

NORWEGIAN SCHOOL OF ECONOMICS  
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**Economic Costs of the Dutch Disease:  
Empirical Estimates From the Netherlands**

MASTER THESIS - ECONOMIC ANALYSIS

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This thesis was written as a part of the Master of Science in Economics and Business Administration at NHH. Please note that neither the institution nor the examiners are responsible, through the approval of this thesis, for the theories and methods used, or results and conclusions drawn in this work.

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## **Abstract**

The discovery of natural gas in the Netherlands in 1959 has long been considered one of the main reasons for the poor performance of the Dutch economy in the 1970s and the 1980s. The term "Dutch disease" has since its invention in 1977 been used to describe this effect. The Dutch disease has been thoroughly developed as a theoretical concept, but little empirical work has been done to prove its adverse costs to society. I employ the synthetic control method to study the possible negative effects the Dutch disease has had on GDP per capita and productivity in the Netherlands. I find no evidence of any negative effect in the 1970s, and while there seems to be a negative effect in the 1980s, it is not large enough to be significant and may just as well be caused by the 1979 oil crisis and the following recession. This thesis challenges the prevalent notion of the harmful Dutch disease, and while the conclusions are somewhat uncertain I maintain that the fear of the Dutch disease may be exaggerated.

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# 1 Introduction

Since the late 1970s the term Dutch disease has been used to describe the potential adverse effect a natural resource discovery may have on a country's economy, specifically through de-industrialisation and reduced growth. The discovery of the Groningen gas fields in 1959 and later large reserves of natural gas in the North Sea took the Netherlands from being a net importer to a net exporter of energy and gave the Dutch government a huge revenue stream.<sup>1</sup> The increased government revenue was largely spent on transfers and expansion of the welfare state, and many has claimed that this increased spending and the boom in the energy sector caused de-industrialization, reduced productivity and reduced growth in the economy.

This claim has been backed up by several theoretical papers on booming sectors and endogenous growth, but the Dutch disease in the Netherlands has not to my knowledge been studied empirically. Whilst there has been a host of papers on the Dutch disease and foreign aid, and some studies linking the Dutch disease to the resource curse, the causal link between the discovery of natural gas and the poor performance of the Dutch economy has not been thoroughly researched.

In this thesis I will use the synthetic control method developed by Abadie et al. (2010) and study the possible negative effects of the Dutch disease on GDP per capita and productivity. I will use a panel data set of 19 OECD countries to construct a synthetic Netherlands, generating the economic development of the country had it not contracted the Dutch disease.

The remainder of this thesis is structured as follows. In section 2, I will summarize the theoretical work on the Dutch disease as well as the empirical studies that have been performed on the subject. I will also take a brief look at Baumols cost disease, since it relies on similar assumptions as the Dutch disease. Section 3 is devoted to descriptive statistics and the symptoms of the Dutch disease, while section 4 will tackle the identification problem. In

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<sup>1</sup>The development described in this section may be found in a number of books on contemporary economic history. van Zanden (2005) is one reference

section 5 I describe the data used in this thesis and the results are presented in section 6. Finally, I draw some conclusions in section 7.

## **2 Theories on the Dutch Disease**

The term Dutch disease was first used in an edition of *The Economist* in 1977 and has since been a part of any economists vocabulary. The term was used to describe the apparent problems and rather sluggish performance of the Dutch economy in the 1970s. After a long period of rapid growth in the 1950s and 1960s, the 1970s brought rising unemployment and falling productivity. The *Economist* claims that the discovery and rapid extraction of the natural gas led to an overvalued guilder, and a crowding out of the manufacturing sector through increased costs and large government consumption and transfers (*The Economist* 1977).

Since the term was invented in 1977, numerous theoretical models have been developed and refined. I choose to classify them into two groups, booming sector models and endogenous growth models, depending on whether they study the growth impact of the Dutch disease, or merely describe the effects on the sectoral composition of the economy. I will treat these two types of Dutch disease models separately below. I will also review some of the empirical work that has been done on the subject.

### **2.1 Booming sector models**

One of the most frequently cited booming sector papers is written by Corden and Neary in 1982. They study the effects a boom in one sector has on the other sectors of the economy. There are as many labels on these sectors as there are papers written on the subject, so for consistency I will stick with the labels used in the paper by Corden and Neary. These are also the most suitable labels when discussing the Dutch economy.

In the economy analysed by Corden and Neary there are three sectors. Two of these sectors produce tradable goods and sell them at the prices

given by the world market. Following Corden and Neary I label these the energy sector and the manufacturing sector. The last sector produces goods for domestic consumption only, that is non-tradable goods, and is labelled the services sector. The boom in the energy sector is assumed to be a Hicks-neutral technological improvement<sup>2</sup>, and the effects of this boom is very sensitive to the underlying assumptions and parametrization of the model. Due to the large number of variations and the rather ambiguous conclusions this model gives, I will only discuss the main findings.<sup>3</sup>

The boom in the energy sector leads to two separate effects. I continue following the terminology developed by Corden and Neary and call them the *resource movement effect* and the *spending effect*. Because of the boom, the energy sector will be able to pay more for its input factors. Assuming that the economy has an efficient market for input factors, this means resources will be drawn from the manufacturing and the services sector into the energy sector. The output of services and manufactured goods will therefore decrease. This effect is also called direct de-industrialisation. The boom in the energy sector will also mean that the sector<sup>4</sup> will increase its demand for both manufactured goods and services. This increased demand will lead to higher prices of services but, since the manufacturing sector is competing internationally, the prices of manufactured goods will remain unchanged. This real appreciation will further reduce the output in the manufacturing sector.

