a small influence of these deregulations on the SCM outcome.

Table 12
Table depicting the years of first implemented measures in relation to financial deregulation in SCG countries

Country	Financial deregulation (year of first implemented measure)	Source
Denmark	1980	Jes-Iversen and Sjögren (2014)
Finland	1980	Honkapohja et al. (1999)
France	1984	Melitz (1990)
Italy	1990	Casti (2018)
Norway	1979	Gerdrup (2003)

In table 12 above, the years in which the first measures of financial deregulation were implemented in the countries composing the synthetic controls for the four income inequality measures are listed. Restricting attention to the countries in question, Italy began to deregulate the financial sector in 1990 (Casti, 2018). Measures included, among others, unification of commercial and investment banks, partial privatisation of the banking sector, and the introduction of three kinds of banks of which two were permitted to branch out and own subsidiaries performing a wide range of financial activities. Casti discusses that one of the main consequences of the financial deregulation was a higher degree of concentration within the banking sector due to bank consolidations. In Finland, Honkapohja et al. (1999), state that the Finnish financial deregulation measures were focused on removal of regulations for domestic bank lending rates as well as facilitating the accumulation of foreign debt. In part due to regulations for lending rates being laxer than the same for deposit rates, banks and other financial institutions became more eager to lend. Hence, debt levels rose fast.

Honkapohja et al. further put forth that a large part of the outstanding credit was used for real estate investments, which in turn led to an increase in real asset prices. The first measure of the Norwegian financial deregulation was implemented already in 1979, when banks were absolved from from holding zero net positions in the spot market for currency (Gerdrup, 2003). Bårdsen and Klovland (2000) write that, in 1984, credit rationing for households and small businesses became more lenient. Moreover, reserve requirements were later on removed. The financial deregulation led to a lending boom in part caused by the abolishment of regulations for maximum lending interest rates (Bårdsen and Klovland, 2000). Turning instead to Denmark, the deregulation of the financial sector began in the early 1980s when restrictions on lending and interest rates were relaxed thus leading to amplified risk-taking and outstanding credit levels of banks. Later in the 1990s, international regulation standards were implemented. Furthermore, the banking sector became more concentrated as a result of larger banks procuring insurance companies, mortgage institutions, and investment banks (Jes-Iversen and Sjögren, 2014). Lastly, in France, the deregulation consisted, for example, of the introduction of new instruments and markets, abstraction from the division between investment and commercial banks, and removal of the practice where the Bank of France each morning set the trading price for which it would undertake its transactions in a given day (Melitz, 1990). Melitz moreover states that the financial deregulation led to non-financial corporations to a much larger extent using internally sourced funding for investments whereas households on the other hand became more reliant on bank lending to finance investments and consumption.

The deregulations in the SCG countries, as reviewed above, overall entailed relatively similar measures as the financial deregulation in Sweden. For two of the SCG countries, the first measures of the deregulations were implemented in the later half of or after the pre-treatment period (France and Italy). For the three Scandinavian SCG countries, on the other hand, the deregulations began in the middle of the pre-treatment period. Therefore, this may have a confounding effect on the estimation of the synthetic control group which can explain the poor pre-treatment fit between Sweden and synthetic Sweden for three out of four income inequality measures. Having reviewed the financial deregulations of the SCG countries, it can indeed be concluded that the comparison financial sectors were dynamically evolving around the same time period as the “November revolution”. The difference between Sweden and synthetic Sweden should therefore not be assumed to rely on a counterfactual fully in absence of treatment. Rather, the effects arise despite the fact that the counterfactual incorporates the changing nature of the financial sectors in the SCG countries.

9.2 Limitations of the synthetic control method

For any econometric method, there are of course drawbacks. The shortcomings of the SCM have been reviewed in section 5.2.4. One of the limitations, financial deregulations in countries of the donor pool, has been discussed in section 9.1 above.

In addition, there are restrictions in terms of over-fitting with respect to the number of countries in the donor pool. In the paper of Abadie et al. (2015) where the effects of California's Tobacco Control Program are evaluated, 38 of the US states are included in the donor pool. The maximum number of countries in the donor pool with respect to data availability in this paper is 13. Therefore, the problem of over-fitting should not be large. Another possible issue with the SCM is that heterogeneity in either the observed or unobserved variables have an impact on the income inequality measures. Normally in the SCM, this is counteracted with a large number of pre-treatment periods. As reasoned in section 9.4, the number of pre-intervention periods has had to be restricted in favour of including more countries in the donor pool. This may be one of the reasons for the relatively bad fit of three of the synthetic controls. Some authors, for example Firpo and Possebom (2018), have put forth criticism with respect to the constructed p-value in that all countries in the donor pool are assigned the same probability of being treated, a somewhat unrealistic assumption. They therefore propose a new test statistic that takes probabilities of treatment into account. Moreover, they suggest a re-specification of the null hypothesis to include cost and benefit dimensions of the treatment. This is, however, beyond the scope of this thesis, but worthwhile mentioning as a limitation.

9.3 Scandinavian legal origin

The inclusion of the dummy capturing legal origin, and specifically Scandinavian legal origin, will automatically bias the synthetic control to include two of the other Scandinavian countries (Finland and Norway). This arises since the SCM algorithm matches the average values of the pre-treatment period for Sweden against the average values of countries in the donor pool. Only the other Scandinavian countries, apart from Denmark, share the same value as Sweden. Thus, given the relatively few countries in the donor pool as well as the quite low number of control variables, this can be expected to exert influence on the assigned unit weights. However, this is not necessarily bad, since the goal of the SCM is also to match the synthetic control to the pre-treatment characteristics of the treated country, Sweden. It is likely that the Scandinavian countries share other traits with Sweden, so that they should be included, and assigned quite large weights, in the counterfactual.

9.4 Trade-off between time-span and number of countries

As mentioned partly in section 5.1, there is a trade-off between the number of countries included in the donor pool and the number of years used in the pre-treatment period due to the lack of long-span data for some variables and countries. While including more countries in the donor pool is beneficial since it alleviates the pre-selectivity in the data, it is also beneficial to allow a relatively large number of observations for the algorithm to estimate the synthetic control. In this case, as shown under sections 7 and 8 in the Appendix, most of the variables exhibit quite strong trends over time.

Therefore, it is most likely preferable to prioritise a larger number of countries over a longer time span.

9.5 Interpolations

Some of the time-series of both independent and dependent variables have been interpolated (for further information, see tables A3 and A4 in the Appendix). Interpolating the data of course brings with it some unreliability. Moreover, the interpolation results depend on the method used. The main concern is associated with the interpolations of the independent variables, since they make up the main part of the analysis. Firstly, however, as a robustness test, the SCM has been applied to the non-interpolated data (see figure A1 and tables A5-A7 in the Appendix) which produce similar results as for the interpolated data series. Secondly, the majority of the interpolations are performed on years outside the estimation window. Thirdly, the countries mostly subject to the interpolations are assigned zero weight in the synthetic control hence implying little to no effect on the outcome. In conclusion, this should pose a limited drawback.

9.6 Income inequality measures

A downside of the inequality measures used in the analysis is that they do not take into account for example years of education and working experience. The Gini coefficients from the Standardized World Income Inequality Database (Solt, 2019), are based on household level data whereas the pre-tax top percentile income shares are based on tax data. It is not wrong, per se, with different incomes based on factors such as the educational attainment. Rather it is important with an education premium in order to spur the completion of secondary and tertiary education. However, it should be considered in the analysis of income inequality. A further issue with using the Gini coefficient approach to measure income inequality, especially with respect to time, is that it does not account for within- or across-group changes in income. For example, as put forth by Gastwirth (2017), the Gini coefficient tends to be more receptive to top-to-bottom changes than mid-distribution changes. This implies that for income groups in the middle, inequality could increase while not being fully captured by the Gini coefficient. Finally, the pre-tax and -transfers Gini coefficient and the pre-tax income shares of the top percentiles do not reflect the true distribution of income, as they are dependent on the re-distributional system in a given country. However, they are still able to capture the initial inequalities of the income distribution. Although these arguments do not constitute something inherently incorrect in the paper, the factors mentioned above pose as limitations of the income inequality measures.

10. Conclusion

In this paper, the Swedish financial deregulation and its impact on income inequality has been studied through the use of the relatively recent synthetic control method (SCM). While the relationship between income inequality and financial deregulation has been studied before, also with the use of the SCM, this has not been executed in a Swedish setting. The main contributions of this paper are the novelty of studying the income inequality effects of the financial deregulation in Sweden using the SCM, as well as adding to the rather limited literature on income inequality studies in the context of the SCM.

The Swedish financial deregulation began in 1982 and was finalised in 1985 with a decision referred to as the “November revolution”. Ultimately, the deregulation resulted in banks and other financial institutions being able to lend more than before, as well as independently set the interest rates.

