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Natural Resources and Income Inequality in Developed Countries: Synthetic Control Method Evidence

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Abstract

We examine the causal effect of natural resource discoveries on income inequality using the synthetic control method on data from 1947 to 2009. We focus on the natural discoveries in Denmark, Netherlands and Norway in the 1960–1970s and use top 1% and top 10% income share as the measure of income inequality. Many previous studies have been concerned that natural resources may increase income inequality. To the contrary, our results suggest that natural resources decrease income inequality or have no effect. We attribute this effect to the high institutional quality of countries we examine.

JEL-Classification: D31, O13, O15, Q33

Keywords: Natural resources, income inequality, synthetic control method

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1. Introduction

The issue of income inequality within countries, its consequences, and, in particular, its drivers, has received enormous attention in the economics profession recently, including inter alia Piketty (2014), Milanovic (2016), and Alvaredo et al. (2017). Dabla-Norris et al. (2015) have highlighted several drivers of income inequality discovered in the literature, including skill-based technological change, trade and financial openness, changes in labor market institutions, and disparities in education.

A small-but-growing subset of this literature has also focused on the effect of natural resources on income inequality, theorizing that resource-based economies would see higher levels of within-country inequality than resource-scarce economies. Extant research has provided several possible channels through which resources could contribute to inequality, including via substantial concentration in the ownership of resources (Bourguignon and Morrison, 1990), fostering institutional distortions related to rent-seeking and political control of resources (Sokolo and Engerman, 2000), and creating labor market effects, such as drawing workers into the least innovative sector (Gylfason and Zoega, 2002). An underlying theme in nearly all of the papers in this literature is a familiar one in the resource curse, namely that resources have deleterious institutional effects, damaging both political and economic institutions. As a second-order effect, malfunctioning institutions then lead to a slew of sub-optimal economic outcomes, including stagnant growth, depressed human capital, and, eventually, income inequality.

Given the purported chain of causality from natural resources to inequality, from an empirical standpoint, testing the relationship has been more difficult. Most prominently, many studies use as a baseline for natural resources either the resource abundance of a country at time t or a country's natural resource export intensity, rather than modelling abrupt shifts in resources and tracing the effects on inequality thereafter. This approach confounds other societal or cultural variables which can determine institutions with the effect of resources, making the causal effects of natural resources on income inequality problematic from an econometric standpoint. Indeed, much of the work on the natural resource/inequality nexus has only shown an association between the two rather than a direct causal link.

This paper advances the literature on natural resources by addressing this issue, directly examining the causal link between natural resources and within-country inequality via the use of the synthetic control method. The synthetic control approach, originally developed by Abadie and Gardeazabal (2003) and further refined in Abadie et al. (2010), builds on the standard difference-in-differences estimator but allows for time-varying individual-specific unobserved heterogeneity.[1] The method requires an exogenous policy intervention which has minimal effects on the outcome variable of the control group, with this non-response used to form a counterfactual of the policy treatment. In the case of the natural resource/inequality nexus, our paper uses the synthetic control method to treat the discovery of natural resources (rather than merely their abundance) as a policy intervention, allowing us to create a counterfactual of what the income inequality of a given country would be if natural resources had not been discovered. The synthetic control method has been recently applied to study the effect of natural catastrophes on economic activity (Cavallo et al., 2013; Smith, 2015), the effect of trade liberalization on economic growth (Billmeier and Nannicini, 2013), the labor market effects of refugee waves (Peri and Yasenov, 2018) or the effect of natural resources on economic growth in Norway (Mideksa, 2013).

Using a recently developed dataset on natural resource discoveries (Smith, 2015), and examining five developed economies over several decades, our results from this experiment suggest that resources may be important for lessening inequality; depending upon the specific country, natural resources either have no significant effect on income inequality in our analysis or can actually reduce within-country inequality. Our results differ from the pioneering analysis of Goderis and Malone (2011) in showing that resource booms have the potential to permanently lower income inequality, with effects that reverberate far beyond the year in which resources are discovered or first brought on-line. In addition, we differ from Goderis and Malone (2011) in examining the effect of natural resource discoveries on inequality rather than the effect of commodity price changes.[2] In general, it appears that natural resource discoveries in already-developed economies pose little threat for income inequality.

[1] Similarly, fixed-effects model allows for the individual-specific unobserved heterogeneity but restricts the effect of this heterogeneity to be constant in time.

[2] The exclusion restrictions do not necessarily have to be valid given than commodity price changes are correlated with inequality.

We attribute this effect to the high institutional quality of countries under examination, suggesting that there is a Kuznets curve in the relationship between resources and inequality conditioned on which institutional framework they operate in and the timing of the discovery. This result is along the lines of Mehlum et al. (2006), who found that resources can raise incomes in a producer-friendly institutional environment; similarly, Hartwell (2016) has established the importance of institutions in mediating the usage of natural resources in the economy, correcting for the simultaneous influence of institutions on resource use and resources on institutional development. We believe that the exigencies of our dataset, namely the use of exclusively developed economies, shows that stable institutional environments can mitigate against the channels in which inequality may be created, as strong institutions such as democracy allow for resisting massive state-based corruption, ability of governments to redistribute public revenues (Parcero and Papyrakis, 2016) or sustained political ownership of resources, while effective institutions such as property rights allow for economic diversification away from resource-based industries. By examining stable and already-strong institutional environments, we observe that the negative effects of natural resources on inequality can be mostly mitigated.

The rest of the paper is organized as follows: Section 2 discusses the previous literature examining the natural resources/inequality nexus, including a further explanation of the theoretical channels in which resources can impact a country's income distribution. Section 3 presents the synthetic control model, while Section 4 outlines our dataset and Section 5 contains our results. Section 6 concludes with some thoughts on future research and applications of this method. Additional results are available in the Appendix.

2. Related Literature

The literature on the effects of natural resources has a long pedigree, focused mainly on the "resource curse" and how the presence of resources could retard a country's development (Sachs and Warner, 1997). Comparatively less work has been done on the linkages between resources and income inequality, but a sizeable literature nonetheless exists linking natural resource abundance with wage and income inequality (Gylfason and Zoega, 2002; van der Ploeg, 2011). As noted above, several channels have been theorized as causing this result, with the three key culprits identified as the effect that resources have on labor markets, economic structure and exports, and institutional distortions.

With regard to labor markets, Leamer et al. (1999) develop a theoretical model to show that in resource-scarce countries, production is labor-intensive, and thus, human capital and wages are distributed more equally than in resource-abundant countries. Leamer et al. (1999) also provide empirical evidence that land-abundant Latin American countries have less skilled workforce and higher wage inequality than land-scarce Asian countries. Spilimbergo and Szekely (1999) also argue that since labor income is only a part of total income, increased wage inequality does not necessarily lead to increased income inequality. Building on Bourguignon and Morrison (1990)'s model, the authors develop a theoretical framework to analyze the role of the prices and ownership of factors of production on income distribution. Also, employing a panel of nearly 100 countries over the period 1965–1992, Spilimbergo and Szekely (1999) find that land- and capital-rich countries have greater income inequality. More recent work from Iacono (2016) also suggests that natural resource endowments also drive income inequality and labor productivity in Norway.

As a follow-on effect to labor market distortions, the literature has also explored how natural-resource-intensive production and, especially, exports, have a significant effect on inequality. As Fishlow and Hansen (1978) suggest, with worldwide industrialization, demand for sophisticated products and services has increased faster than the demand for raw materials. To catch up with this trend, natural resource-rich countries export more natural-resource-intensive products, a reality which benefits the owners of natural resources, as income concentrates in their hands. The seminal paper from Bourguignon et al. (1990) confirms this finding: using cross-sectional data, they find that resource-intensive exports increase inequality, concentrating a higher proportion of wealth in the top 20% share of a country and decreasing the lower 40% and 60% shares of the income distribution. Additional research from Gylfason and Zoega (2002) also suggests that natural resource abundance is positively correlated with wage inequality and negatively correlated with the economic growth, due to unequal distribution of natural resources ownership, while Buccellato and Alessandrini (2009) find that greater proportions of the export of ores and metals increases income inequality within the exporting country. Auty (2007) also makes the point that a focus on resource-intensive exports means a failure to absorb surplus labor in society, leading to widening income inequality (and, additionally, a bloated public sector as make-work jobs are created as a form of redistribution).

Finally, natural resource abundance has been found to negatively affect inequality through effects on institutions, vitiating institutional quality and impeding the ability of individuals to improve their income potential. The most immediate effect institutional deterioration has is on human development (Carmignani, 2013), with Cockx and Francken (2016) finding that natural resource abundance decreases education spending. Caselli (2006) also shows that natural resources generate power struggles for their control, struggles which reduces the incentive for the ruling group to invest in long-run development. This effect may be mitigated depending upon the ethnic make-up of the country in question, as Fum and Hodler (2010) find that ethnically homogenous countries have lower income inequality in the face of resource abundance. However, the ramifications of this finding is that countries which are highly fractionalized tend to have investment projects with negative social surplus, using overinvestment as a way to credibly redistribute funding but in a less efficient manner (van der Ploeg, 2011).