Although not discussed by the authors explicitly, the framework developed above could be used to describe the effect of government taxation and consumption. If the government taxes the booming sector and spends the revenues on consumption or transfers, this might lead to a further appreciation and thereby a reduction of manufacturing output. As mentioned above,

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<sup>2</sup>A Hicks-Neutral technological improvement means production increases without affecting the relative use of input factors

<sup>3</sup>For a complete review of the different assumptions and conclusions I refer to Corden and Neary (1982) and Corden (1984)

<sup>4</sup>The sector should here be thought of as both the firms constituting the industry and the workers employed there

the results and conclusions from this model rest heavily on the underlying assumptions. Nevertheless, there does seem to be an agreement that the effects described here are the common symptoms of the Dutch disease.<sup>5</sup>

While the changes to the composition of the economy described above may be both important and interesting, they hardly qualify to the description of a disease. In fact, classical Ricardian trade theory states that the boom in the energy sector constitutes a change in the comparative advantage of the economy, and that the de-industrialisation that follows should simply be embraced. This point has been stressed in several papers (Neary (1982), Krugman (1987), van Wijnbergen (1984)) and will be further discussed in the next section.

## **2.2 The importance of endogenous productivity**

van Wijnbergen (1984) is the first paper to discuss the Dutch disease with endogenous productivity effects. van Wijnbergen introduces industry specific productivity externalities to the manufacturing sector in the form of learning by doing (LBD) effects. These positive externalities call for government subsidies of the manufacturing sector regardless of the boom. The de-industrialisation caused by the booming energy sector will further increase the optimal subsidy level as long as the revenue from the booming sector is not invested abroad.

Similar results are found in Krugman (1987). Here the concern is that a foreign transfer, which has the same interpretation as a windfall discovery of natural resources, will crowd out the manufacturing sector. If the transfer is sufficiently large and lasts long enough then the manufacturing sector will not recover, and the LBD effects may be lost, reducing future growth.

In addition to these two papers, Sachs and Warner (1995) employ a model based on endogenous growth, where productivity is generated in the traded sector and there is a perfect spillover to the non-traded sector. Gylfason et al.

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<sup>5</sup>The results here are derived under the more plausible assumptions, the actual effects of a boom will still remain an empirical question (Corden and Neary 1982)

(1997) further develop the framework by including exchange rate volatility as a source of de-industrialisation.

The unambiguous negative effect of the boom found in the four papers is the result of a rather restrictive assumption. They all assume that LBD effects come solely from the manufacturing sector. This assumption is relaxed in Torvik (2001) and as would be expected, the results become less clear cut. Torvik develops a two sector, dynamic model with endogenous productivity. In contrast to previous Dutch disease models, both the traded and non-traded sector will create LBD externalities on the industry level and both sectors generate spillovers. Whether the booming sector causes pro- or de-industrialisation will depend on the relative sizes of the direct LBD-effects and the spillovers created.

More recent developments of the theoretical framework of the disease has also been made, although the focus seems to have shifted towards effects on developing countries and the management of the windfall gains. van der Ploeg (2011) and van der Ploeg and Venables (2010) discuss how absorption constraints may be a more likely reason for Dutch disease inefficiencies in developing economies and that windfall gains should be placed in a sovereign wealth fund while the necessary infrastructure is being built up to absorb the gains. The appropriateness of such a wealth fund is also discussed by Andersen (2013), who uses an overlapping generations model with endogenous growth to compare a full transfer of the windfall to the current generation to a permanent income transfer that lasts indefinitely. Lastly, Cherif (2013) studies how the relative productivity vis-à-vis trading partners is linked to the crowding out of manufacturing, and how the LBD in this sector leads to a self-reinforcement of the crowding out effect.

### **2.3 Empirical evidence of the disease**

While research on the theoretical consequences of the Dutch disease has been both thorough and comprehensive, the empirical evidence of the predictions is either weak or non-existing. To my knowledge, no research has been done

to actually confirm the suspected adverse effects of gas discoveries on the Dutch economy. Some studies on the subject have been done using data from other countries, and in this section I will outline the main findings.

I am unable to find empirical research on the Dutch disease in the Netherlands, but there has been at least one study on Norway and the United Kingdom. These countries also benefited from the oil and gas resources of the North Sea, albeit a decade later than the Netherlands. Bjørnland (1998) studies the effects of the North sea oil discoveries on the manufacturing industries of Norway and the UK. She uses a structural vector autoregressive regression (SVAR) model<sup>6</sup> to identify oil supply shocks. Bjørnland finds weak evidence of Dutch disease in the UK, while the Norwegian manufacturing sector seems to have benefited from the oil discoveries. While Bjørnland finds some small effects on the output of the manufacturing sector, she does not investigate whether these effects cause any harm to the growth rates or total output in the economy.

### 2.3.1 Links to the resource curse

While the empirical literature that explicitly studies the Dutch disease is rather limited, the work done on what is known as the resource curse is extensive. The resource curse is founded on the observations that resource rich countries perform worse on average than resource poor countries on a number of macroeconomic indicators.<sup>7</sup> There exist several explanations of the resource curse. One of them is the Dutch disease, meaning the low growth rates associated with resource abundance come from de-industrialisation and loss of manufacturing production externalities. The evidence of a resource curse is weak and inconsistent, and the literature has been riddled with empirical challenges as discussed in van der Ploeg and Poelhekke (2010). While

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<sup>6</sup>While this framework is a popular tool for forecasting, its use in causal empirics has been criticised for relying on a priori assumptions on the structural links in the economy (Benati 2010)

<sup>7</sup>Sachs and Warner (2001), Brunnschweiler and Bulte (2008) and van der Ploeg and Poelhekke (2010) gives a summary of the resource curse

the Dutch disease might be a cause for the resource curse, the studies done so far have not been able to separate the Dutch disease from the other possible causes, such as rent seeking activities or increased political instability.