The synthetic control method was developed by Abadie and Gardeazabal (2003) and Abadie et al. (2010; 2015). In short, a synthetic counterfactual to a country experiencing some kind of treatment is constructed by assigning weights to countries belonging to a donor pool. The weights are assigned based on a set of control variables, in which the goal is to match the pre-treatment path of the treated country as closely as possible. A proper synthetic control is then assumed to depict the outcome path of the treated unit in absence of treatment.

Four different inequality measures are used: the pre-tax and -transfers Gini coefficient, the post-tax and -transfers Gini coefficient, the pre-tax income share of the top 10 percentile, and the pre-tax income share of the top 1 percentile. Only for one of the measures, the pre-tax and -transfers Gini coefficient, a good synthetic control can be constructed that adequately approximates the pre-treatment path of Sweden. The outcome of the SCM suggest a rise of close to two (2) percentage points five years after the “November revolution”. The SCM outcomes are supported by three separate robustness tests, rendering support mainly to the outcome of the pre-tax and -transfers Gini coefficient. To explain the rise in income inequality, two hypotheses are presented and subsequently tested. The first pertains to the “November revolution” leading to increased household indebtedness which in turn increased income inequality. The second relates to financial sector expansion and rises in income inequality because of increases in the extensive and/or the intensive margin. Support is found for both hypotheses with respect to the pre-tax and -transfers Gini coefficient. It is however unlikely that either channel can exhaustively account for the increase in income inequality over time.

Some suggestions for further study is firstly to decompose the financial sector expansion to attribute income inequality changes to the intensive and/or the extensive

margin. Secondly, as mentioned in section 9.6, constructing income inequality measures that are corrected for education attainment and work experience would add an extra dimension of depth to the analysis. Thirdly, an exhaustive comparison using different methods would be beneficial, given the relatively poor fit of the synthetic controls to the true outcome paths. Finally, related to the aforementioned point, which control variables should be included in determining the synthetic control group is a possible topic for future research.

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A. Appendix

1. Data availability of dependent variables per country

Table A1 presents the data availability in terms of years per country and income inequality measure, respectively. Time series denoted by * signify that full series are not available and that they have been subject to linear interpolation.

Table A1
Data availability of dependent variables per country

	Variable			
Country	Gini coefficient (pre-tax and -transfers)	Gini coefficient (post-tax and -transfers)	Pre-tax income share of top 10 percentile	Pre-tax income share of top 1 percentile
Australia	1967-2016	1967-2016	1941-2015	1940-2015
Canada	1971-2016	1971-2016	1941-2010	1940-2010
Denmark	1976-2017	1976-2017	1940-2010*	1940-2010*
Finland	1966-2016	1966-2016	1990-2009	1940-2009*
France	1962-2016	1962-2016	1940-2014	1940-2014
Germany	1960-2016	1960-2016	1950-2013*	1950-2013*
Ireland	1973-2017	1973-2017	1975-2015*	1975-2015*
Italy	1967-2016	1967-2016	1974-2009*	1974-2009*
Japan	1961-2015	1961-2015	1947-2010	1940-2010*
Netherlands	1977-2016	1977-2016	1941-2012*	1941-2012*
New Zealand	1982-2017	1982-2017	1940-2014*	1940-2014
Norway	1970-2017	1970-2017	1948-2011*	1940-2011*
Spain	1974-2016	1974-2017	1981-2012	1981-2012
Sweden	1960-2016	1960-2016	1941-2013*	1941-2013*
Switzerland	1980-2015	1980-2015	1941-2014*	1941-2014*
United Kingdom	1961-2017	1961-2017	1981-2016	1981-2016
United States	1961-2017	1961-2017	1962-2014	1962-2014

Notes: Time series denoted by * signify full series time series not being available. Information regarding what years are missing, and hence interpolated, is available in section 3 in the Appendix.

2. Data availability of independent variables per country

Table A2 presents the data availability in terms of years per country and control variable, respectively. Time series denoted by * signify that full series are not available and that they have been subject to linear interpolation.

Table A2
Data availability of independent variables per country

	Variable					
Country	Trade union density	Employment tax rate (%)	Political orientation of chief executive	GDP growth (%)	GDP per capita (constant 2010US$)	Export of goods and services (% of GDP)
Australia	1960-2016	1960-1985	1975-2012	1969-2017	1969-2017	1969-2017
Canada	1960-2015	1960-2000	1975-2012	1969-2017	1969-2017	1969-2017
Denmark	1960-2016	1960-2003	1975-2012	1969-2017	1969-2017	1969-2017
Finland	1969-2016	1960-2003	1975-2012	1969-2017	1969-2017	1969-2017
France	1960-2015	1960-2003	1975-2012	1969-2017	1969-2017	1969-2017
Germany	1960-2015	1960-2003	1975-2012	1971-2017	1970-2017	1970-2017
Ireland	1960-2011*	1960-2003*	1975-2012	1971-2017	1970-2017	1969-2017
Italy	1960-2016	1960-2003	1975-2012	1969-2017	1969-2017	1969-2017
Japan	1960-2017	1960-2003	1975-2009	1969-2017	1969-2017	1969-2016
Netherlands	1960-2016	1960-2003	1975-2012	1969-2017	1969-2017	1969-2017
New Zealand	1960-2016	1960-1985	1975-2012	1971-2017	1970-2017	1970-2016
Norway	1960-2015	1960-2002	1975-2012	1969-2017	1969-2017	1969-2017
Spain	1977-2015	1960-2003	1978-2012	1969-2017	1969-2017	1969-2017
Sweden	1960-2012	1960-2002	1975-2012	1969-2017	1969-2017	1969-2017
Switzerland	1960-2015	1960-1990	*missing*	1981-2017	1980-2017	1969-2017*
United Kingdom	1960-2016	1960-2000	1975-2012	1969-2017	1969-2017	1969-2017
United States	1960-1980	1960-2003	1975-2012	1962-2014*	1962-2014*	1969-2016

Notes: The data availability for the Legal origin-dummy is not included in the table since it is considered to be static over time, and hence available for all countries and years of interest. Time series denoted by * signify full series time series not being available. Information regarding what years are missing, and hence interpolated, is available in section 4 in the Appendix.

3. Interpolated time series per country and variable: dependent variables

Table A3 displays over which years data were missing for a given income inequality measure and country. Country-specific time series denoted by "-" have not been subject to interpolation.

Table A3
Interpolated time series of dependent variables per country

	Variable			
Country	Gini coefficient (pre-tax and -transfers)	Gini coefficient (post-tax and -transfers)	Pre-tax income share of top 10 percentile	Pre-tax income share of top 1 percentile
Australia	-	-	-	
Canada	-	-	-	
Denmark	-	-	1969	1969
Finland	-	-	-	1990-1992
France	-	-	-	-
Germany	-	-	1951-1960, 1962-1964, 1966-1967, 1969-1970, 1972-1973, 1975-1976, 1978-1979, 1981-1982, 1984-1985, 1987-1988, 1990-1991, 1994-1994, 1996-1997, 1999-2000	1951-1953, 1955-1956, 1962-1964. 1966-1967, 1969-1970, 1972-1973, 1975-1976, 1978-1979, 1981-1982, 1984-1985, 1987-1988, 1990-1991, 1994-1994, 1996-1997, 1999-2000
Ireland	-	-	1944-1974	1944-1974
Italy	-	-	1996-1997	1996-1997
Japan	-	-	-	1946
Netherlands	-	-	1942-1945, 1947-1949, 1951, 1954-1956, 1960-1961, 1963, 1965 1968-1969, 1971-1972, 1974, 1976, 1978-1979, 1982-1984, 1986-1988	1942-1945, 1947-1949, 1951, 1954-1956, 1960-1961, 1963, 1965 1968-1969, 1971-1972, 1974, 1976, 1978-1979, 1982-1984, 1986-1988
New Zealand	-	-	1941-1944, 1961	1941-1944, 1961
Norway	-	-	1956	1956
Spain	-	-	-	-
Sweden	-	-	1942	1942
Switzerland	-	-	Every 2nd year: 1942-1994	Every 2nd year: 1942-1944
United Kingdom	-	-	-	-
United States	-	-	1963, 1965	1963, 1965

Note: Countries and variables with denoted with "-" have not been interpolated.

4. Interpolated time series per country and variable: independent variables

Table A4 displays over which years data were missing for a given control variable and country. Country-specific time series denoted by "-" have not been subject to interpolation.