Beyond the human capital element, the more direct link between resources and poor governing institutions is also well-known, as Bulte et al. (2005) show how natural resources impair the development of key economic and political institutions across a large sample of developed and developing economies (Isham et al. (2005) further note that this effect dominates in point-source exporting countries). Focusing on the example of Russia, Buccellato and Mickiewicz (2009) argue that natural resources increase within-country income inequality in Russia via corruption and distorted economic institutions (a more generalized version of this effect on political institutions can be found in Ross (2001)). Similarly, Sokoloff and Engerman

(2000) show how natural resource ownership induces the development of institutions that protect elites, ossifying income and wealth inequality in place, a result which Cervellati et al. (2008) formally model to show how initial levels of inequality can be locked-in as a result of resources. Taking a longer-term view, Angeles (2007) noted that colonialism also created a political structure which ensured inequality, aggregating resource wealth to colonizers and restricting access to capital and land for indigenous people.

These studies have focused on the role of natural resource abundance for wage or income inequality, but comparable research on natural resource discoveries and booms in natural resources exploitation remains scarce; indeed, much of the work is often country-specific and generally inconclusive. For example, oil discoveries have been found to reduce income inequality in Kazakhstan (Howie and Atakhanova, 2014), an admittedly ethnically homogenous society, while similar results have been found on poverty and income inequality in Iran (Farzanegan and Habibpour, 2017). On the other hand, Loyaza and Rigolini (2016) have found that mining booms have increased income inequality in Peru, while Marchand (2015) provides evidence to a U-shaped effect of energy booms on wage inequality in Western Canada (with energy booms increasing wages in both the lower and top income deciles). Other country-specific work has been less conclusive, with Zabsonre and Haffin (2017) suggesting that gold mining reduces poverty, but has no impact on income inequality, in Burkina Faso, and Tano and Stjernstrom (2016) showing that the mining boom in Sweden increased labor income even in industries not directly related to mining.

Where cross-country studies on the impact of natural resource booms exist, they too have conflicting findings on resource discoveries and inequality (with no sense of direct causality). Goderis and Malone (2011) using fixed-effects estimation on a panel of 90 countries over 1965–1999 to argue that oil and mineral resources booms decrease income inequality in the short run (though only in developing countries), while, in the long run, there is no impact of natural resource booms on income distribution.[3] Smith and Wills (2018), using data on 36 countries,

[3] To reach these results, Goderis and Malone (2011) identify the impact of natural resource booms through export prices variation and a country's dependence on the export of particular goods, constructing a country-specific commodity export price index and analyzing its impact on income inequality. The index reflects a country's export of particular commodities and the same country's dependence on world prices for those commodities. Thus, the index is larger for commodity-dependent countries.

suggest that exogenous oil prices shocks and giant oil discoveries increase the gap in economic activity between urban and rural areas and do not reduce rural poverty, indirectly contributing to income inequality. In a similar vein, while natural resource discoveries have been found to have a positive effect on GDP per capita (Smith, 2015), they are also associated with an increase in unemployment and child labor and a negative effect on school attainment (Santos, 2018), and brain drain (Steinberg, 2017). These additional effects, although not explicitly linked with income inequality, appear to be factors which would exacerbate inequality within an economy. But the lack of an explicit connection between these effects and inequality, along with the absence of a definitive causal link from resources to inequality, calls for a deeper examination of the relationship.

3. Synthetic Control Method

In order to estimate the effect of natural resource discoveries on income inequality, we follow in the footsteps of Smith (2015) and Cavallo et al. (2013) and apply the synthetic control method first developed by Abadie and Gardeazabal (2003) and Abadie et al. (2010).[4] The synthetic control method is designed for comparative case studies in which the goal is to isolate the effect of an intervention (for example, the introduction of a new law or, in our case, the discovery of natural resources) in a single unit under observation on the outcome variable of interest.[5] Much as in the medical literature, the unit exposed to the intervention is classified as a "treated unit," while other units that are unexposed to the intervention are "untreated."

The innovation of the synthetic control method is that it forms a weighted combination of untreated units (prior to the intervention) such that the values of its outcome variable match as closely as possible to the values of outcome variable of the treated unit. This weighted combination of untreated units represents the 'synthetic control', creating a counterfactual of what would likely happen to the treated unit if it were not a subject to the intervention. Its outcome variable trajectory in the post-intervention period is an estimate of the outcome variable path that would have been observed for the treated unit in the absence of this intervention. The success of synthetic control method depends crucially on the ability of the synthetic control's outcomes to be sufficiently close to those of the treated unit in the pre-intervention period.

The effect of the intervention can then be inferred from the difference between the actual outcome variable path of the intervention unit observed after the intervention and the synthetic one determined by weighting the outcomes of control units with the weights representing their importance in the resulting synthetic control.

More formally, assume that for $j = 1, \dots, J + 1$ units and $t = 1, \dots, T$ time periods we observe data on the variable of interest (outcome variable) and several other variables which can be used to predict the outcome variable. Let the last country $(J + 1)$-th be the only one that has been exposed to the intervention of interest in period $T_0 + 1$, implying that there are T_0 pre-intervention periods, $1 \leq T_0 < T$. The remaining J countries are those that did not experience

[4] Smith (2015) and Cavallo et al. (2013) use the synthetic control method to examine (respectively) the impact of natural disasters and resource discoveries on economic growth.

[5] A unit can be, for example, country, city, school, etc. In our analysis, a unit is a country.

similar intervention during the sample period, and thus form a "donor pool" of potential control units. Furthermore, their predictors and outcome variable are assumed not to be affected by the intervention for $t = 1, \dots, T$. Predictors and outcome variable of the treatmentcountry should not be influenced by the intervention for $t = 1, \dots, T_0$. Therefore, if the intervention has some effects, for example, in the form of expectations, on either the predictors or the outcome variable of the treatment country in the pre-intervention period, T_0 must be redefined to be the last year in which the intervention has no such effects.

Let Y_{J+1t}^{I} be the value of the outcome variable in country $J + 1$ at time $t = 1, \dots, T$ that is observed when country $J + 1$ is exposed to the intervention in periods $T_0 + 1, \dots, T$ and Y_{jt}^{N} be the corresponding value that is observed in the absence of the intervention. Then, by assumption, $Y_{jt}^{I} = Y_{jt}^{N}$ for $t \leq T_0$ and $j = 1, \dots, J + 1$. Also, for $j = 1, \dots, J$ potential controls and for $t = 1, \dots, T$ time periods, the outcome observed is equivalent to the outcome without the intervention, $Y_{jt} = Y_{jt}^{N}$.

We are interested in estimating the effect of the intervention that occurred in country $J + 1$ in period $T_0 + 1$. Therefore, we want to determine, for $t = T_0 + 1, \dots, T$:

$$Y_{J+1t}^{I} - Y_{J+1t}^{N} = Y_{J+1t} - Y_{J+1t}^{N} \tag{1}$$

where Y_{J+1t}, $t = T_0 + 1, \dots, T$, is the value of the outcome variable which is known (observed) for the country that has been exposed to the intervention. As shown in Abadie et al. (2010), this effect can be estimated by:

$$Y_{J+1t} - \sum_{j=1}^{J} w_j^{\star} Y_{jt} \tag{2}$$

where $w_j^{\star}$, $j = 1, \dots, J$, is a time-invariant weight assigned to country j from the donor pool such that $w_j^{\star} \geq 0$ for $j = 1, \dots, J$ and $\sum_{j=1}^{J} w_j^{\star} = 1$, and Y_{jt}, $j = 1, \dots, J$, is the (observed) outcome for country j from the donor pool. Synthetic control algorithm aims to find the weights that generate the synthetic control for a given treatment country that replicates its behavior during the pre-intervention period most closely.

Assume that the number of predictors[6] for the outcome variable is K. Let $\mathbf{X_1}$ be a $(K \times 1)$ vector of their pre-intervention values for the treatment country and $\mathbf{X_0}$ be a $(K \times J)$ matrix of the correspondingvalues for the J possible control countries. Denote $\mathbf{V}$ a $(K \times K)$ diagonal matrix that contains only nonnegative components. Each element of $\mathbf{V}$ on the main diagonal represents a relative importance of a particular outcome variable predictor. As demonstrated by Abadie and Gardeazabal (2003), the optimal weights $w_j^\star$, $j = 1, \dots, J$, are calculated in two steps. The first step is to find $\mathbf{W} = (w_1, \dots, w_J)'$ whose elements are non-negative and sum up to one that minimizes the following function:

$$(\mathbf{X_1} - \mathbf{X_0}\mathbf{W})'\mathbf{V}(\mathbf{X_1} - \mathbf{X_0}\mathbf{W}) \tag{3}$$

This means that the algorithm finds $\mathbf{W}^\star(\mathbf{V})$ such that the pre-intervention characteristics of the synthetic control best match those of the treatment country. The solution to this problem, $\mathbf{W}^\star(\mathbf{V})$, is a function of $\mathbf{V}$, and thus depends on the relative importance of the different outcome variable predictors, which is to be determined in the second step of the procedure.

Let $\mathbf{Y_1}$ be a $(T_0 \times 1)$ vector containing the values of the outcome variable in all T_0 pre-intervention periods for the treatment country. $\mathbf{Y_0}$ is a $(T_0 \times J)$ matrix of the corresponding values for the J potential control countries. In the second step, the algorithm searches among all diagonal $(K \times K)$ matrices with nonnegative elements to select $\mathbf{V}$ such that the deviation of the outcome variable path of the synthetic control defined by $\mathbf{W}^\star(\mathbf{V})$ from the outcome variable path of the treatment country is minimized during the pre-intervention period. Therefore,

$$\mathbf{V}^\star = \underset{\mathbf{V} \in \mathcal{V}}{\arg\min}(\mathbf{Y_1} - \mathbf{Y_0}\mathbf{W}^\star(\mathbf{V}))'(\mathbf{Y_1} - \mathbf{Y_0}\mathbf{W}^\star(\mathbf{V})) \tag{4}$$

where $\mathcal{V}$ is the aforementioned set of all diagonal $(K \times K)$ matrices with nonnegative elements. Resulting $\mathbf{V}^\star$ is then used to construct the optimal weights[7] $\mathbf{W}^\star = \mathbf{W}^\star(\mathbf{V}^\star)$ which indeed determine the optimal synthetic control – the one used for the estimation of counterfactual outcome variable path after the intervention.