### **2.3.2 Foreign aid and Dutch disease**

Another strain of the empirical Dutch disease literature investigates the seemingly weak link between foreign aid and economic growth. As noted in Krugman (1987), the discovery of a natural resource is in many ways equivalent to a foreign exchange gift. The effect of such an exchange gift will not lead to any direct de-industrialisation through the resource movement effect, as there is no booming sector to draw out the resources. The spending effect will however occur, as the foreign aid may lead to a real appreciation and therefore indirect de-industrialisation.

Rajan and Subramanian (2011) study the effect of foreign aid on the manufacturing sector using a panel of 47 developing countries, correcting for fixed effects and reverse causality bias. They find that an increase in aid reduces the growth in the manufacturing sector. There has also been a wide array of country specific studies on the effect of aid on the real exchange rate. Martins (2013) provides an overview of the recent estimates and also studies the effect on Ethiopian real exchange rate. As is often the case with empirical studies of the Dutch disease, results vary. The recent studies find both positive and negative effects of aid inflow on the exchange rate, and Martins (2013) finds that the large inflow of both aid and remittances has not hurt Ethiopian competitiveness.

To sum up the review of the empirical literature, I believe the previous empirical studies of the Dutch disease are inadequate in at least two ways. Firstly, there has been much attention devoted to identifying the existence of the resource movement effect and the spending effect, but these effects are not very relevant to policy makers without knowing the extent of the LBD externalities. Secondly, the literature on the resource curse has been focused on the possible growth implication of windfall discoveries, but has

been unable to distinguish the Dutch disease from other possible culprits. This thesis seeks to improve on both of these shortcomings.

### 3 Symptoms of the Dutch disease

From the theoretical discussion above there appears to be several symptoms of the Dutch disease which should present themselves in the data.<sup>8</sup> The booming sector models make the prediction that there should be a contraction of the manufacturing sector and an expansion of services output following the discovery of natural gas. In figure 1 I have plotted output indices for the mining sector, manufacturing sector and a non-tradable sector, as well as the mining sector's share of total GDP.<sup>9</sup> The boom in the mining sector is clearly evident and a direct result of the gas discoveries. The predicted effects on the manufacturing and services sector are less evident. There seems to be a more or less constant positive trend in both sectors. This does not mean that there are no effects. Structural breaks in time series with a trend might be hard to spot. I have therefore plotted the growth rates for manufacturing and services in figure 2.

From this plot it is possible to see a downward trend in the manufacturing growth rate from 1960 to circa 1979. This coincides with the boom in the mining sector discussed above and might be a symptom of the disease. There is no discernible effect of the boom on the services sector, which seems to have a more or less stationary growth rate. In figure 7 in the appendix I have plotted the growth rates of manufacturing for the Netherlands and two non-resource dependent economies, Sweden and Denmark. The downward trends in the manufacturing output in these three countries are very similar, meaning the reduction in manufacturing might have other causes than gas discoveries.

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<sup>8</sup>The data used in this section is described in section 5 and in appendix A

<sup>9</sup>The non-tradable index consists of sectors G through P as defined in the United nation ISIC revision 3.1. While some of the sub-categories in these sectors might be tradable, they mostly consist of services or goods normally considered non-tradable.

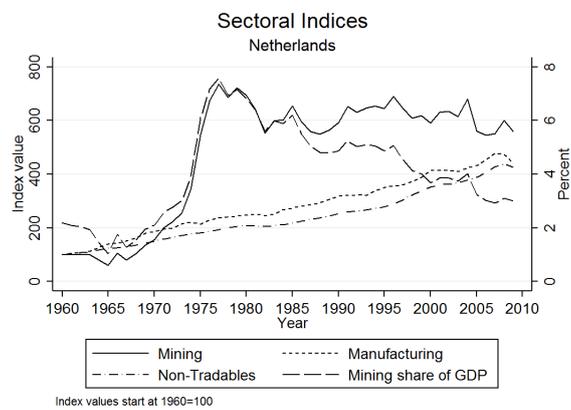


Figure 1: Output indices for the mining, manufacturing and public services sector in the Netherlands. Mining sector as a share of GDP on right axis.

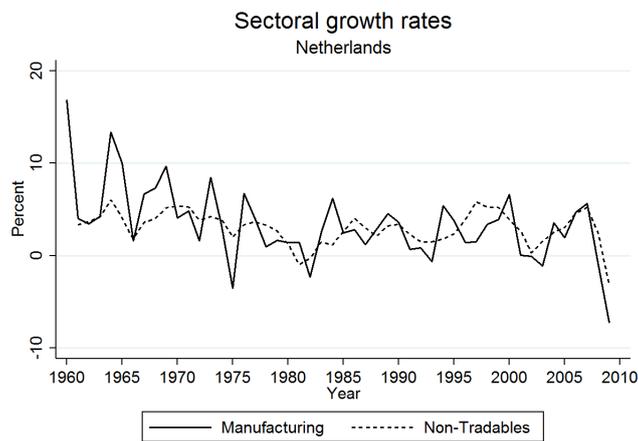


Figure 2: Output growth for the manufacturing and public services sector in the Netherlands

While there is little evidence of Dutch disease symptoms in the sectoral composition, there are other predictions to study. The most important prediction postulated in the papers on endogenous growth and LBD externalities is that the crowding out of the manufacturing sector will cause a drop in productivity for the whole economy. In figure 3 I have plotted labour productivity growth, defined as growth in GDP per person employed,<sup>10</sup> and gas production. The rapid rise in gas production seems to be followed by a structural break in the productivity growth rate, which is exactly what the theory predicts.