Table A4
Interpolated time series of independent variables per country

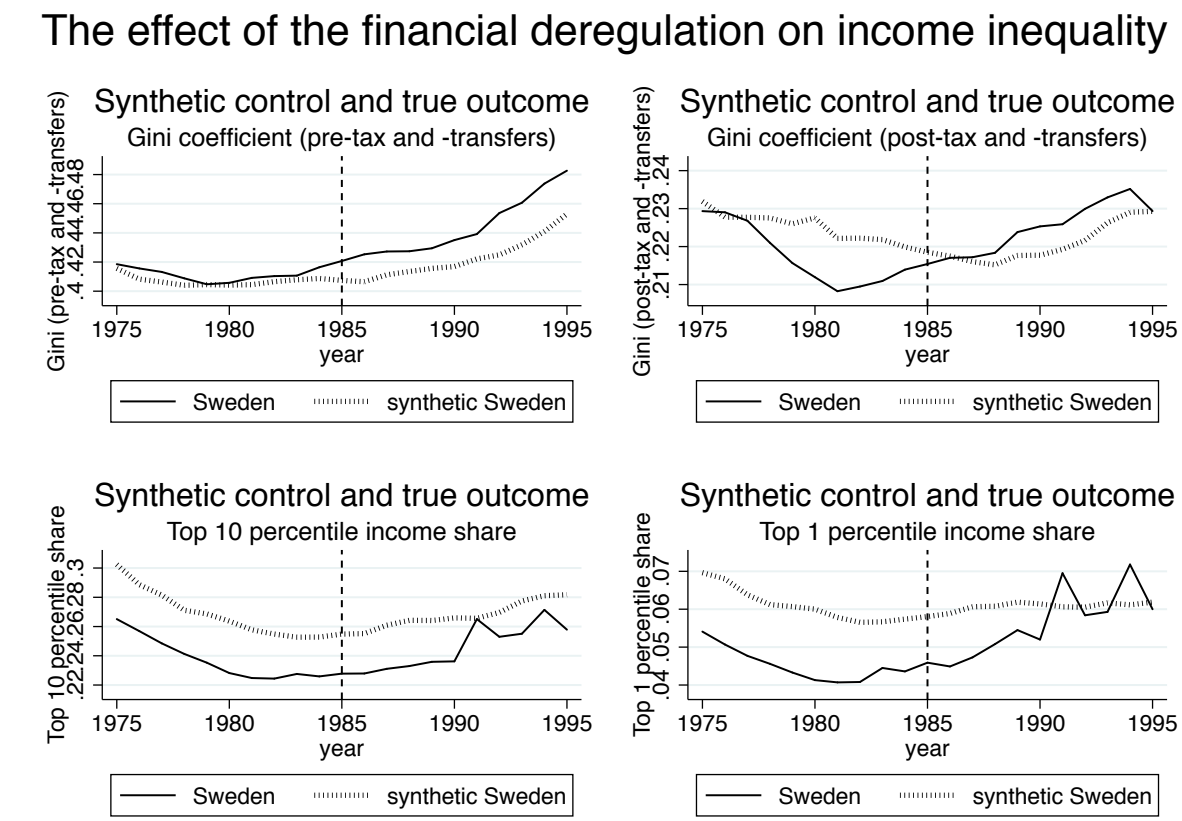
	Variable					
Country	Trade union density	Employment tax rate (%)	Political orientation of chief executive	GDP growth (%)	GDP per capita (constant 2010US$)	Export of goods and services (% of GDP)
Australia	1997-2016	-	-	-	-	-
Canada	-	-	-	-	-	-
Denmark	-	-	-	-	-	-
Finland	-	-	-	-	-	-
France	-	-	-	-	-	-
Germany	-	-	-	-	-	-
Ireland	2012, 2014-2015	1990-1994	-	-	-	-
Italy	-	-	-	-	-	-
Japan	-	-	-	-	-	-
Netherlands	-	-	-	-	-	-
New Zealand	-	-	-	-	-	-
Norway	-	-	-	-	-	-
Spain	-	-	-	-	-	-
Sweden	-	-	-	-	-	-
Switzerland	-	-	-	-	-	-
United Kingdom	-	-	-	-	-	-
United States	-	-	-	1965	1965	-

Note: Countries and variables with denoted with "-" have not been interpolated.

5. Synthetic control method outcomes using non-interpolated data

In figure A1, the synthetic control method outcomes for each income inequality measure can be seen. Compared to figure 4, non-interpolated time series have been used in estimating the effect of the financial deregulation on income inequality.

Figure A1
The estimated effect of the financial deregulation in Sweden for each of the four income inequality measures using non-interpolated data



Notes: The solid lines represent the actual outcome in Sweden per year, pre- and post-treatment. The dashed lines represent the estimated outcome in Sweden in the absence of financial deregulation. The year in which the financial deregulation was finalised is represented by the vertical dashed line. The pre- and post-treatment period are restricted to a $\pm$ 10-year window from 1985, hence ranging from 1975 to 1995.

Consistent with figure 4, the synthetic control group (SCG) for the pre-tax and -transfers Gini coefficient exhibits the most compelling performance with respect to the true pre-treatment outcome path of Sweden. Starting in 1984, the SCG and the true outcome start to deviate from each other, suggesting that the financial deregulation caused an increase in income inequality as measured by the pre-tax and -transfers Gini coefficient. For the post-tax and -transfers Gini coefficient, the pre-treatment match between the true outcome and the SCG is lacking in terms of fit. Any further conclusions will therefore be difficult to argue.

The outcome with respect to income inequality as measured by the pre-tax income share of the top 10 percentile is very similar to the outcome presented in figure 4. The pre-treatment trends between SCG and the true outcome seem be parallel, albeit different in levels. However, no direct conclusions can be drawn post-deregulation.

Notably, for the pre-tax income share of the top 1 percentile, the SCG and the Sweden display parallel pre-treatment trends that differ only in levels. Post-deregulation, the trend of Sweden seems to be slightly increasing income inequality levels compared to the SCG but not much can be inferred from this.

Table A5
Values for the control variables for the treated unit, Sweden, and each synthetic control group

		Inequality measure				
Variables	Sweden	Gini (pre-tax and -transfers)	Gini (post-tax and -transfers)	Top 10 percentile	Top 1 percentile	Mean
GDP growth (%)	1.755	2.735	3.132	2.916	2.439	2.805
GDP per capita	31,112.910	25,420.230	301,87.450	32,844.490	31,834.810	30071.745
Employment tax rate (%)	24.564	11.132	9.900	15.927	8.999	11.489
Exports as % of GDP	29.360	26.275	30.023	28.353	28.098	28.187
Scandinavian legal origin	1.000	0.757	0.935	0.250	0.000	0.486
Political orientation of chief executive	0.000	0.104	0.139	0.217	0.236	0.174
Union density (%)	77.793	55.903	62.106	56.994	66.015	60.254

Notes: Weighted values of the control variables that are utilised to find the optimal synthetic control group for each separate income inequality measure. A good synthetic control should display control variable values that closely resembles the control variable values for the treated unit. The control variables are further described in section 5.1.2.

Table A6 presents the country weights in each synthetic control on per-income inequality measure basis.

Table A6
Control group unit weights per country and income inequality measure

	Unit weights			
Country	Gini (pre-tax and -transfers)	Gini (post-tax and -transfers)	Top 10	Top 1
Australia	0	0	0	0
Canada	0	0	0	0
Denmark	0*	0*	0.245	0.628
Finland	0.757	0.713	0*	0*
France	0.243	0.065	0	0
Germany	0	0	0*	0*
Ireland	0*	0*	0*	0*
Italy	0	0	0.505	0.372
Japan	0	0	0	0
Netherlands	0*	0*	0*	0*
New Zealand	0*	0*	0	0
Norway	0	0.222	0.250	0
Spain	0*	0*	0*	0*
Switzerland	0*	0*	0*	0*
United Kingdom	0	0	0*	0*
United States	0*	0*	0*	0*

Note: Unit weights denoted by * were excluded in the analysis due to lack of data.

The other Scandinavian countries in the sample, Denmark, Finland, and Norway, are assigned relatively large weights in all synthetic control groups where data are available. As reasoned earlier, in section 6.3, this is not surprising given that the Scandinavian countries tend to share similar traits with respect to, for example, the institutional setting. Also France and Italy are included, which at a first glance is a bit confounding. Looking at the descriptive statistics in section 6 below, this is explained by the relatively similar per-variable statistics of France and Italy to the Scandinavian donor countries.

Below in table A7 the root mean-squared percentage errors (RMSPEs) for each SCG per income inequality measure are displayed.

Table A7
Root mean-squared percentage errors (RMSPEs) for each synthetic control group

	Inequality measure				
	Gini (pre-tax and -transfers)	Gini (post-tax and -transfers)	Top 10	Top 1	Mean
RMSPE	0.006	0.009	0.031	0.016	0.016

Note: The RMSPEs are presented in decimal form, and not in percentages.