[6] A predictor can be a pre-intervention value of any variable, including the outcome variable, or the linear combination of them. For example, years of schooling one year before the intervention can be one predictor, years of schooling averaged over 5–10 years before the intervention can be another predictor, and outcome variable 1, 3 and 5 years before the intervention can also appear among predictors. Predictors help to determine countries with similar pre-intervention characteristics as the treatment country.

[7] To achieve the uniqueness of the solution, the Eucledian norm of $\mathbf{V}^\star$ is normalized to one.

Overall, the major benefit of synthetic control method is the possibility to estimate the causal effect and to obtain the counterfactual of what income inequality would be if natural resources were not discovered. On the other hand, synthetic control method is not explicit on actual transmission mechanism Abadie et al. (2010).

4. Data

The data used in this paper to apply the synthetic control method combines several existing country-level datasets on income inequality, economic variables, and natural resource discoveries, using annual data from 1947 to 2009. In the first instance, our outcome variable Y_{jt}^{I} is defined as one of two separate metrics on inequality, either the pre-tax national income share held by the top 1% of a country's income distribution or the income share held by the top 10% (pre-tax national income is defined as the sum of pre-tax labor and capital incomes, both calculated after taking into account deductions for pensions but before accounting for taxes and transfers). Data on these pre-tax income shares are freely available from World Wealth & Income Database, although the time and country coverage of this database is not consistent. The data is limited for emerging markets, not providing sufficient time coverage (e.g. several decades) surrounding a natural resource discovery. For this reason, we identify three developed countries which fulfill the condition of sufficient time coverage of income inequality data and which at the same time experienced a natural resource boom: Denmark, Netherlands and Norway (the descriptive statistics for the dependent variables as well as explanatory variables are available in the Appendix). We follow many researchers in the field of income inequality and use top income shares as our measure of ineuqality (such as Alvaredo et al. (2017); Piketty (2014) among many others). Leigh (2007) shows that top income shares are strongly related to other measures of income inequality such as the Gini coefficient and suggests that researchers can use top income shares in case the Gini coefficients are not available or are of low quality.[8] We treat the natural resource discoveries as exogenous in developed countries. This is because the explorations of natural resources is unlikely to be affected by the quality of institutions and income inequality. On the other hand, this exogeneity assumption can be somewhat disputable in developing countries where explorations can become endogenous to poor institutions (such as lower government effectiveness); see Arezki et al. (2016); Tsui (2011).

[8] An alternative data source on income inequality is internationally comparable Gini coefficients, for instance, from Solt (2016). However, the Solt data exists only starting from the 1960s, a period which coincides with the timing of natural resource discoveries. To identify the impact of natural resource discoveries on income inequality, data for a longer time period is required. In addition, the data are also available for the United Kingdom but the natural resource discovery in the 1970s has been followed by another major shock – financial market deregulations in the 1980s. This creates difficulties to identify the effect of natural resource shock on income inequality within the synthetic control method. We refer the reader to Tanndal and Waldenstrom (2018), who examine the effect of financial deregulation on top incomes in the UK using the synthetic control method. See Atkinson and Sogaard (2016) on the long-term evolution of income inequality in Denmark.

Each synthetic control analysis requires a selection of an appropriate event year in which the intervention – in our case, an oil or gas discovery – occurred. We obtain the event years from Smith (2015), who collected data on oil and gas production for 17 countries which became resource-rich during the last 70 years.[9] The Smith dataset includes the year of resource discovery, the year of first production, and the "event year," which he defines as the first year in which the growth in oil and gas production increased by 0.5 barrels per capita.[10] The event years for our treatment countries are available in Table 1 along with the sample periods corresponding to the income inequality data. When we examine the natural resource rents to GDP (from World Bank dataset), we observe that the natural resource rents to GDP ten years after vs. one year before the event year increase approximately 3 times for Denmark and 13 times in Norway (the data for the Netherlands are not available because the World Bank reports the natural resource rents from 1970 onwards, in case we take the first available year 1970 instead of 1966 and compare it to the year 1980, we observe that natural resource rents to GDP in the Netherlands increased 42 times).

All treatment countries did not record the production of any amounts of oil or gas at the beginning of the sample period, but after the discovery they became producers and remained as such until the end of the examined period (a necessary condition for the application of SCM).[11]

Table 1: Treatment countries: Event Year and Sample Period

Treatment country	Event year	Sample period – Income Inequality	
		Top 1% share	Top 10% share
Denmark	1981	1976–2004	1976–2005
Netherlands	1966	1947–2004	1951–2009
Norway	1971	1947–2009	1951–2009

Note: Event year is defined to be the first year in which the growth in oil and gas production increased by 0.5 barrels per capita. Based on Smith (2015) – Data Appendix with Stata Code.

[9] For resource production data, Smith (2015) uses UN Industrial Commodities Statistics; for oil discovery dates, he utilizes the 2007 and 1994 editions of the Oil and Gas Journal Data Book.

[10] For gas producing countries, Smith converted natural gas production to its oil barrel energy equivalent using the conversion rate of 0.00586152 oil barrels per terajoule.

[11] The event year can be endogenous to economic growth if countries invest in exploitation only in periods of high oil prices (Smith, 2015). However, for our purposes, high oil prices are less of a concern in case of studying income inequality.

After identifying the event year for each treatment country[12], we need to select countries that would form the donor pool for the synthetic analysis. These donors should be countries that did not discover any natural resources before or during the sample period and thus remained resource-poor throughout the entire period. One possibility, often used in the SCM literature, is to form the donor pool from countries that are geographically close to the treatment country, with the belief that those would be most likely to match the treatment country's pre-intervention characteristics; therefore, the donors would also closely replicate the outcome variable path before treatment. However, geographical proximity can be a poor indicator of outcome variable proximity before the intervention, especially when the pre-intervention values of treatment country's predictors do not lie in the convex hull of the control countries' predictors. Therefore, in our baseline estimations, we do not restrict the possible pool of donor countries only to those geographically close; however, as a robustness check, we do reestimate the analysis using only control countries that lie in the treatment country's region. The list of control countries for each treatment country – outcome variable pair is provided in the Appendix.[13]

Finally, we also include data on control predictors which might affect the outcome variable. For each treatment country – outcome variable pair we used a different set of predictors, including lagged outcome variables and a series of population, institutional, and economic performance variables. To put the structure on our empirical model, we motivate the set of predictors by previous literature (Roine et al., 2009; Smith, 2015).[14] In particular, the most

[12] We also checked that these event years broadly correspond to the evolution of natural resource rents to GDP from the World Bank Dataset. We also experimented with a different event year,shifting the event year three years before to match it closer to the discovery year, which did not have a systematic effect on our results. Smith (2015); Roine et al. (2017) argue that it typically takes about 4 to 6 years from drilling to production.

[13] Another issue in applying SCM is the data availability requirement. Essentially, data on the outcome variable (in our case, income inequality data) cannot have any missing values during the sample period for the treatment country and for all countries in the donor pool. Predictors that are not lagged outcome variable can have missing values, but they cannot be missing for the entire pre-treatment period for any country, because they are averaged over this period. Those predictors can also be averaged over a subset of a pre-treatment period; accordingly, they cannot be missing for the entire period they are averaged over. Income inequality data were missing for some years for the majority of the possible sample countries, so we decided to fill those missing values using linear interpolation. We opted for linear interpolation in favor of cubic spline interpolation because, even though the latter produced qualitatively similar results, we obtained a lower mean square prediction error (MSPE) with linearly interpolated values. Another solution would be to discard all years with missing outcome variable values for at least one (treatment or control) country, but that would leave us with only a few pre-treatment years available for each analysis.

[14] As a robustness check, we also used more restricted set of predictorsbut the results remained largely the same.

plausible candidates for impact on income inequality derived from the inequality literature are GDP per capita, ethnic fragmentation, population, democracy score, infant mortality, the average years of schooling (as a proxy for human capital), and financial and trade openness. GDP and population data are taken from Maddison Historical Statistics, where GDP is measured in 1990 International Geary-Khamis dollars. Ethnic fragmentation data comes from Alesina et al. (2003), who construct a Herfindahl index taking values from zero (the country's population is completely homogeneous) to one (each citizen is from a different ethnic group). For each country in the data set, fragmentation remains constant over the sample period. Democracy scores are obtained from the Polity IV Project and range from zero (hereditary monarchy) to ten (consolidated democracy), while we utilize infant mortality data from the 2010 Revision of the United Nations World Population Prospects. For human capital, data on the average years of schooling are taken from Barro and Lee (2013) with observations available for every fifth year over the period 1950 to 2010. In addition, we include two other variables, domestic credit to private sector to GDP and an openness measure (sum of exports and imports over GDP), to control for the possible effect of financial development and trade on income inequality. The choice of predictors used for a particular treatment country and its outcome variable is summarized in Table A2.