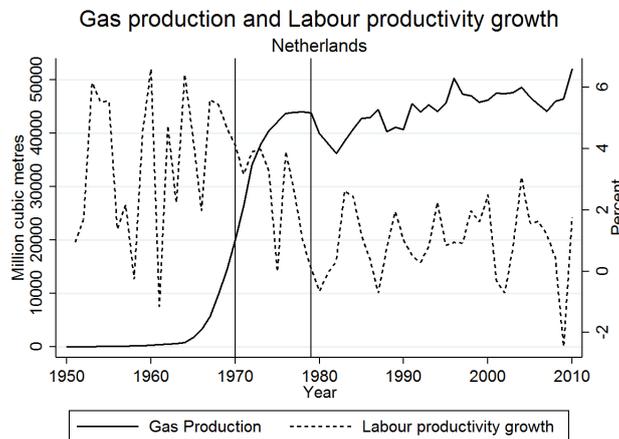


Figure 3: Gas production and Labour Productivity Growth in the Netherlands

Below, I have included similar plots for government consumption, unemployment rate and the investment rate. They all seem to confirm the theories on the Dutch disease, in that the sudden exploitation of natural resources reduces investments and increases government consumption and unemployment. The years 1970 and 1979 are of special interest, since they seem to be possible sources of structural breaks in several of these plots. While the symptoms might seem evident, there are no causal links to be drawn from simply looking at these plots. In fact, it may very well be that this is exactly what

<sup>10</sup>Using GDP per hour worked gives more or less the same results

the Economist did in 1977, and rather than the development described above being symptoms of a disease, the disease was created to explain the symptoms. These macroeconomic time series are a result of complex processes, and the possible underlying causes of shifts in any of them are countless.

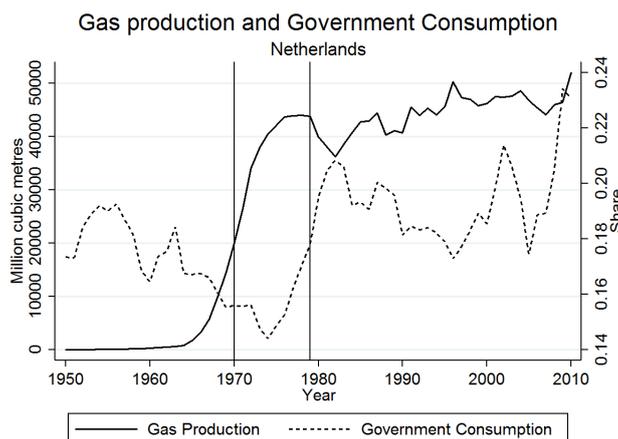


Figure 4: Gas production and Government Consumption as share of GDP in the Netherlands

As already mentioned, figure 7 shows that the negative trend in the manufacturing growth rate is not a development specific to the Netherlands, nor to countries with abundant natural resources. Another plausible cause of these symptoms is given in Piketty (2014). He describes the long term evolution of capital and real growth rates, and how the 1970s is the decade in which western Europe "catches up" with the United States at the technological frontier. Rather than the 1970s and 1980s being decades of slow and sluggish growth, Piketty states that the 1950s and 1960s were years of exceptional growth caused by capital reconstruction after the destruction of the two world wars. In this case the symptoms of the Dutch disease may merely be the adjustment to a regime of slower growth at the world's technological frontier. The same explanation may also be found in Maddison (1994).

To be able to extract the true effect of the Dutch disease from the myriad of other possible explanations, I need a proper identification scheme. This