Consistent with the main results, see table 8 in section 6.3, the SCG for pre-tax and -transfers Gini coefficient exhibits the lowest RMSPE at 0.006, or 0.6 percent. Noteworthy is that the RMSPEs for the pre-tax income shares of the top 10 and top 1 percentile at 0.031 and 0.016, respectively, are higher than the RMSPE for the the post-tax and -transfers Gini coefficient at 0.009. Although the fit in terms of parallel trends are better for the top percentile SCGs, the RMSPE does not take into account parallel trends in levels. Therefore, the outcome for the top percentile is relatively poor in terms of the RMSPEs, but significantly better than the post-tax and -transfers Gini coefficient when examined graphically.

6. Descriptive statistics for countries in the synthetic control groups

In tables A8-A12, per-country descriptive statistics for all countries assigned weights in the SCGs are presented in alphabetical order.

Table A8
Descriptive statistics for Denmark

		Statistic					
Country	Variable	Min	Mean	P50	Max	Sd	N
Denmark	Top 10 percentile	0.245	0.292	0.293	0.390	0.041	70
	Top 1 percentile	0.050	0.074	0.066	0.138	0.023	69
	Gini (post-tax and -transfers)	0.220	0.238	0.234	0.269	0.013	42
	Gini (pre-tax and -transfers)	0.372	0.432	0.435	0.491	0.032	42
	GDP growth (%)	-4.907	1.972	1.964	6.322	2.069	49
	GDP per capita	29,953.019	47,179.990	45,803.400	61582.170	10,549.130	49
	Employment tax rate (%)	0.000	0.550	0.500	1.800	0.514	44
	Exports as share of GDP (%)	26.406	39.450	36.852	55.676	9.405	49
	Scandinavian legal origin	0.000	0.000	0.000	0.000	0.000	79
	Right-wing chief executive	0.000	0.579	1.000	1.000	0.500	38
	Union density (%)	56.808	69.758	71.469	80.125	7.211	57

Note: Descriptive statistics are provided on full-sample basis in terms of years.

One thing that stands out is that Denmark is not classified as having Scandinavian legal origin, whereas all the other Scandinavian countries (Finland, Norway, and Sweden) in the sample do. Denmark exhibits relatively high and, over time, compact income inequality levels looking at all the income inequality measures. Moreover, Denmark has had a majority of right wing chief executives between the years 1975-2012, with a mean value of 0.579. The union density levels are skewed towards the higher half of the interval, with a minimum and maximum levels of ≈ 57 percent and ≈ 80 percent, respectively. Looking at the GDP growth, in percent, there is a large range with a minimum of -4.907 percent and a maximum of 6.322 percent. Note also that the standard deviation exceeds the mean value.

Table A9
Descriptive statistics for Finland

Country	Variable	Statistic					
		Min	Mean	P50	Max	Sd	N
Finland	Top 10 percentile	0.271	0.299	0.302	0.328	0.018	20
	Top 1 percentile	0.035	0.077	0.083	0.115	0.021	67
	Gini (post-tax and -transfers)	0.205	0.231	0.234	0.256	0.019	51
	Gini (pre-tax and -transfers)	0.381	0.433	0.441	0.478	0.036	51
	GDP growth (%)	-8.269	2.663	2.992	9.593	3.224	49
	GDP per capita	17,377.440	34,000.060	31,997.000	49,363.700	9,900.185	49
	Employment tax rate (%)	4.000	10.339	6.050	24.900	7.602	44
	Exports as share of GDP (%)	21.254	32.157	31.366	45.078	7.107	49
	Scandinavian legal origin	1.000	1.000	1.000	1.000	0.000	79
	Right-wing chief executive	0.000	0.105	0.000	1.000	0.311	38
	Union density (%)	31.503	64.449	68.413	81.224	13.643	57

Note: Descriptive statistics are provided on full-sample basis in terms of years.

Finland portrays a relatively similar pattern as Denmark with respect to the income inequality measures over time. One difference between Denmark and Finland is that Finland over time has had a majority centre- or left-wing chief executives, with a mean value of 0.105. Considering the GDP growth in percent, the range is quite large with a minimum value of -8.269 percent and a maximum value of 9.593 percent. With respect to the union density, Finland exhibits a larger range than Denmark, with minimum and maximum values of ≈ 32 percent and ≈ 81 percent, respectively. Also the standard deviation is higher at ≈ 14 percent. In similarity with the other Scandinavian countries, apart from Denmark, Finland is classified as having a Scandinavian legal origin.

Table A10
Descriptive statistics for France

		Statistic					
Country	Variable	Min	Mean	P50	Max	Sd	N
France	Top 10 percentile	0.293	0.338	0.334	0.422	0.025	75
	Top 1 percentile	0.073	0.103	0.104	0.168	0.016	75
	Gini (post-tax and -transfers)	0.276	0.292	0.289	0.324	0.012	55
	Gini (pre-tax and -transfers)	0.454	0.476	0.476	0.494	0.011	55
	GDP growth (%)	-2.941	2.347	2.085	6.991	1.871	49
	GDP per capita	19,148.510	32,930.910	33,216.010	42,567.740	7,183.406	49
	Employment tax rate (%)	17.700	25.332	26.600	29.800	3.615	44
	Exports as share of GDP (%)	14.012	23.549	22.623	30.882	4.322	49
	Scandinavian legal origin	0.000	0.000	0.000	0.000	0.000	79
	Right-wing chief executive	0.000	0.583	1.000	1.000	0.500	36
	Union density (%)	7.794	13.798	11.581	22.193	5.730	56

Note: Descriptive statistics are provided on full-sample basis in terms of years.

What stands out in the descriptive statistics for France is, in relation to the Scandinavian countries, the range of the union density with a minimum of ≈ 8 percent and a maximum of ≈ 22 percent. Moreover, France has in common with Denmark that in a majority of the years 1975-2012, the chief executive has had a right-wing political orientation with a mean value of 0.583. With respect to the income inequality measures, France exhibits relatively high values overall and small standard deviations in proportion to the minimum and maximum values. In addition, France seems to have had a relatively more stable positive GDP growth over the years in comparison to Denmark and Finland.

Table A11
Descriptive statistics for Italy

Country	Variable	Statistic					
		Min	Mean	P50	Max	Sd	N
Italy	Top 10 percentile	0.260	0.301	0.300	0.341	0.027	34
	Top 1 percentile	0.063	0.080	0.078	0.099	0.011	34
	Gini (post-tax and -transfers)	0.307	0.336	0.333	0.381	0.020	50
	Gini (pre-tax and -transfers)	0.427	0.472	0.471	0.524	0.027	50
	GDP growth (%)	-5.482	1.901	1.687	7.126	2.414	49
	GDP per capita	16,858.410	29,788.630	31,531.690	38,236.800	6,542.754	49
	Employment tax rate (%)	17.800	22.825	22.800	27.100	2.604	44
	Exports as share of GDP (%)	15.211	22.400	21.939	31.297	4.241	49
	Scandinavian legal origin	0.000	0.000	0.000	0.000	0.000	79
	Right-wing chief executive	0.000	0.289	0.000	1.000	0.460	38
	Union density (%)	24.678	37.214	36.420	50.467	7.073	57

Note: Descriptive statistics are provided on full-sample basis in terms of years.

As expected, Italy is classified as not having Scandinavian legal origin. France and Italy share very common value ranges for the income inequality measures as seen in tables A10 and A11. Differently from e.g. France, Italy has had a right-wing politically orientated chief executive in a minority of the years 1975 to 2012, with a mean value of 0.289. Moreover, in comparison to Denmark, the employment tax rate in Italy is higher, with minimum and maximum values of 17.8 percent and 27.1 percent, respectively. The union density in percent is concentrated to the lower half of the distribution, with the highest value over the years being ≈ 50 percent. The GDP growth over the years has fluctuated much, which can be seen as the standard deviation at ≈ 2.4 percent exceeds the mean value at ≈ 1.9 percent.