5. Results

We present the results on the effect of natural resource discoveries on income inequality in this section. Figures 1–3 show the paths of top 1% and top 10% shares for each treatment country and its synthetic control, i.e., a weighted average of countries chosen from the donor pool. Table A1 displays the weights of control countries making up each treatment country's synthetic control.[15] In the figures, vertical dashed line represents the event year. We can say that the intervention is estimated to have an effect on a particular income inequality measure if there is a considerable difference between the trajectory of the measure for the treatment country and the trajectory for its synthetic control after the event year. The fit of the synthetic control can then be inferred from its deviation from the treatment country during the pre-intervention period.

In case of Denmark (Figure 1), pre-trends in top 1% and top 10% shares are well-replicated by the respective synthetic controls, suggesting that the synthetic trajectories of top 1% and top 10% shares in the post-intervention period provide a reasonable approximation to the trajectories that would occur if Denmark did not experience any resource discovery. The estimated effect of resource discovery on top 1% and top 10% share appears to be large and negative, as the difference between the true and synthetic trajectory in the post-intervention period is negative for both shares. Therefore, our results suggest that natural resources has contributed to lower income inequality in Denmark. This result is consistent with the argument natural resources may lead to lower income inequality if a country redistributes the resource rents on welfare state (van der Ploeg, 2011).

For another treatment country – Netherlands – we also obtain negative effects of resource discovery on top 1% and top 10% share, however, the pre-intervention match between Netherlands and its synthetic counterpart for both shares is slightly worse than in case of Denmark. In case of Norway's top 10% share, the effect of natural resources on income inequality is negative, except one large spike in 2005 but this has been caused by the announcement of tax reform. The tax on dividends increased as of 2006giving the incentive to increase the payment of dividends in 2005 (Aaberge et al., 2017). Therefore, our results suggest that natural resources decrease income inequality or that have no effect.

[15] Only control countries with nonzero weights are included.

In order to assess the significance of these results further, we conduct placebo tests for each treatment country in which the intervention of interest is repeatedly assigned to each country in the donor pool as if this was the country that experienced the intervention, and the remaining countries (including the real treatment country) serve as its control countries. We present the results for each treatment country and outcome variable in Appendix. For each treatment country and outcome variable, we compute the gap between its actual outcome variable path and its synthetic control's outcome variable path and depict it along with the gaps associated with each placebo run in which the pre-intervention MSPE was at most 20 and 5 times higher than the MSPE of the real treatment country, respectively. This excludes countries with the worst pre-intervention fit between them and their respective synthetic controls as they are unsuitable for SCM analysis. We also include a histogram of the ratios of post- and pre-intervention MSPE for each treatment country and all its placebo countries to further evaluate the size of the treatment country's gap relative to those of placebo countries. Whenever the intervention should have had any effect on the outcome variable, the ratio for the treatment country should be high, because, provided that the pre-intervention MSPE is very low (i.e., good fit between the treatment country and its synthetic control), post-intervention MSPE is high if there is any effect.

As can be seen from Figures A7 – A21, placebo tests are in line with our interpretation of SCM results above. The effect of resource discovery on both measures of income inequality is strongly confirmed in case of Denmark, as there is essentially no pre-intervention gap between Denmark and its synthetic version, but after the intervention the gap becomes large relative to placebo gaps, (moving from A1 to A2 for top 1% share andA4 to A5 for top 10% share). Histograms reveal that the post/pre-intervention MSPE is by far the highest for Denmark, further documenting the existence of an effect of natural resources on income inequality.

Placebo tests for Netherlands and Norway's top 10% share tell a similar story, although they reflect the fact that the fit between them and their respective synthetic controls in the pre-intervention period is a bit worse than in case of Denmark. Rather small post/pre-intervention MSPE observable for Netherlands and Norway's top 10% share could partly be attributed to the way in which SCM selects control countries to form a synthetic control. As described above, the algorithm selects countries that best match pre-intervention characteristics of a treatment country. Therefore, it might be the case that for some control countries, if they are treated as treatment countries during placebo runs, there exist countries that better imitate them during the pre-intervention period than countries that were selected to make up a real treatment country, resulting in lower pre-intervention MSPE than the one of the real treatment country.

For Norway's top 1% share, placebo tests suggest that there is not any effect of resource discovery, as the gaps are not significantly different from the placebo gaps in the post-intervention period and MSPE ratios are not unusually large.

Denmark

Top 1% share **Top 10% share**

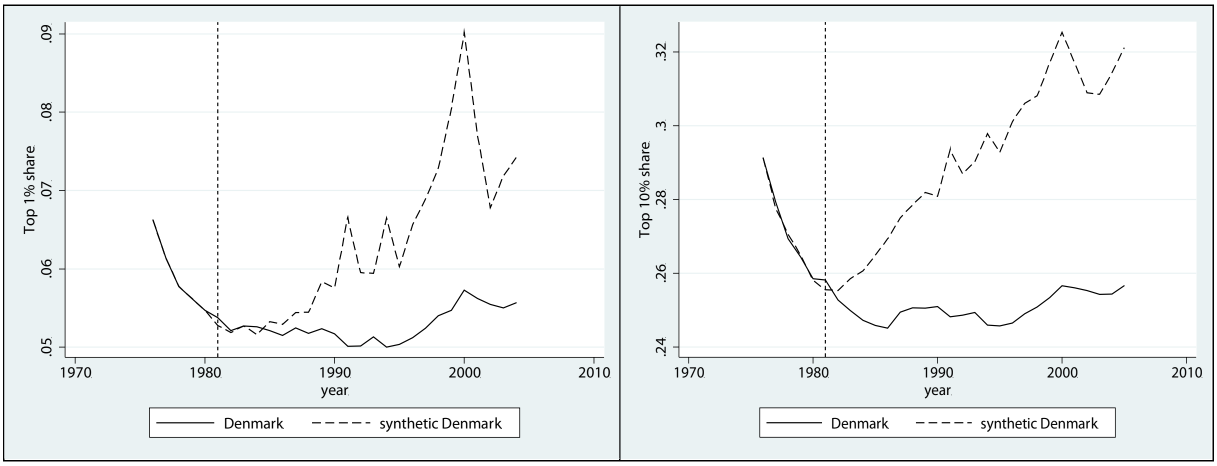


Figure 1: Trajectories of top 1% and top 10% shares: Denmark vs. synthetic Denmark. The dashed vertical line denotes the event year

Netherlands

Top 1% share **Top 10% share**

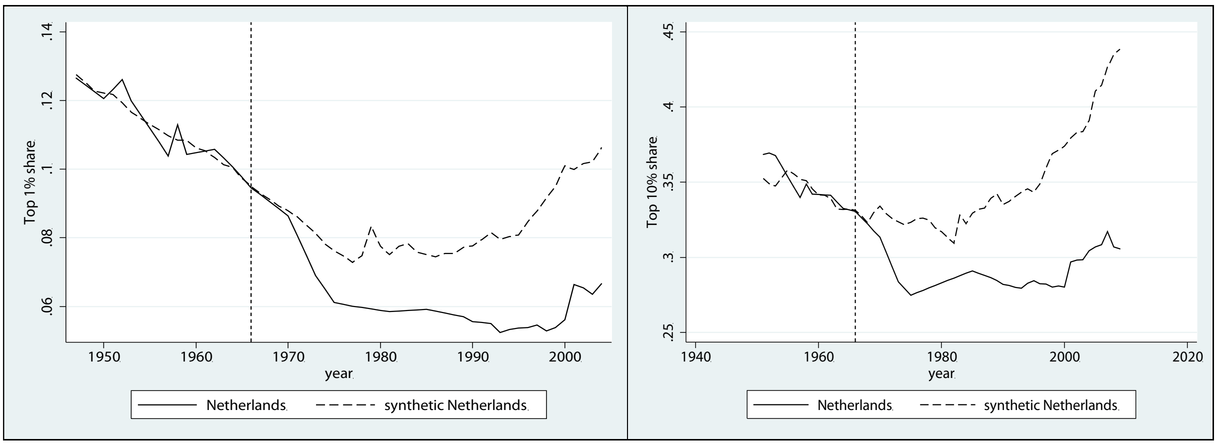


Figure 2: Trajectories of top 1% and top 10% shares: Netherlands vs. synthetic Netherlands. The dashed vertical line denotes the event year

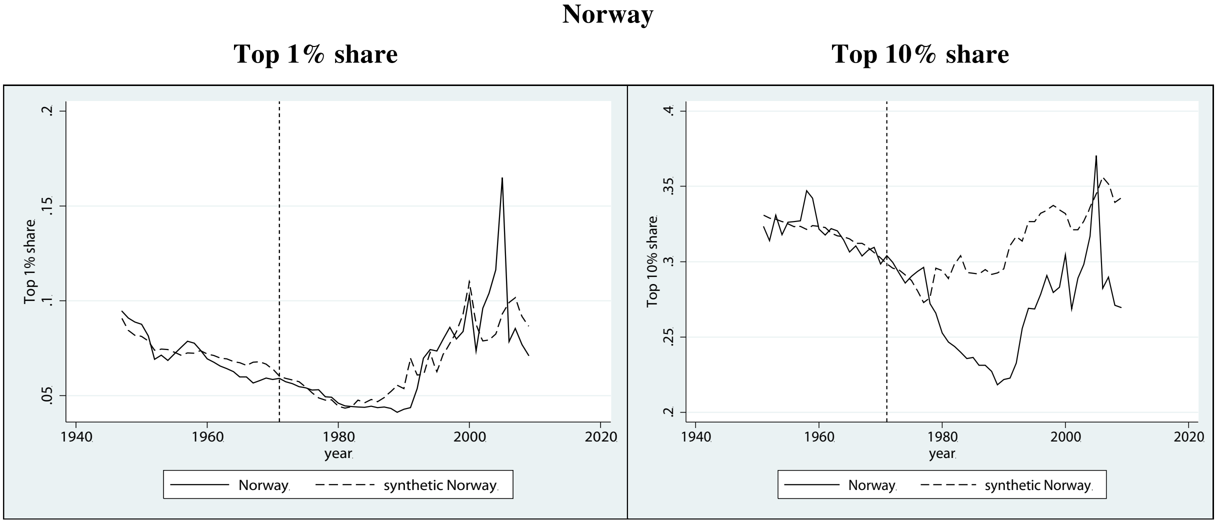


Figure 3: Trajectories of top 1% and top 10% shares: Norway vs. synthetic Norway. The dashed vertical line denotes the event year.