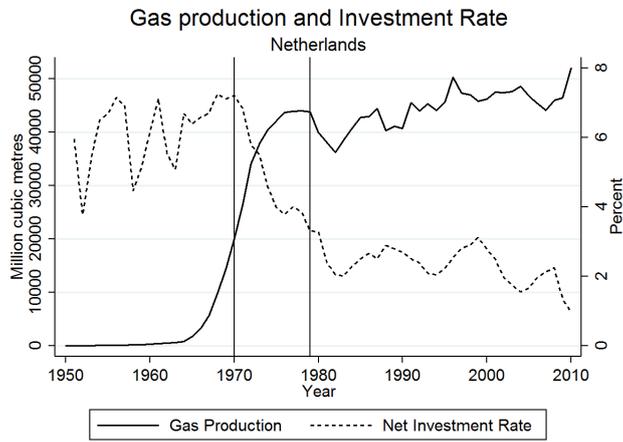


Figure 5: Gas production and investment rate in the Netherlands

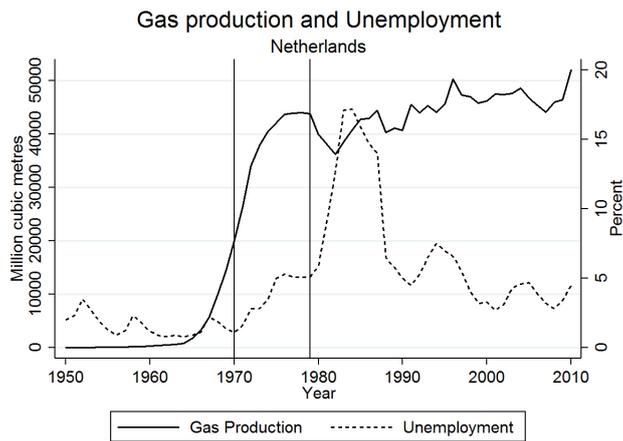


Figure 6: Gas production and Unemployment in the Netherlands

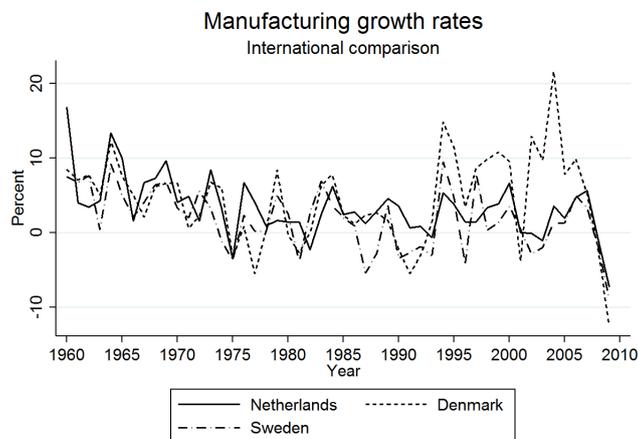


Figure 7: Manufacturing growth rates in three western european countries

will be the subject of the next section.

## 4 Identification

The problem of identification is to identify and capture the causal relationships between different observable factors.<sup>11</sup> In this thesis I want to capture the causal effect of the Dutch disease on economic performance. The problem is to determine what would have happened to the Netherlands had it not contracted the disease, the so called counterfactual outcome. Since the Dutch disease is an event that affects a whole country, it is evident that I need a data set of multiple countries to study the effect of the disease. The Dutch disease is also such a rare event, seldom more than one country suffer from the disease at any given time, so observations of these countries would be needed over several years. Given such a panel data set, several strategies might be considered. A common strategy when dealing with such data is to construct a variable representing the Dutch disease. I may then use least squares estimators to determine the effect this variable has on some other

<sup>11</sup>The following few paragraphs will recite well known results from the literature on causal empirics. Angrist and Pischke (2008) is an excellent reference on the subject.

variable approximating economic performance.

The least squares estimation technique relies on some restrictive assumptions, and violation of these assumptions will lead to biased results and any causal interpretation would be invalid. A tempting option in this thesis would be to identify the years and countries which contracted the Dutch disease and create a Dutch disease dummy that takes the value of 1 when the Dutch disease is present. I could then run a fixed effect (FE) or difference in difference (DiD) model and study the coefficient of this dummy. The most obvious problem with this strategy is that there is no general agreement on which countries has and has not contracted the Dutch disease in which time periods. The discussion of the empirical results above shows how difficult it is to identify whether a country has suffered from the Dutch disease. A solution to this problem would be to use some better defined variable such as gas extraction or resource abundance, but this quickly leads us into the territory of resource curse studies, which has problems of it's own that I have already discussed.

Even when I assume that I have a proper "Dutch disease variable", the FE and DiD estimators will most likely be biased and invalid. Consider the following model of the Dutch disease

$$Y_{i,t} = \alpha + \delta_t + \theta^\top Z_{i,t} + \beta D_{i,t} + \mu^\top \lambda_{i,t} + \varepsilon_{i,t}$$

In this model,  $Y_{i,t}$  is the outcome variable measuring economic performance,  $\alpha$  is the constant term and  $Z_{i,t}$  is a vector of observable covariates.  $\delta_t$  is a vector of unobservable time specific factors that are constant across units,  $D_{i,t}$  is the Dutch disease dummy variable<sup>12</sup> while  $\lambda_{i,t}$  is a vector of unobservable factors that varies across units and may vary over time.  $\theta^\top$  and  $\mu^\top$  are vectors of parameters to be estimated,  $\beta$  is the effect of the Dutch disease and  $\varepsilon_{i,t}$  is an idiosyncratic error term. Estimating this model will require the unobserved effects to be uncorrelated with the Dutch disease variable  $D_{it}$ . The time-specific factors in  $\delta_t$  are easily controlled for through time-dummies, but the factors in  $\lambda_{it}$  are more troublesome. If any of these factors

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<sup>12</sup>In the FE model this could also be a normal variable

are correlated with  $D_{i,t}$ , that is  $Cov(D_{i,t}, \lambda_{i,t}) \neq 0$ , then OLS estimates will be biased. Consider as an example the factor "work morale". High work morale would definitely lead to better economic performance, but may also be correlated to the Dutch disease.<sup>13</sup> Such a factor is in the literature called a confounding factor. Confounding factors such as this must be controlled for to obtain unbiased estimates with causal interpretations.

The FE estimator may very well obtain unbiased estimates if all unobserved effects such as work morale are constant over time in each country. In this model, this means we require

$$\lambda_{i,t} = \lambda_{i,t+k} = \lambda_i \quad \forall \quad k$$

This assumption seems very unlikely in the case of the Dutch disease. The time period in question is 1950-2010, which is a very long period for factors such as "work morale" to remain constant. The DiD estimator is a little less restrictive. If I introduce a new dummy  $T$  that takes the value of 1 in time periods after the Dutch disease has been contracted, the model may be rewritten as

$$Y_{i,t} = \alpha + \delta_t + \theta^\top Z_{i,t} + \beta_1 D_{i,t} + \beta_2 T_{i,t} + \beta_3 (D_{i,t} * T_{i,t}) + \mu^\top \lambda_{i,t} + \varepsilon_{i,t}$$