Table A12
Descriptive statistics for Norway

		Statistic				
	Variable	Min	Mean	P50	Max	Sd	N
Norway	Top 10 percentile	0.218	0.288	0.291	0.371	0.036	63
	Top 1 percentile	0.041	0.068	0.068	0.165	0.021	63
	Gini (post-tax and -transfers)	0.217	0.247	0.246	0.268	0.013	48
	Gini (pre-tax and -transfers)	0.367	0.418	0.426	0.455	0.027	48
	GDP growth (%)	-1.691	2.939	2.845	6.052	1.802	49
	GDP per capita	31,882.780	66,299.170	65,097.070	91,617.28	20,129.4	49
	Employment tax rate (%)	5.600	14.04884	15.100	17.700	3.857	43
	Exports as share of GDP (%)	31.762	38.936	39.192	45.886	3.391	49
	Scandinavian legal origin	1.000	1.000	1.000	1.000	0.000	79
	Right-wing chief executive	0.000	0.368	0.000	1.000	0.489	38
	Union density (%)	51.848	55.856	55.573	60.815	2.437	56

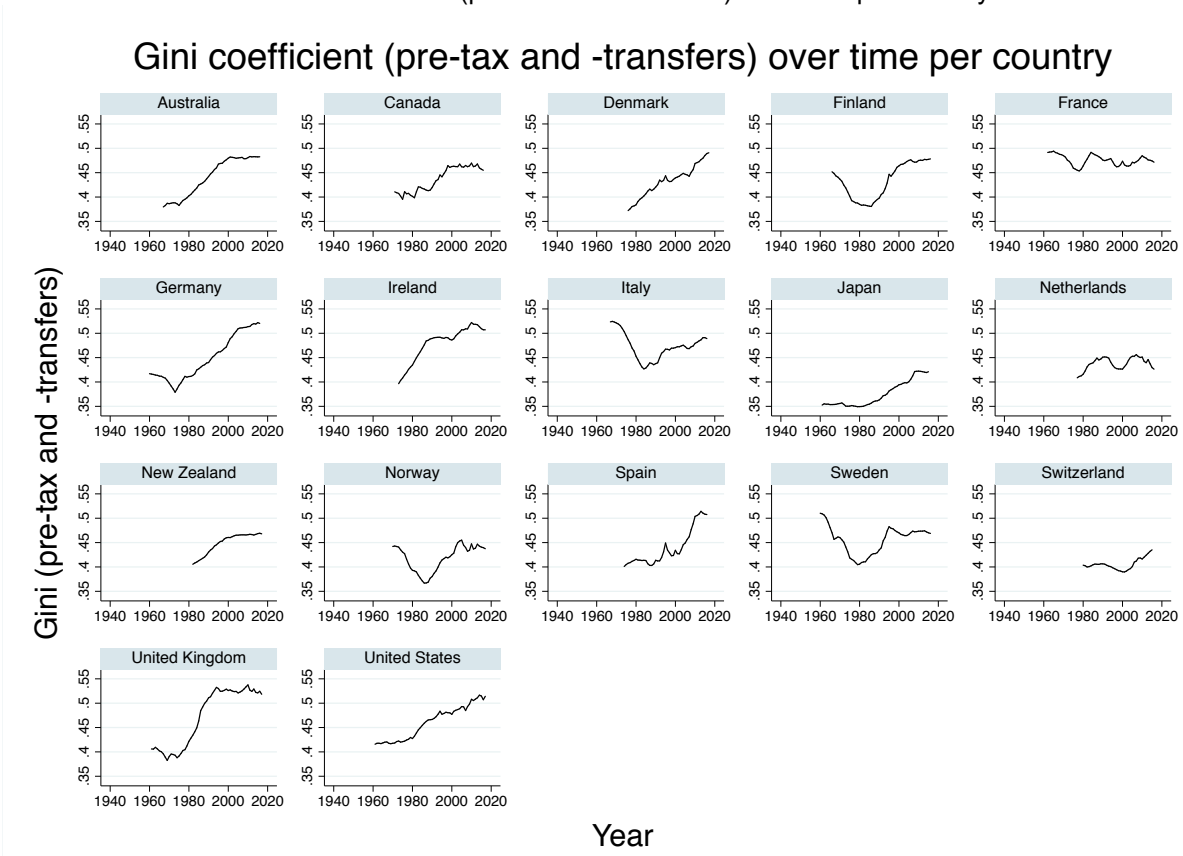
Note: Descriptive statistics are provided on full-sample basis in terms of years.

For Norway, the income inequality measures are in line with the other Scandinavian countries over time. Moreover, the GDP growth has been relatively stable over time, with a mean value of ≈ 2.9 percent and a standard deviation of ≈ 1.8 percent. The employment tax rate holds up quite well with respect to the employment tax rate in Finland, for which Norway has minimum and maximum levels of 5.6 and 17.7 percent, respectively. In likeness with Finland, Norway is also classified as having Scandinavian legal origin and in a minority of the years 1975 to 2012, Norway has had a chief executive with a right-wing political orientation.

7. Time lines of dependent variables per country

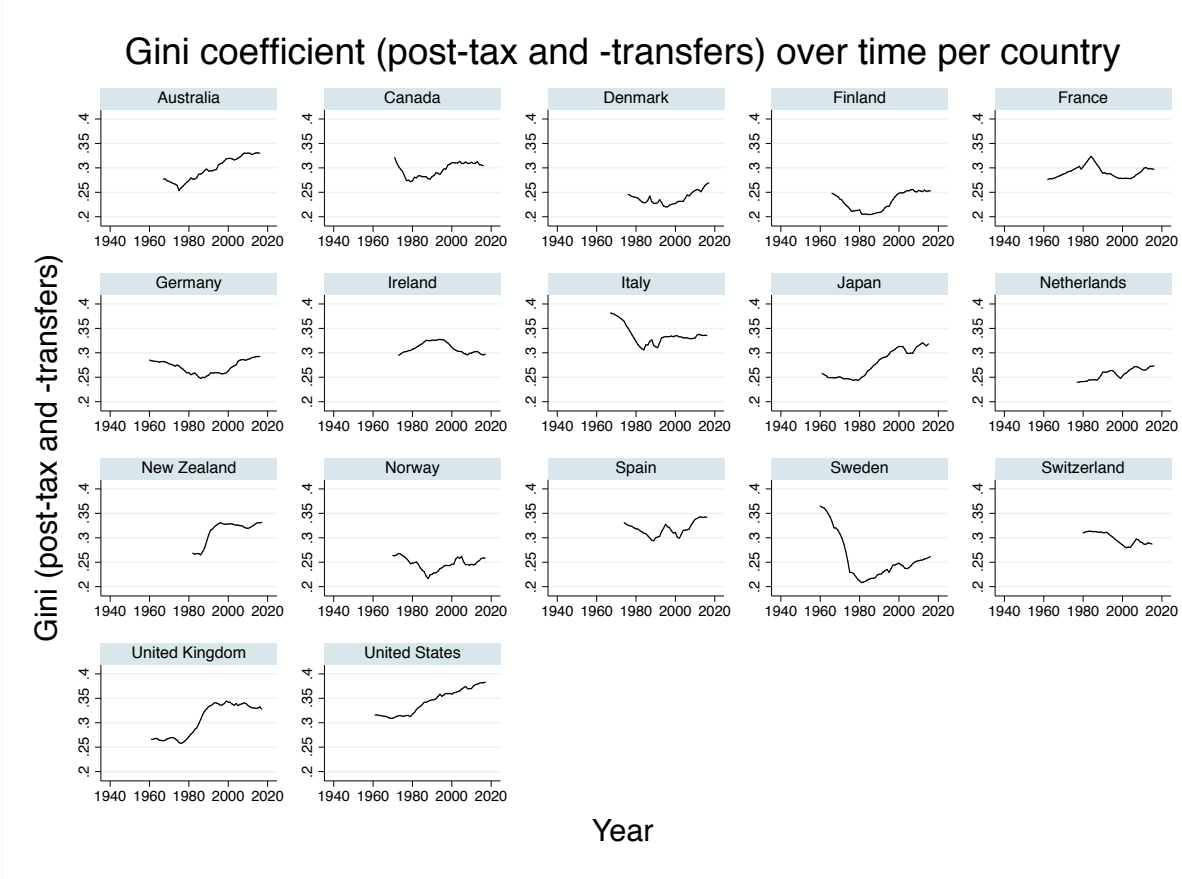
In figures A2-A4, the dependent variables, i.e. the income inequality measures, are plotted over time at a per country-basis.