5.1 Robustness Checks

This subsection presents results of the above analyses repeated using only control countries from the same geographical region as the treatment country. All treatment countries are from the same region – Northern Europe. Therefore, we are left with the following control countries forming the donor pool for each treatment country: Finland, France, Germany, Ireland, Sweden, and Switzerland.[16] Predictors and sample periods for each particular treatment country – outcome variable analysis below match those of the baseline model with unrestricted donor pool.[17]

The results correspond to those of the baseline model, although it can be seen from the discrepancies between pre-event trajectories that for the majority of treatment countries, pre-intervention paths of top 1% and top 10% shares are not replicated very well by their respective synthetic controls, because the donor pool contains only a few countries, making the selection of appropriate control countries more difficult. As a consequence, this justifies our choice not to restrict the donor pool geographically.

[16] Smith (2015) included also Belgium to this region but there is not any data on either the top 1% or top10% share for Belgium at the World Wealth & Income Database.

[17] See Table A2 for predictors in each analysis and Table 1 for sample periods.

Denmark

Top 1% share **Top 10% share**

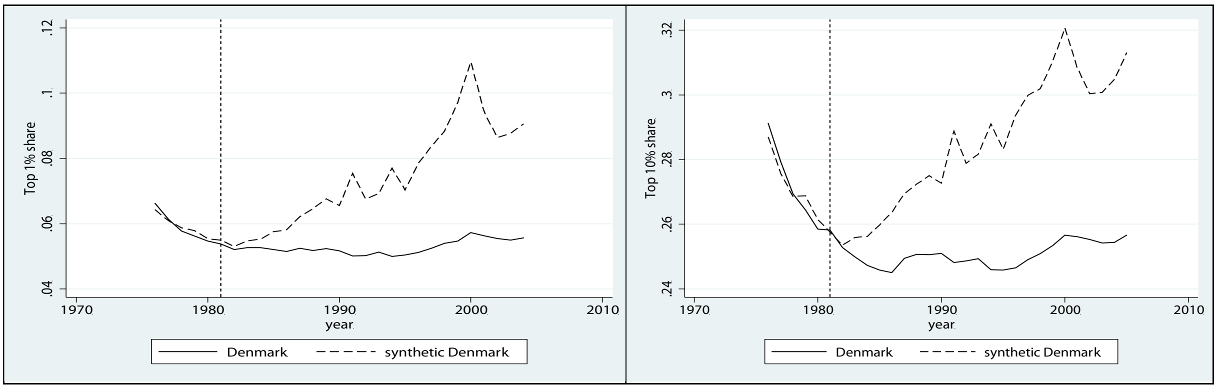


Figure 4: Trajectories of top 1% and top 10% shares: Denmark vs. synthetic Denmark. Donor pool is restricted to countries from the Northern Europe region. Individual countries' weights in the resulting synthetic Denmark are: Finland – 0.06, France – 0.243, Sweden – 0.599, Switzerland – 0.098 for top 1% share and France – 0.426, Sweden – 0.574 for top 10% share.

Netherlands

Top 1% share **Top 10% share**

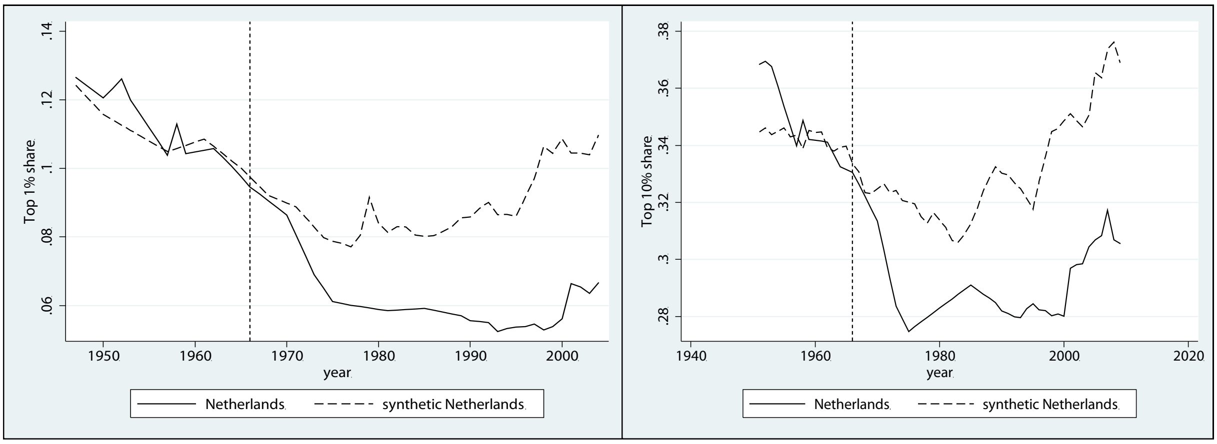


Figure 5: Trajectories of top 1% and top 10% shares: Netherlands vs. synthetic Netherlands. Donor pool is restricted to countries from the Northern Europe region. Individual countries' weights in the resulting synthetic Netherlands are: Germany – 0.431, Ireland – 0.569 for top 1% share and France – 0.383, Germany – 0.617 for top 10% share.

Norway

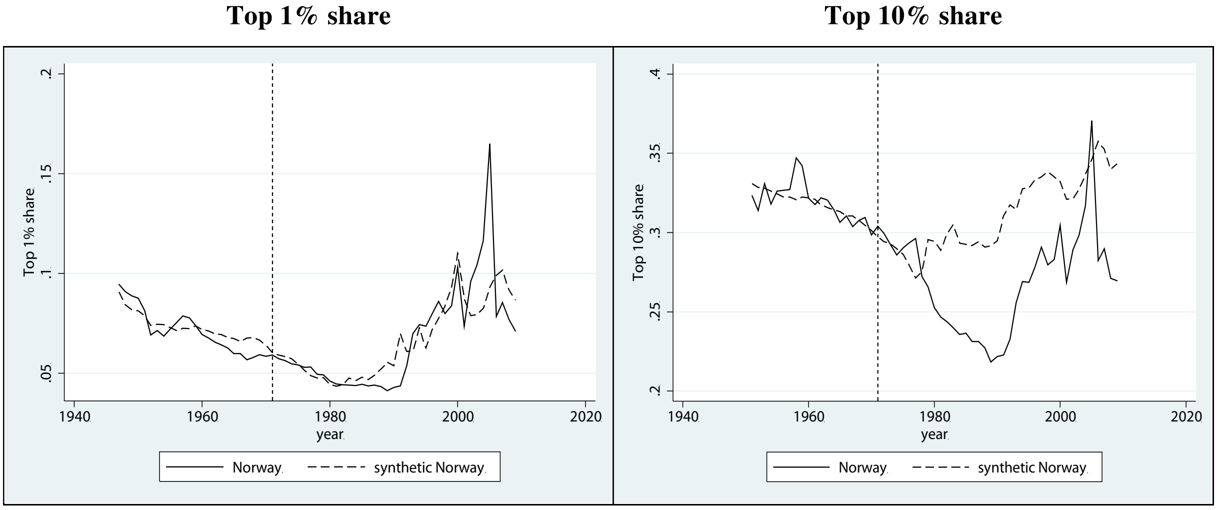


Figure 6: Trajectories of top 1% and top 10% shares: Norway vs. synthetic Norway. Donor pool is restricted to countries from the Northern Europe region. Individual countries' weights in the resulting synthetic Norway are: Ireland – 0.124, Sweden – 0.876 for top 1% share and France – 0.103, Ireland – 0.67, Sweden – 0.227 for top 10% share.

6. Conclusions

This paper has explored the causal links between natural resource discoveries and income inequality in a sample of three Northern European countries using the synthetic control method. Our results suggest that, contrary to prior analyses (e.g. Goderis and Malone (2011)), income inequality is permanently decreased by natural resource discoveries. For countries such as Denmark, the difference between the untreated country and the actual results are striking, with inequality of the top 10% nearly 8 percentage points lower in reality than in the counterfactual. Similar results are obtained for the Netherlands and Norway.

Taken together, our result of resource booms leading to permanent reductions in inequality appears to be a consequence of the idiosyncrasies of our sample: as we exclusively examine developed countries, the natural resource discoveries detailed here occurred at a point when country political and economic institutions were already well-formed. This reality means that many of the channels in which resources could have worsened inequality – including inducing corruption and fostering economic concentration -were already closed off. In this sense, natural resource discoveries do indeed appear to be a windfall gain for a developed economy, much as economic theory would predict. More importantly, this gain appears to be shared by much of the population and notjust elites.

In terms of future research, there are several avenues which researchers may travel down from our modest starting point. Most obviously would be to examine if these results hold using emerging economies rather than developing ones, applying the synthetic control method to countries such as Iran, Russia, or Kazakhstan instead of Netherlands and Norway. How did weak institutional environments cope with resource bonanzas and did it have the predicted effect in worsening income inequality? Such an exercise would require excellent data on in-country inequality in these countries (not always easy to find) but would be a worthwhile way to move the literature forward.