The estimate of  $\beta_3$  would here give us the effect of the Dutch disease. The unobservable confounding factors in  $\lambda_{i,t}$  are no longer required to be constant over time, but it is required that the trend of these factors development is identical in all countries. Formally, for the estimates of  $\beta_3$  to be unbiased, it is required that

$$\Delta \lambda_{i,t} \equiv \lambda_{i,t} - \lambda_{i,t-1} = \Delta \lambda_{j,t} \quad \forall \quad i, j$$

This means I need the "work morale" to increase or decrease in tandem for all the countries in my sample. I may of course not test if this assumption will hold, since the confounding factors are unobservable. Economic

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<sup>13</sup>In periods of low economic activity, such as Dutch disease years, work morale may fade due to any number of reasons.

reasoning does however permit me to conclude that it is highly unlikely that all unobservable confounding factors will have the same trend in all countries. Fortunately, there exists one method that neither relies on any of the assumptions above, nor the crisp definition of a "Dutch disease variable".

The Synthetic Control Method (SCM) was first described and utilized in Abadie and Gardeazabal (2003) and further developed in Abadie et al. (2010) and Abadie et al. (2014). For a full formal description and derivation of this statistical procedure I refer to these articles. I will however present a brief outline to be used as a reference in this thesis.

The synthetic control method is a data driven procedure in which the aim is to create a synthetic version of some aggregated unit, be it a country, region, state or other large entity. This synthetic entity is then used as a counterfactual to identify a causal effect of some intervention. In my case the aggregated unit is the Netherlands and the purpose of using the SCM is to create a synthetic version of this country to estimate the causal effect of the Dutch disease on an outcome variable.

The synthetic control unit is created using a set of  $J$  entities of the same type. Abadie et al. (2010) refers to this set of units as the donor pool, and I will stick with their terminology. In my case the donor pool will consist of 18 other OECD countries. The data for the 19 countries will be observed over  $T$  periods of time, where country  $i = 1$  is the Netherlands. Using the potential outcome framework, the two potential outcomes can be denoted as  $Y_{1,t}^I$  and  $Y_{1,t}^N$  where  $I$  denotes the treated outcome and  $N$  denotes the non-treated outcome. Setting the time of treatment to be  $t = T_0$ , the observed outcome may be written as

$$Y_{1,t} = Y_{1,t}^N + \alpha_{1,t}D_{1,t} \quad D_{1,t} = \begin{cases} 1 & \text{if } t \geq T_0 \\ 0 & \text{if } t < T_0 \end{cases}$$

$\alpha_{1,t}$  is the effect of the Dutch disease on the outcome variables and is defined as  $\alpha_{1,t} = Y_{1,t}^I - Y_{1,t}^N$ . My goal is to estimate this effect for  $t = T_0, T_0 + 1, \dots, T_0 + k$ , but to do so requires an estimate of the non-treated

outcomes  $Y_{1,t}^N$  for the post-treatment period. Suppose that  $Y_{i,t}^N$  is given by the following factor model

$$Y_{i,t}^N = \delta_t + \theta_t Z_i + \lambda_t \mu_i + \varepsilon_{i,t}$$

In this model,  $Z_i$  is a vector of observed covariates. These covariates are predictors of the outcome variable that we may observe and assign values to.  $\lambda_t$  is a vector of unobserved common factors.  $\theta_t$  and  $\mu_i$  are vectors of unobserved parameters and factor loadings, while  $\delta_t$  is a vector of unobserved common factors that are constant across units and  $\varepsilon_{it}$  are transitory unobserved shocks assumed to have a mean of zero. The troublesome part of this equation is  $\lambda_t \mu_i$ , as this constitutes a matrix of unobservable and possibly confounding factors that may bias any results obtained through least squares estimation strategy.

The SCM avoids this problem by utilizing a set of weights

$$W = (w_2, w_3, \dots, w_{J+1}) \quad \text{where} \quad \begin{cases} w_j \geq 0 \quad \forall j \\ \sum_{j=2}^{J+1} w_j = 1 \end{cases}$$

Abadie et al. 2010 show that if there exists a set of these weights  $W^* = (w_2^*, w_3^*, \dots, w_{J+1}^*)$  such that

$$\sum_{j=2}^{J+1} w_j^* Y_{j,1} = Y_{1,1}, \quad \sum_{j=2}^{J+1} w_j^* Y_{j,1} = Y_{1,2}, \quad \dots, \quad \sum_{j=2}^{J+1} w_j^* Y_{j,T_0} = Y_{1,T_0}, \quad \sum_{j=2}^{J+1} w_j^* Z_j = Z_1, \quad (1)$$

then the treatment effect can be estimated using

$$\hat{a}_{1,t} = Y_{1,t} - \sum_{j=2}^{J+1} w_j^* Y_{j,t}$$

as an estimator. There will most likely not exist a set of weights such that equation 1 holds exactly. However, it may hold approximately, meaning the estimator also approximates the true causal effect. Moreover, the

discrepancy between equation 1 holding and failing is measurable. I may therefore evaluate these discrepancies and determine whether the estimates of the treatment effect are valid or not.

## 4.1 Outcome variables, predictors and treatment period

The results in this model will depend on what variables and what time periods I choose to include. I will therefore elaborate on these choices here.

My outcome variables will be GDP per capita and GDP per person employed, depending on whether I am analysing the welfare effects of the Dutch disease or the effects on productivity. The main interest of this paper is to calculate the cost of the Dutch disease. I will define this cost according to the Hicks-Kaldor efficiency criterion. This implies that the cost of the Dutch disease will only be a cost if it outweighs the benefits from the gas extraction. Defining a cost in this way means I implicitly disregard all distributive effects of the Dutch disease as long as society has a theoretical possibility of redistributing the gains and compensate anyone who may suffer from the effects of the Dutch disease. To measure this type of cost, the most obvious choice is to use GDP per capita. If the Dutch disease reduces GDP per capita, this will be a cost according to the Hicks-Kaldor criterion. If, however, GDP per capita remains unchanged, redistribution is theoretically possible and there is no cost to society.