Figure A2
The Gini coefficient (pre-tax and -transfers) over time per country



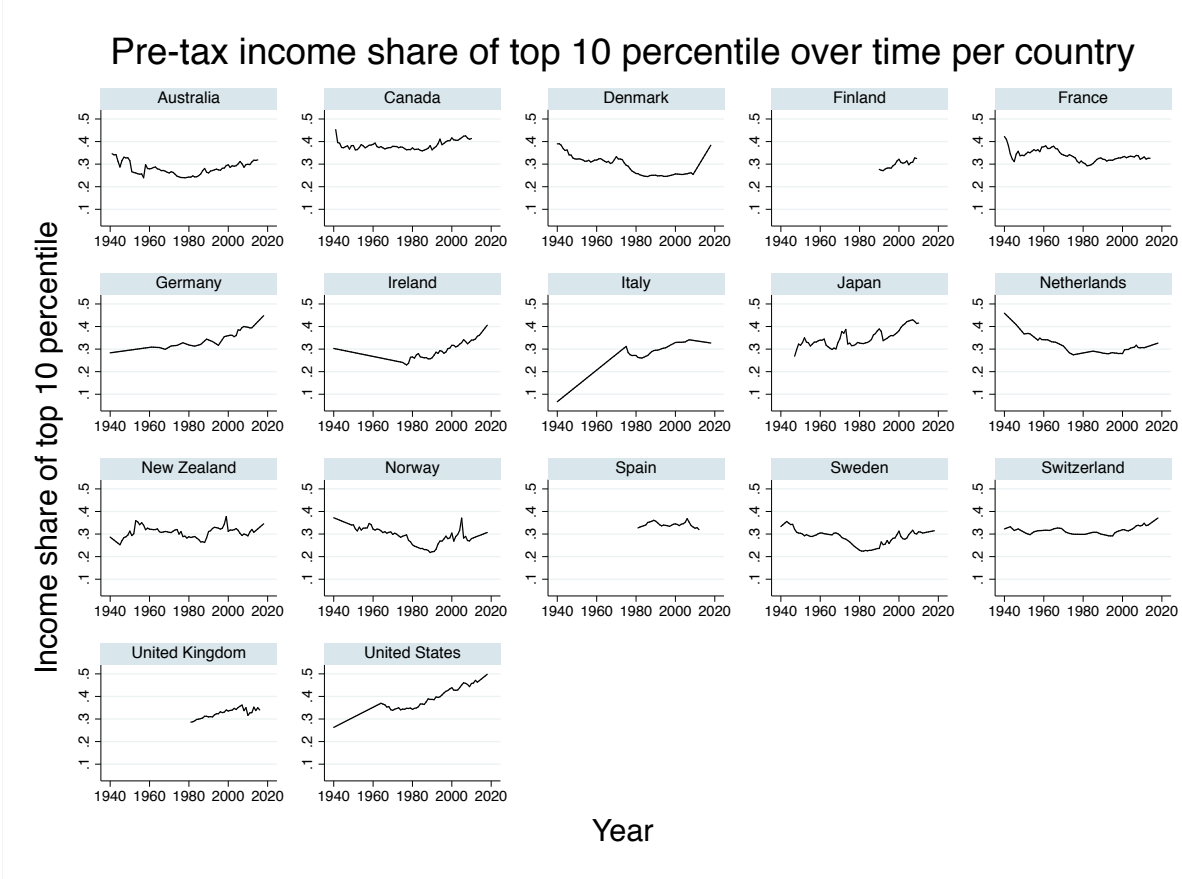
What is easy to conclude is that for in principle all the countries in the sample, the pre-tax and -transfers Gini coefficient has been subject to large fluctuations over time. Some countries, such as Finland, Italy, Norway, and Sweden have pre-tax and -transfers Gini coefficient that roughly take on the form of inverted U-curves. Other countries, for example the United States, Denmark, and Australia, exhibit overall positive trends over time.

Figure A3
The Gini coefficient (post-tax and -transfers) over time per country



The post-tax and -transfers Gini coefficient exhibits relatively similar patterns as the pre-tax and -transfers Gini coefficient over time, albeit with a smoother distribution. Due to the relatively expansionary re-distributional systems that tend to characterise modern societies, the post-tax and transfers Gini coefficients are overall lower than the pre-tax and -transfers Gini coefficients (see figure A2).

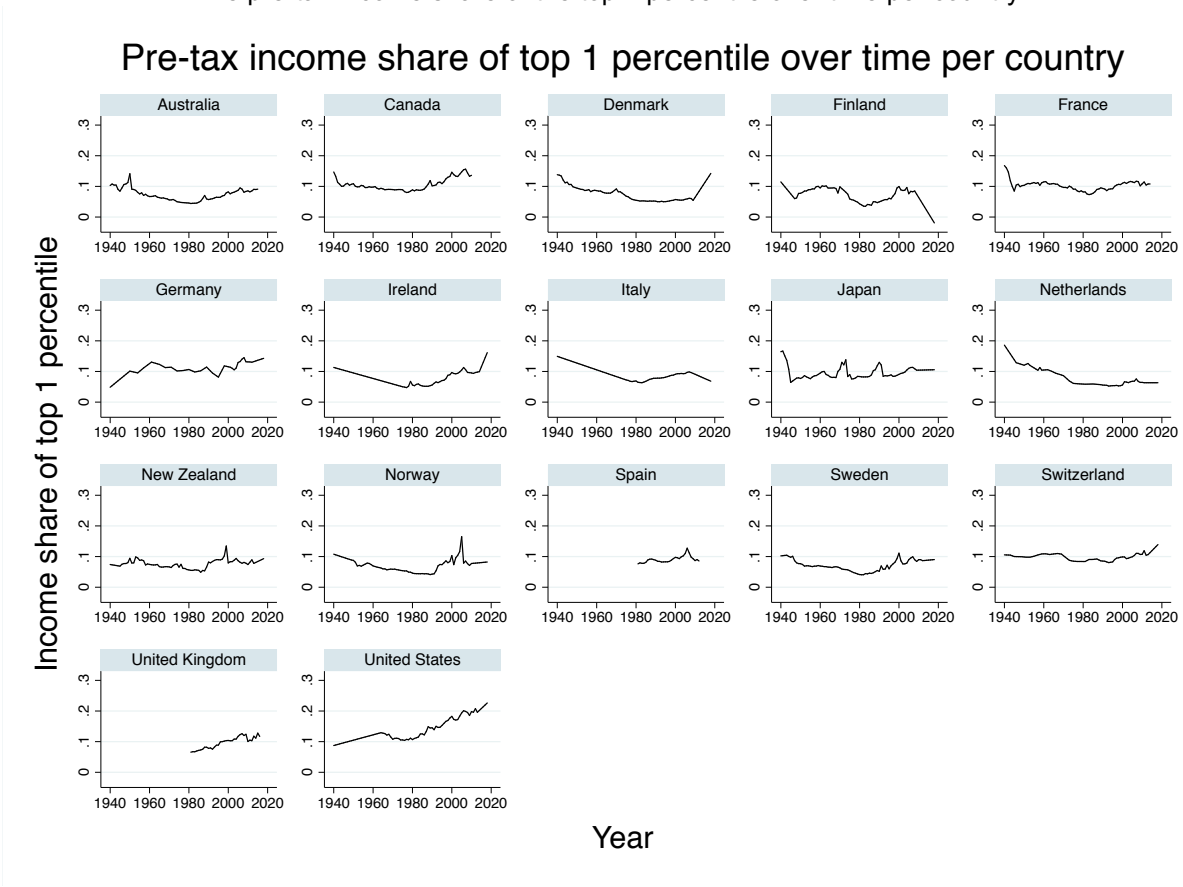
Figure A4
The pre-tax income share of the top 10 percentile over time per country



The pre-tax income shares of the top 10 percentile, compared to the Gini coefficients, are more stable over time. However, for example the United States and Italy display very strong positive time trends, especially between the 1940s and the 1960s (the United States), and between the 1940s and the 1980s (Italy). The time patterns of Japan, New Zealand, and Norway are relatively volatile, whereas the trends for, for example, Canada and Switzerland seem not to change much at all over time.

With respect to the pre-tax income share of the top 1 percentile, the pattern is very similar to the trends exhibited by the top 10 percentile, albeit at a lower level (see figure A4).

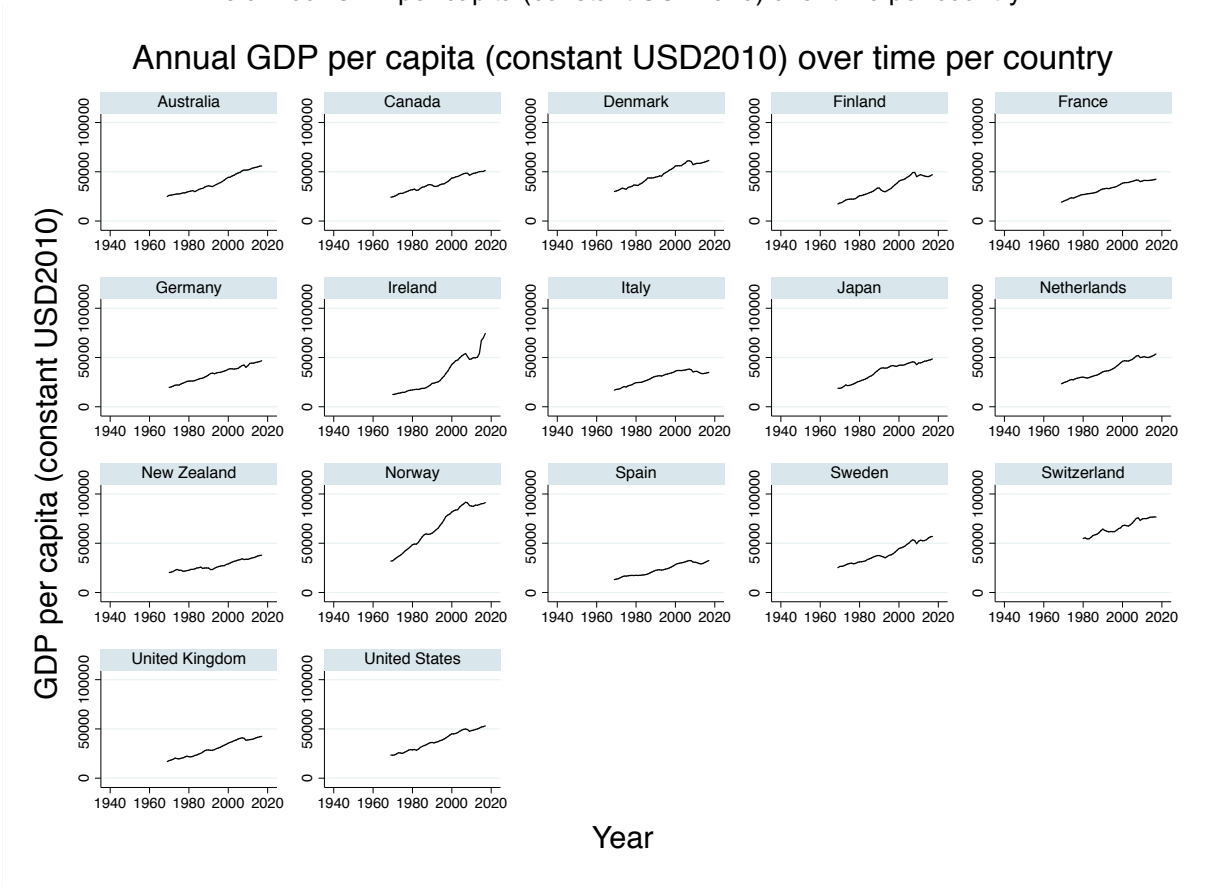
Figure A5
The pre-tax income share of the top 1 percentile over time per country