Beyond the issue of income inequality, it would also be worthwhile to examine the causal effect of natural resource discoveries on wealth inequality. Does wealth inequality follow the same pattern as income inequality in developed or developing economies? Are there situations where income inequality decreases while wealth inequality increases following the discovery of point-source natural resources? And what about other resource discoveries other than point-source?

Regardless of which avenue is explored, we believe that the application of the synthetic control method to these questions can help to advance our knowledge of the effects of natural resources on various economic metrics. At the very least, it provides a mechanism to evaluate the causal link between resources and economic outcomes, a link which has heretofore been difficult to find.

References

Aaberge, R., T. Atkinson, and J. H. Modalsli (2017). On the Measurement of Long-Run Income Inequality: Empirical Evidence from Norway, 1875–2013. IZA Discussion Papers 10574, Institute for the Study of Labor (IZA).

Abadie, A., A. Diamond, and J. Hainmueller (2010). Synthetic control methods for comparative case studies: Estimating the effect of California tobacco control program. *Journal of the American Statistical Association 105* (490), 493–505.

Abadie, A. and J. Gardeazabal (2003). The economic costs of conflict: A case study of the Basque country. *American Economic Review 93* (1), 113–132.

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

Alvaredo, F., L. Chancel, T. Piketty, E. Saez, and G. Zucman (2017). Global inequality dynamics: New findings from wid.world. *American Economic Review 107* (5), 404–09.

Angeles, L. (2007). Income inequality and colonialism. *European Economic Review 51* (5), 1155–1176.

Arezki, R., F. Toscani, and F. R. van der Ploeg (2016). Shifting frontiers in global resource wealth: The role of policies and institutions. CEPR Discussion Papers 11553, C.E.P.R. Discussion Papers.

Atkinson, A. B. and J. E. Sogaard (2016). The Long-Run History of Income Inequality in Denmark. *Scandinavian Journal of Economics 118* (2), 264–291.

Auty, R. M. (2007). Natural resources, capital accumulation and the resource curse. *Ecological Economics 61* (4), 627–634.

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

Billmeier, A. and T. Nannicini (2013). Assessing Economic Liberalization Episodes: A Synthetic Control Approach. *The Review of Economics and Statistics 95* (3), 983–1001.

Bourguignon, F. and C. Morrison (1990). Income distribution, development and foreign trade: A cross-sectional analysis. *European Economic Review 34* (6), 1113–1132.

Buccellato, T. and M. Alessandrini (2009). Natural resources: A blessing or a curse? The role of inequality. Discussion Paper 98, Center for Financial and Management Studies.

Buccellato, T. and T. Mickiewicz (2009). Oil and gas: A blessing for the few. Hydrocarbons and inequality within regions in Russia. *Europe–Asia Studies 61* (3), 385–407.

Bulte, E., R. Damania, and R. Deacon (2005). Resource intensity, institutions, and development. *World Development 33* (7), 1029–1044.

Carmignani, F. (2013). Development outcomes, resource abundance, and the transmission through inequality. *Resource and Energy Economics 35*, 412–428.

Caselli, F. (2006). Power struggles and the natural resource curse. Research Paper 4926, London School of Economics and Political Science.

Cavallo, E., S. Galiani, I. Noy, and J. Pantano (2013). Catastrophic natural disasters and economic growth. *Review of Economics and Statistics 95* (5), 1549–1561.

Cervellati, M., P. Fortunato, and U. Sunde (2008). Hobbes to Rousseau: Inequality, institutions and development. *Economic Journal 118* (531), 1354–1384.

Cockx, L. and N. Francken (2016). Natural resources: A curse on education spending? *Energy Policy 92*, 394–408.

Dabla-Norris, M. E., M. K. Kochhar, M. N. Suphaphiphat, M. F. Ricka, and E. Tsounta (2015). Causes and consequences of income inequality: A global perspective. IMF Staff Discussion Note 13, International Monetary Fund.

Farzanegan, R. and M. Habibpour (2017). Resource rents distribution, income inequality and poverty in Iran. *Energy Economics 66*, 35–42.

Fishlow, A., C. D.-A. R. F. and R. Hansen (1978). *Rich and poor nations in the world economy*. McGraw-Hill.

Fum, R. and R. Hodler (2010). Natural resources and income inequality: The role of ethnic divisions. *Economics Letters 107* (3), 360–363.

Goderis, B. and S. Malone (2011). Natural resource booms and inequality: Theory and evidence. *The Scandinavian Journal of Economics 113* (2), 388–417.

Gylfason, T. and G. Zoega (2002). Inequality and economic growth: Do natural resources matter? Working Paper 712(5), CESifo.

Hartwell, C. A. (2016). The institutional basis of efficiency in resource-rich countries. *Economic Systems 40* (4), 519–538.

Howie, P. and Z. Atakhanova (2014). Resource boom and inequality: Kazakhstan as a case study. *Resources Policy 39*, 71–79.

Iacono, R. (2016). The Nordic model and the oil nation. Working Paper 05, CWED.

Isham, J., M. Woolcock, L. Pritchett, and G. Busby (2005). The varieties of resource experience: Natural resource export structures and the political economy of economic growth. *World Bank Economic Review 19* (2), 141–174.

Leamer, E., H. Maul, S. Rodriguez, and P. Schott (1999). Does natural resource abundance increase Latin American inequality? *Journal of Development Economics 59* (1), 3–42.

Leigh, A. (2007). How Closely Do Top Income Shares Track Other Measures of Inequality? *Economic Journal 117* (524), 619–633.

Loyaza, N. and J. Rigolini (2016). The local impact of mining on poverty and inequality: Evidence from commodity boom in Peru. *World Development 84*, 219–234.

Marchand, J. (2015). The distributional impacts of an energy boom in western Canada. *Canadian Journal of Economics 48* (2), 714–735.

Mehlum, H., K. O. Moene, and R. Torvik (2006). Institutions and the resource curse. *Economic Journal 116* (508), 1–20.

Mideksa, T. K. (2013). The economic impact of natural resources. *Journal of Environmental Economics and Management 65* (2), 277 – 289.

Milanovic, B. (2016). *Global inequality*. Harvard University Press.

Parcero, O. J. and E. Papyrakis (2016). Income inequality and the oil resource curse. *Resource and Energy Economics 45*, 159 – 177.

Peri, G. and V. Yasenov (2018). The Labor Market Effects of a Refugee Wave: Synthetic Control Method Meets the Mariel Boatlift. *Journal of Human Resources*, forthcoming. Piketty, T. (2014). *Capital in the Twenty-First Century*. Harvard University Press.

Roine, J., J. Vlachos, and D. Waldenstrom (2009). The long-run determinants of inequality: What can we learn from top income data? *Journal of Public Economics 93* (7–8), 974–988.

Roine, J., J. Vlachos, R. Waldenstrom, Daniel Arezki, V. Ramey, and L. Sheng (2017). News Shocks in Open Economies: Evidence from Giant Oil Discoveries. *Quarterly Journal of Economics 132* (1), 103–155.

Ross, M. (2001). Does oil hinder democracy? *World Politics 53* (3), 325–361.

Sachs, J. D. and A. M. Warner (1997). Sources of Slow Growth in African Economies. *Journal of African Economies 6* (3), 335–376.

Santos, R. J. (2018). Blessing and curse. the gold boom and local development in Colombia. *World Development 106*, 337–355.

Smith, B. (2015). The resource curse exorcised: Evidence from a panel of countries. *Journal of Development Economics 116* (Supplement C), 57 – 73.

Smith, B. and S. Wills (2018). Left in the dark? oil and rural poverty. *Journal of the Association of Environmental and Resource Economists*, forthcoming.

Sokoloff, K. and S. Engerman (2000). Institutions, factor endowments, and paths of development in the new world. *Journal of Economic Perspectives 14* (3), 217–232.

Solt, F. (2016). The standardized world income inequality database. *Social Science Quarterly 97* (5), 1267–1281.

Spilimbergo, A., J. L. and M. Szekely (1999). Income distribution, factor endowments, and trade openness. *Journal of Development Economics 59* (1), 77–101.

Steinberg, D. (2017). Resource shocks and human capital shocks – brain drain or brain gain? *Journal of Development Economics 127*, 250–268.

Tanndal, J. and D. Waldenstrom (2018). Does financial deregulation boost top incomes? Evidence from the big bang. *Economica*, forthcoming.

Tano, S., O. P. and O. Stjernstrom (2016). Labour income effects of the recent "mining boom" in Northern Sweden. *Resources Policy 49*, 31–40.

Tsui, K. (2011). More oil, less democracy: Evidence from worldwide crude oil discoveries. *Economic Journal 121* (551), 89–115.

van der Ploeg, F. (2011). Natural resources: Curse or blessing? *Journal of Economic Literature 49* (2), 366–420.

Zabsonre, A., M. A.-J. S. and I. Haffin (2017). Gold exploitation and socioeconomic outcomes: The case of Burkina Faso. Working Paper 13, Partnership for Economic Policy.

Appendix

List of control countries by SCM analysis

Treatment countries are in bold followed by the outcome variable.

Denmark – Top 1% share
Finland, France, Germany, India, Indonesia, Ireland, Italy, Japan, Korea, Mauritius, Portugal, Singapore, Sweden, Switzerland.

Denmark – Top 10% share
France, Germany, India, Ireland, Italy, Japan, Portugal, Singapore, Sweden, Switzerland.