All theoretical models that predict a negative effect on growth from the Dutch disease hinge on the assumptions of productivity externalities. It may therefore be of great interest to study the effects of the Dutch disease on productivity. There are several ways of measuring productivity<sup>14</sup>, and both time limitations and data availability prevent me from using all of them. I choose to measure productivity as GDP per person employed. I have also used GDP per hour worked as a robustness check, but the results are more

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<sup>14</sup>For a thorough discussion of productivity measures and measurement I refer to OECD (2001)

or less the same for both variables, so I will only report the results for GDP per person employed. This measure of productivity has the advantage of being easy to obtain for the time period and countries I have chosen. The disadvantage is that it is an imperfect measure of LBD-effects. Increased productivity in terms of GDP per person employed may just as well reflect a change in the capital stock or a host of other factors (OECD 2001).

The predictors I choose are standard predictors found in the growth literature such as capital investments, trade openness, level of education and demographic composition. The predictor vector is the set of observable economic factors that determine GDP per capita or GDP per person employed. In the literature on economic growth, the variables listed above are often considered to be important determinants of growth and output (Barro and Sala-i-Martin 2004). Since this is a study of the Dutch disease, I have also included government consumption and productivity measured as GDP per hour worked, them being important determinants of the disease. The predictors and a short description of them are listed in table 1.

Predictor Name	Predictor Description
capshare	Capital stock as a percentage share of GDP
govconssshare	Government consumption as a share of GDP
humcapindex	Index of Human capital
inflation	Percentage change in CPI
investrate	Percentage growth rate of capital stock
labourshare	Labour as share of production input
labprohour	GDP per hour worked
tradeopen	Traded Merchandise as share of GDP
youthshare	Percent of population aged 5-29

Table 1: The variables used in the predictor vector  $Z$  for the GDP models. When Productivity is used as the outcome variable, GDP per capita is used as a predictor instead of GDP per hour worked

A thorough description of the variables and their data sources are given

in appendix A. In addition to the variables mentioned above I have used several others to check the robustness of the results. These variables and their sources are also listed in appendix A, and the inclusion of these does not alter the results significantly. My predictor variables will all be series of data points, but the SCM routine needs specific values to create the weights. I have therefore chosen to average each predictor variable using the 12 years just prior to the treatment period. These averages will then constitute the predictor vector.

The greatest challenge when identifying the effects of the Dutch disease using the SCM is that there is no specific date that one for certain can say is the day that the Netherlands contracted the Dutch disease. There also seems to be some disagreement in the literature on the matter. While some claim that the effects of the Dutch disease were apparent in the 1970s (The Economist (1977), Neary (1982)), others maintain that the most severe effects of the disease started to appear in the 1980s (Hansen 2001). I choose to focus on two distinctive years, 1970 and 1979. The reason for choosing these years specifically is partly because they are at the start of each decade of interest and partly because they distinguished themselves in the discussion of the symptoms in section 3. Another alternative I explore for finding possible treatment periods is to run the model iteratively, changing the treatment year for every iteration, through the whole time period in question. I will come back to this iteration method in the placebo test sections below.

Given the two candidate treatment periods and the two outcome variables, I will estimate four series of treatment effects:

$$\hat{a}_{1,t}^1 = GDP_{1,t} - \sum_{j=2}^{19} w_j^* GDP_{j,t}, \quad \forall t = 1970, 1971, \dots, 1980 \quad (2)$$

$$\hat{a}_{1,t}^2 = GDP_{1,t} - \sum_{j=2}^{19} w_j^* GDP_{j,t}, \quad \forall t = 1979, 1980, \dots, 1989 \quad (3)$$

$$\hat{a}_{1,t}^3 = Prod_{1,t} - \sum_{j=2}^{19} w_j^* Prod_{j,t}, \quad \forall t = 1970, 1971, \dots, 1980 \quad (4)$$

$$\hat{a}_{1,t}^4 = Prod_{1,t} - \sum_{j=2}^{19} w_j^* Prod_{j,t}, \quad \forall t = 1979, 1980, \dots, 1989 \quad (5)$$

The predictions above could in theory be made for any length of time after the treatment period, but extending it for too long would be problematic. The SCM depends on a set of countries chosen from the donor pool, this means that any shock to GDP or productivity in these countries will carry over to the synthetic counterfactual. If these shocks are country specific, that is, the shocks would not have affected the Netherlands, they will cause biased estimation results. Large shocks can be identified and controlled for, but small shocks are unavoidable and hard to identify. Small shocks will not create a large bias, but the effect of these small shocks will accumulate over time, increasing the potential bias in later periods. I have therefore chosen to restrict my estimates to a 10 years after the treatment year, meaning  $k = 10$ . Ten years is the same length used in Abadie et al. (2014), and seems reasonable here as well.