8. Time lines of independent variables per country

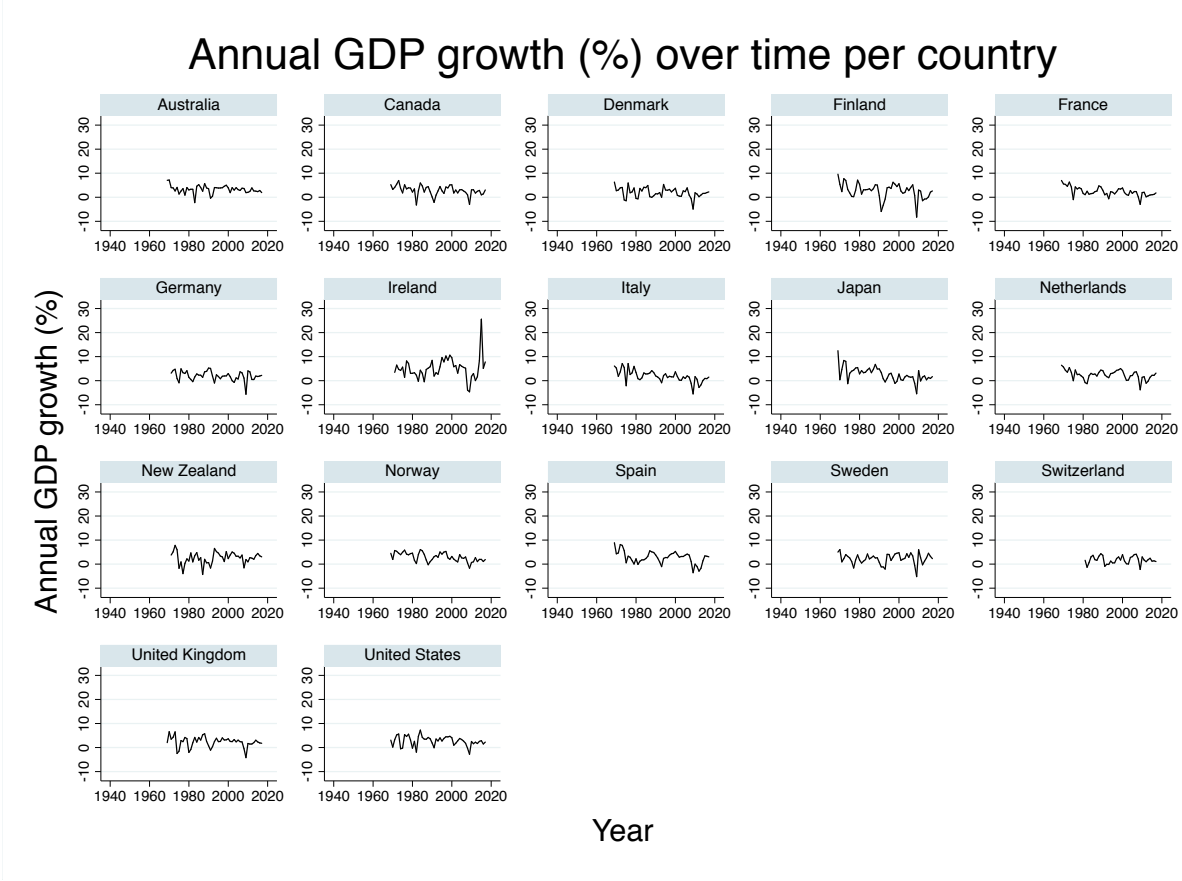
In figures A5-A10, the control variables are plotted over time at a per country-basis. Note that time lines for the dummy-variables for legal origin and the political orientation of the chief executive are not presented due to their relative stability over time.

Figure A6
The annual GDP per capita (constant USD2010) over time per country



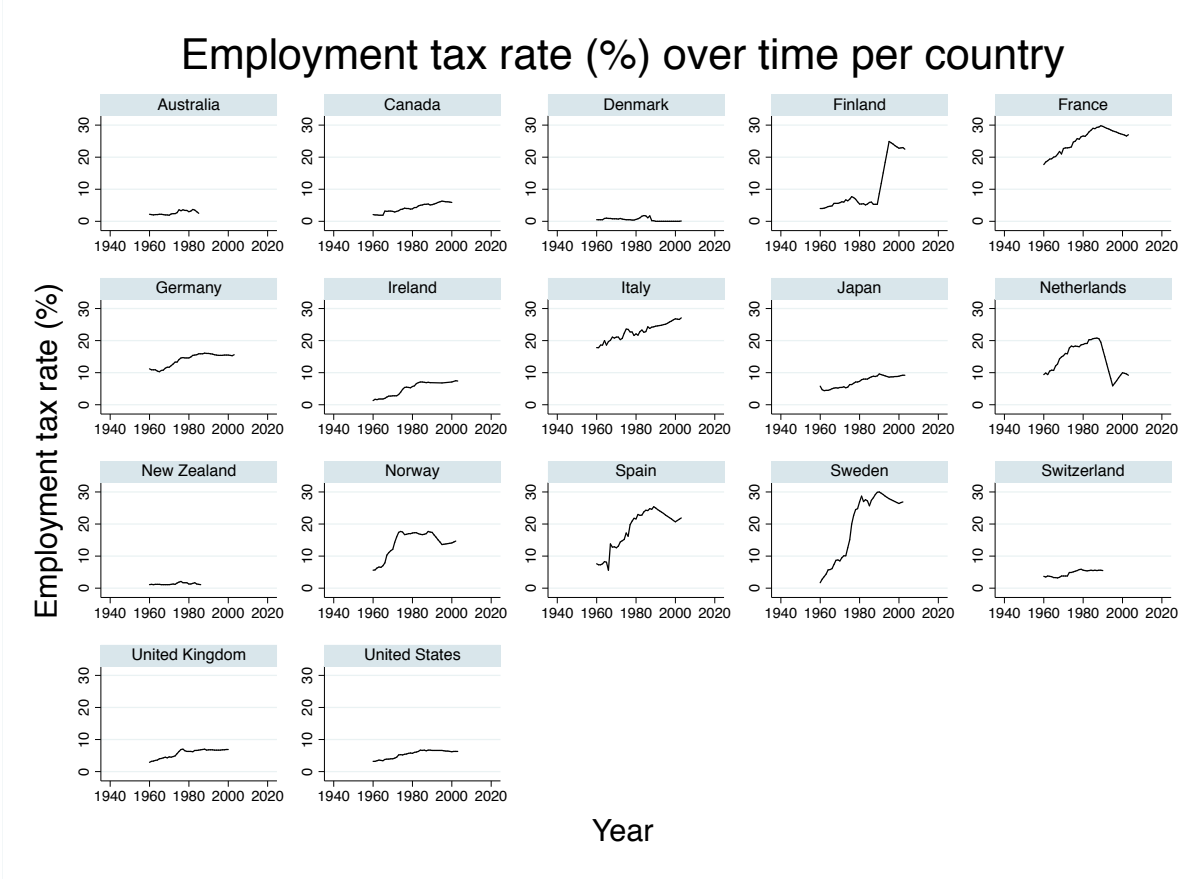
The GDP per capita of practically all countries exhibit very similar trends over time, although different in levels. Two countries that stand out are Ireland and Norway, which experience steeper time trends than the other countries.