Netherlands – Top 1% share
Finland, France, Germany, India, Indonesia, Ireland, Japan, Korea, Mauritius, Singapore, Sweden, Switzerland.

Netherlands – Top 10% share
France, Germany, India, Ireland, Japan, Sweden, Switzerland.

Norway – Top 1% share
Finland, France, Germany, India, Ireland, Japan, Korea, Singapore, Sweden, Switzerland.

Norway – Top 10% share
France, Germany, India, Ireland, Japan, Sweden, Switzerland.

Placebo tests

Denmark

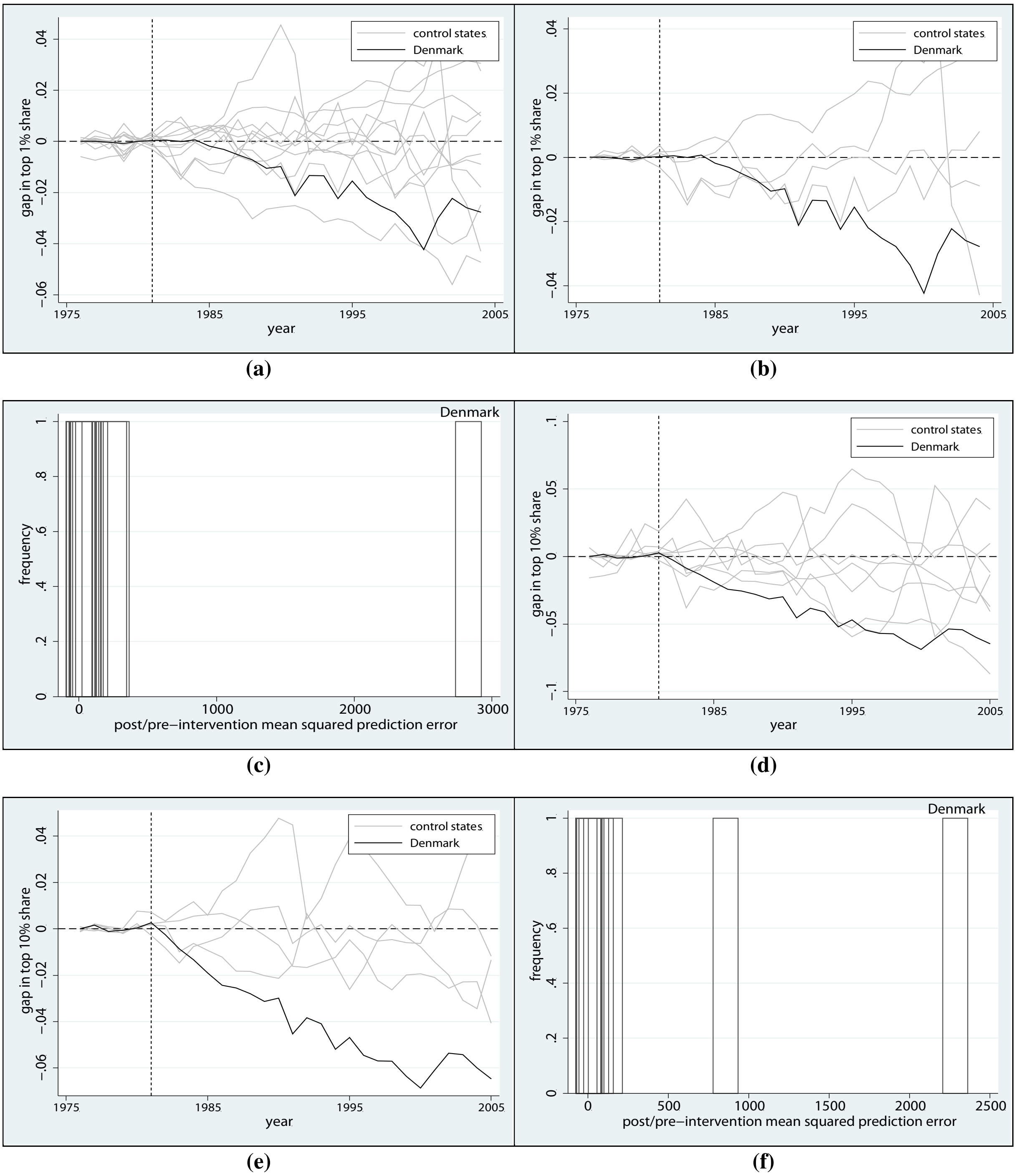


Figure A1: Placebo tests: Denmark, top 1% and top 10% shares. (a), (b): Gaps in top 1% share in Denmark and placebo gaps in its control countries. Countries with pre-intervention MSPE twenty (a) and five (b) times higher than Denmark's are excluded. (c), (f): Ratio of post- and pre-intervention MSPE for Denmark and its control countries: Top 1% share (c) and Top 10% share (f). (d), (e): Gaps in top 10% share in Denmark and placebo gaps in its control countries. Countries with pre-intervention MSPE twenty (d) and five (e) times higher than Denmark's are excluded.

Netherlands

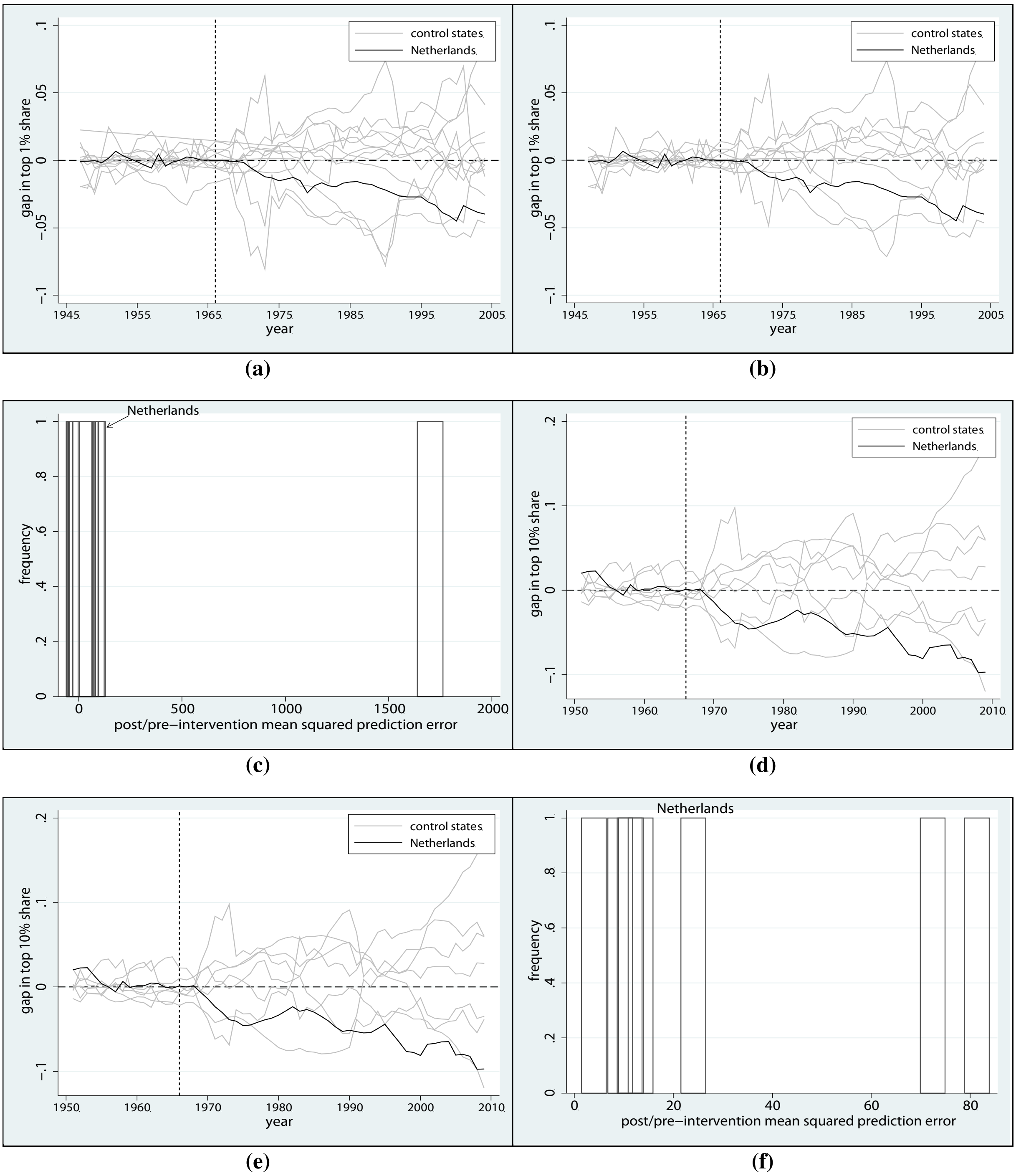
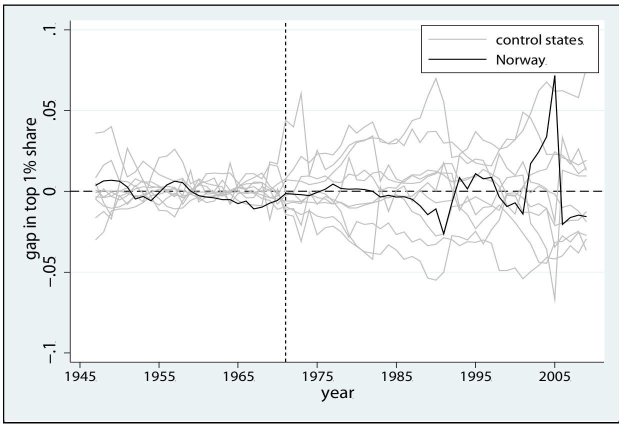
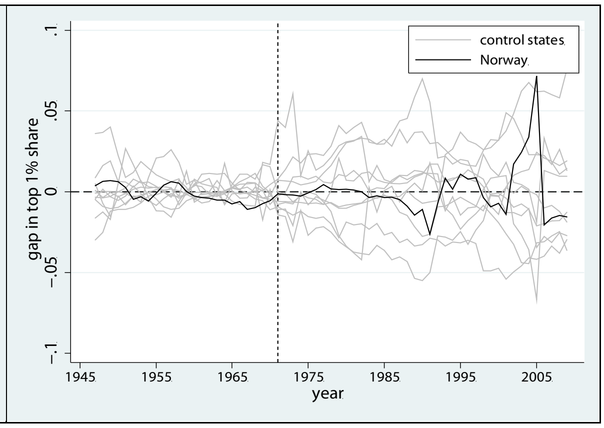


Figure A2: Placebo tests: Netherlands, top 1% and top 10% shares. (a), (b): Gaps in top 1% share in Netherlands and placebo gaps in its control countries. Countries with pre-intervention MSPE twenty (a) and five (b) times higher than Netherlands' are excluded. (c), (f): Ratio of post- and pre-intervention MSPE for Netherlands and its control countries: Top 1% share (c) and Top 10% share (f). (d), (e): Gaps in top 10% share in Netherlands and placebo gaps in its control countries. Countries with pre-intervention MSPE twenty (d) and five (e) times higher than Netherlands' are excluded.

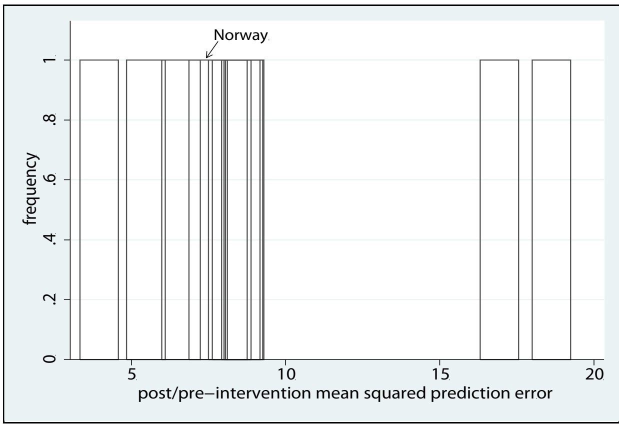
Norway



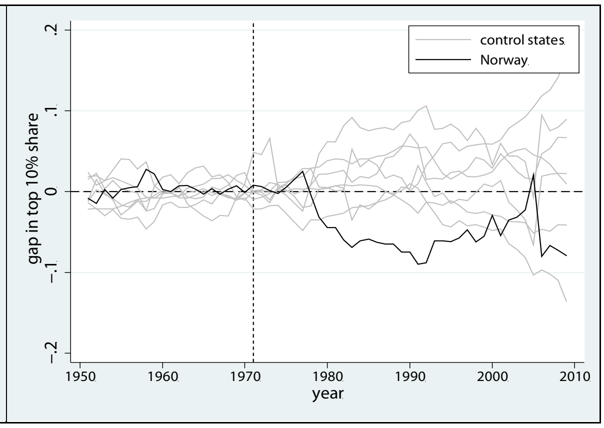
(a)



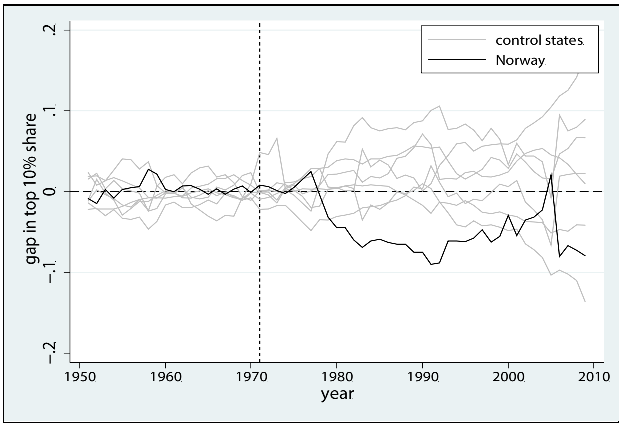
(b)



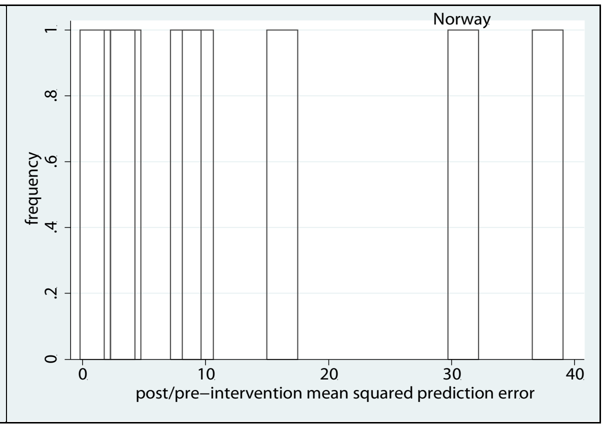
(c)



(d)



(e)



(f)

Figure A3: Placebo tests: Norway, top 1% and top 10% shares. (a), (b): Gaps in top 1% share in the Norway and placebo gaps in its control countries. Countries with pre-intervention MSPE twenty (a) and five (b) times higher than Norway's are excluded. (c), (f): Ratio of post- and pre-intervention MSPE for Norway and its control countries: Top 1% share (c) and Top 10% share (f). (d), (e): Gaps in top 10% share in Norway and placebo gaps in its control countries. Countries with pre-intervention MSPE twenty (d) and five (e) times higher than Norway's are excluded.

Synthetic control weights by SCM analysis

Table A1: Treatment countries (in bold) followed by the examined outcome variable and the weights assigned to countries making up each treatment country's synthetic control. Each treatment country – outcome variable pair denotes one particular SCM analysis.

Denmark – Top 1% share	
Japan	0.014
Mauritius	0.3
Portugal	0.049
Sweden	0.521
Switzerland	0.116
Denmark – Top 10% share	
France	0.271
Portugal	0.114
Sweden	0.426
Switzerland	0.189
Netherlands – Top 1% share	
Germany	0.12
Ireland	0.462
Korea	0.266
Singapore	0.066
Switzerland	0.085
Netherlands – Top 10% share	
France	0.011
Germany	0.614
India	0.375
Norway – Top 1% share	
Ireland	0.124
Sweden	0.876
Norway – Top 10% share	
France	0.13
Ireland	0.638
Sweden	0.224
Switzerland	0.008

Table A2: Treatment countries and their predictors. For each treatment country and outcome variable – Top 1% or Top 10% share – the table shows predictors used in the synthetic control analysis. Other predictors than the lagged outcome variables are averaged over the whole pre-treatment period.

	Denmark		Netherlands		Norway	
	Top 1%	Top 10%	Top 1%	Top 10%	Top 1%	Top 10%
Outcome variable 15 years before the event			x	x	x	x
Outcome variable 10 years before the event			x	x	x	x
Outcome variable 5 years before the event	x	x	x	x	x	x
Outcome variable 3 years before the event	x	x				
Outcome variable 1 year before the event	x	x	x	x	x	x
GDP per capita	x	x	x	x	x	x
Private sector credit (% of GDP)	x	x			x	x
Trade (% of GDP)	x	x			x	x
Ethnic fragmentation			x	x	x	x
Population	x	x	x			
Democracy score				x	x	x
Infant mortality	x				x	x
Average years of schooling	x	x	x	x	x	x

Table A3: Descriptive statistics for Denmark, 1976–2005

	Denmark			
	mean	s.d.	min	max
Income inequality –				
Top 1% share	0.05	0.004	0.05	0.07
Top 10% share	0.25	0.01	0.25	0.29
GDP per capita	18956	3067	14466	23973
Private sector credit (% of GDP)	60.90	42.19	30.26	157.54
Trade (% of GDP)	70.32	8.07	57.05	89.40
Population	5205	112	5073	5432
Infant mortality	0.007	0.002	0.005	0.009
Average years of schooling	9.57	0.27	8.98	10.04

Table A4: Descriptive statistics for Netherlands, 1947–2009

	Netherlands			
	mean	s.d.	min	max
Income inequality –				
Top 1% share	0.08	0.02	0.05	0.13
Top 10% share	0.31	0.03	0.27	0.40
GDP per capita	14341	5448	5996	24695
Ethnic fragmentation	0.11	0	0.11	0.11
Population	13783	1943	10114	16716
Democracy score	10	0	10	10
Average years of schooling	8.99	1.42	6.24	10.81

Table A5: Descriptive statistics for Norway, 1947–2009

	Norway			
	mean	s.d.	min	max
Income inequality –				
Top 1% share	0.07	0.02	0.04	0.16
Top 10% share	0.29	0.04	0.22	0.37
GDP per capita	15111	7267	5430	28500
Private sector credit (% of GDP)	54.55	28.24	30.47	128.06
Trade (% of GDP)	72.49	3.81	65.51	82.40
Ethnic fragmentation	0.06	0	0.06	0.06
Democracy score	10	0	10	10
Infant mortality	0.011	0.006	0.004	0.022
Average years of schooling	9.40	1.30	7.51	12.34