Figure A7
The annual GDP growth (%) over time per country



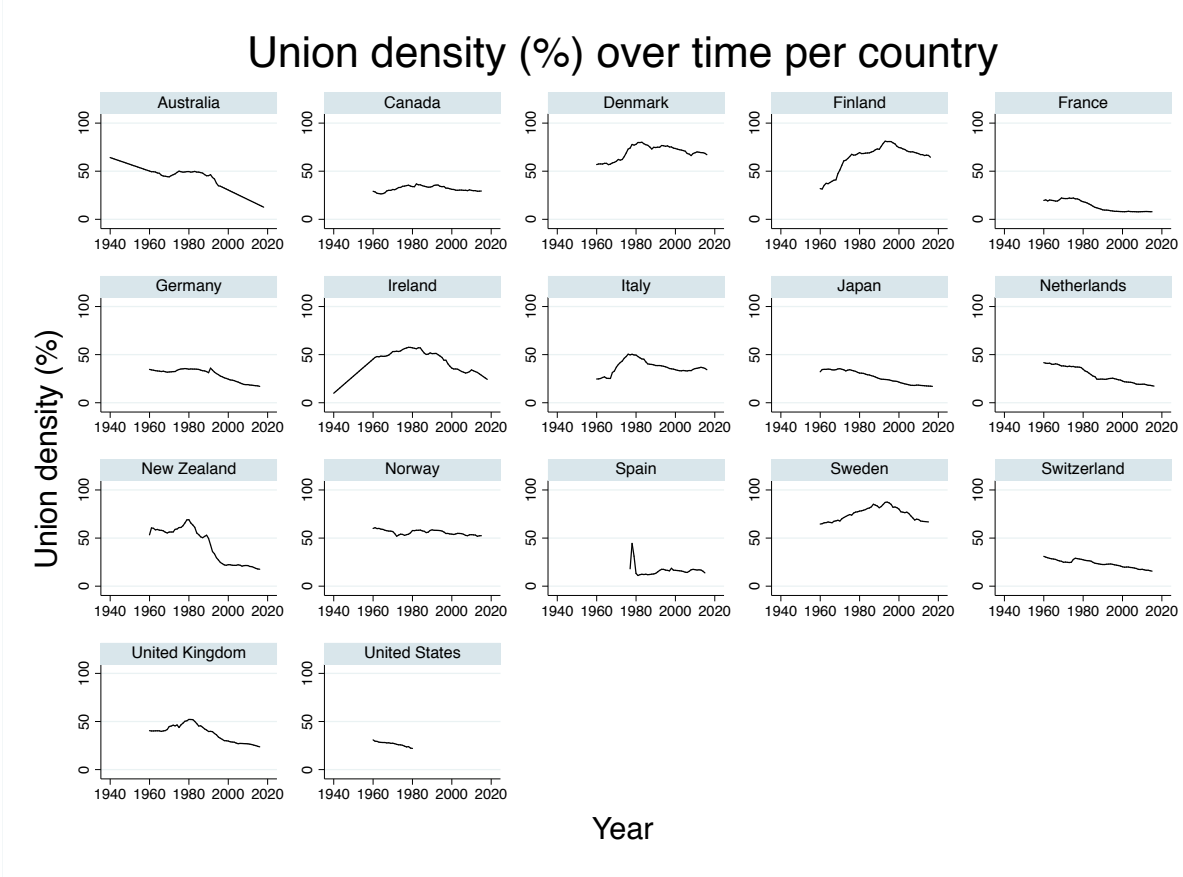
Referencing the descriptive statistics in section 6.1 in the main text and section 6 in the Appendix, the annual GDP growth in percent fluctuates much over time, for all countries. Some countries exhibit more extreme up- and down-turns, for example Finland and Ireland. For Ireland, the dip towards the end of the time series likely depended on the Great Recession of 2008-2009. The same may be true for Finland, but that is less clear. France and Italy both seem to experience overall decreasing GDP growth decrease over time, although the growth in some years still is positive. Sweden, on the other hand, seem to have a mean-reverting time series of the GDP growth albeit experiencing semi-large fluctuations over time, especially around 2008-2009.

Figure A8
The employment tax rate (%) over time per country



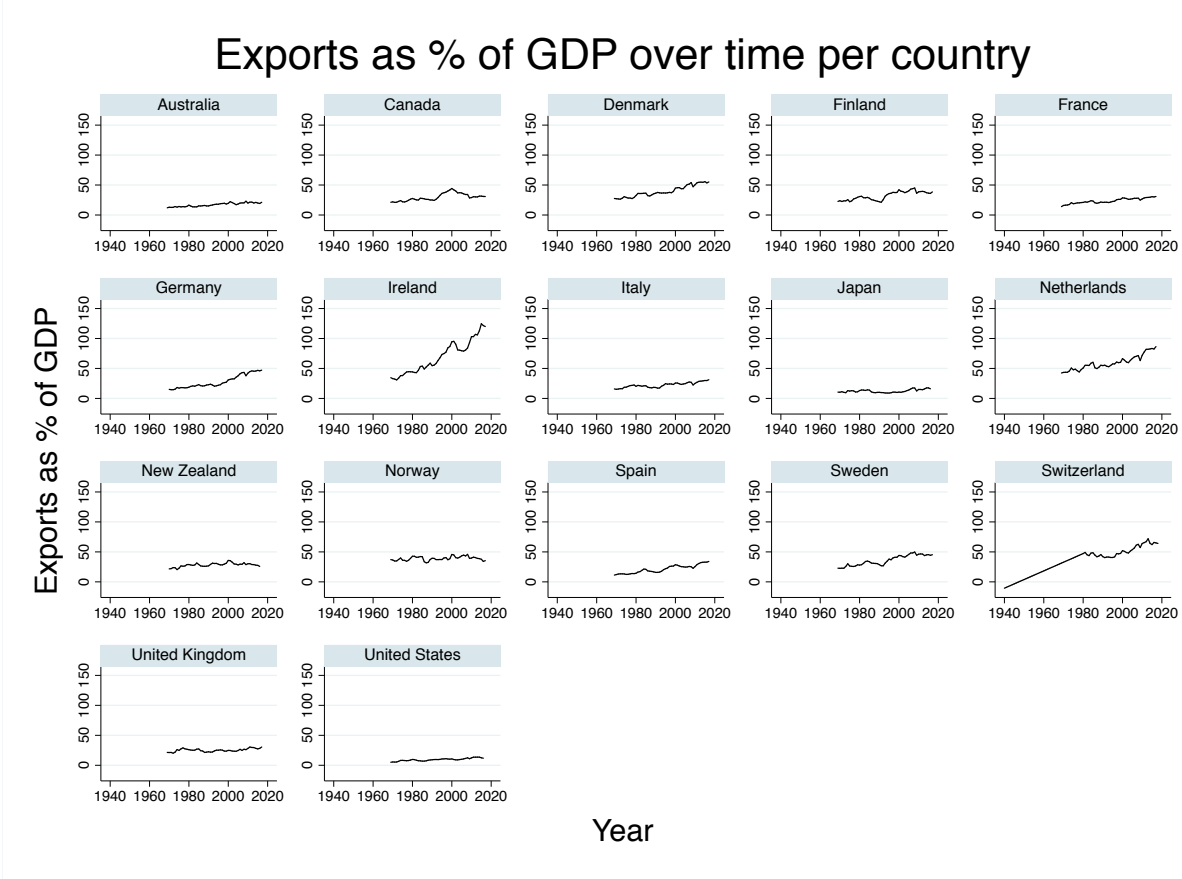
In terms of the employment tax rate, measured in percent, many of the countries display low values over time compared to Sweden. Most noteworthy are Australia, Denmark, Switzerland, and New Zealand. The time lines for the employment tax rate does in part explain why Finland, France, Italy, and Norway were included in the synthetic control groups. Over time, out of the countries in the donor pool, they are the ones that most closely follows the time trend of Sweden.

Figure A9
The union density (%) over time per country



As does not come as a surprise, Denmark, Finland, and Sweden in absolute levels have higher union densities over time compared to the other countries. Whereas the union densities of Denmark and Finland increase more over time, Sweden's peak lie at a higher absolute level. Norway has a relatively stable union density over time, at a relatively high level around 50 to 60 percent.

Figure A10
The exports as % of GDP over time per country



In evaluating the time trends of exports of goods and services as percent of GDP, what is noteworthy is that most of the countries are exhibiting relatively stable patterns of time, albeit different in levels. The exceptions mainly consist of Ireland, Netherlands, and Switzerland, where the pattern has been an increased export share over time.