## 5 Data

The data used in this thesis has been gathered from a great variety of sources.<sup>15</sup> A complete list of all variables in the data set and their sources is given in appendix A. Not all variables were included in the final analysis, but I have used all of them when checking the robustness of my model. The data set is a panel of annual observations from 1946 to 2010 for 23 OECD

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<sup>15</sup>Given the large time period, number of variables and many countries needed for the synthetic control method to give proper estimates, the data collection has been a large part of the effort towards finalizing this thesis. No pre-existing data set was available that satisfied my needs, meaning I have had to dig through enormous amount of source material, both digital files and books, to gather the necessary data. After the data collection, several weeks were needed to code my model in Stata. The synthetic control routine is a downloadable package, but it has been developed recently, and many of the placebo tests are not included, meaning I have had to code most of them manually.

countries. The choice of countries was made partly in consideration of data availability, but mainly based on their similarity to the Netherlands. Due to lacking observations for some variables in some periods I have decided to exclude both Mexico and South Korea from the analysis. The years 1946-1949 were also excluded for the same reason for all remaining countries. Since the synthetic control method will rely on a sub sample of these 23 countries, the results will be biased if any of them have contracted the Dutch disease and is then used as a weight. To avoid this I remove both Norway and the United Kingdom, as they are both candidates for the Dutch disease in the period 1970-1990. I use the name Germany when referring to this country, but all data from before the reunification in 1990 is from West Germany.

Finding consistent sources of data that stretches over the whole period and incorporates enough relevant countries to form a reliable donor pool has been a challenge. I have therefore had to intermix values from different sources to fill gaps in the series. This "gap-filling" is described in the Appendix, but absolute measurement consistency over time cannot be expected from this data set. The problems this causes is however limited due to the way the synthetic control method works. The main outcome variables are both gathered from complete and consistent panels, meaning no gaps had to be filled. The predictors are not all gathered from complete time series, but since they are only used as 12 year averages, any discrepancies in their measurement is likely to be too small to matter. Evidence towards this claim is found by the many robustness checks I have performed, since the results are not very sensitive to changes in the predictor vector.

## 6 Results

The main question of interest in this thesis is to measure the cost of the Dutch disease, so I will start by examining the effects on GDP per capita. Furthermore, the main assumption underlying any negative effects on the economy is that productivity is endogenous and linked to the manufacturing

sector. I will therefore study the effects on labour productivity measured as GDP per person employed.

## **6.1 Effects on GDP per capita - The cost of the Dutch disease**

As discussed in section 4.1, the cost of the Dutch disease will only be a proper cost in the economic sense if it has any effect on GDP per capita. I have estimated this effect under the assumption that the Dutch disease was contracted either in 1970 or 1979. To evaluate the validity of the estimated results I will also employ some inference techniques suggested by Abadie et al. (2010).

### **6.1.1 1970 GDP model**

The estimated cost of the Dutch disease is given in figure 8. The outcome for the synthetic control is given by the dashed line, and the treatment year is marked by a solid vertical line. The graphs suggest that if the disease was contracted in 1970, it has had no discernible effect on GDP per capita for the period 1970-1980. Given the large amount of sources claiming that the Dutch economy suffered from a severe Dutch disease in this decade, this result is rather surprising. One particularly interesting result is that the modest recession in 1973-75 is perfectly captured by the synthetic control, leading me to believe that this was caused by the international oil crisis, rather than being related to the extraction of natural gas.

There are several sources of bias in this model, and I will address them systematically. As stated in section 4, the main assumption for unbiased estimators are given in equation 1. From figure 8 I see that the synthetic and actual outcomes of GDP are more or less identical. The predictors, given by the  $Z$  vector, also need to be equal for the actual and synthetic versions of the Netherlands. The actual and estimated predictors are given by table 2. As mentioned in section 4.1, these predictors are 12 year averages. The

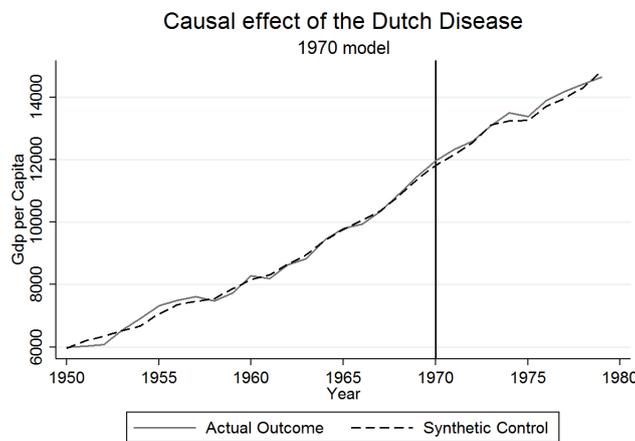


Figure 8: Causal effect of the Dutch Disease on GDP per capita in 1970. Estimation of equation 2

predictor inflation in table 2 will therefore be average inflation between 1957 and 1969. While the predictors in the actual and synthetic Netherlands are not identical, they seem to be close enough to avoid causing a bias in the estimated results. The only predictor that is not closely matched by the synthetic control is *tradeopen*. I do not believe this to cause any problems in this model, but will discuss the explanation for the discrepancy and the problems this may cause to the 1979 model below.

While the main assumption seems to be satisfied, there are other sources of bias. The weights are constructed using pre-treatment data, and for these weights to continue to yield unbiased estimates of the counterfactual outcome there cannot occur country-specific shocks to GDP per capita in the countries selected for the synthetic control. An example might illustrate this point better. Assume that Belgium has been chosen as a synthetic control with a weight of 0.6. Further assume that the Belgian economy suffer a negative shock that is confined to Belgium, that is, the shock does not affect other countries and most importantly, does not affect the Netherlands. Given the weight of 0.6, this shock would cause negative bias in the synthetic control at the magnitude of 60 % of the original shock. The severity of such biases

	Actual	Synthetic
capshare	232.21225	230.9495
govconsshare	.17074895	.11813547
humcapindex	2.3099846	2.516148
inflation	3.3212945	2.5843887
investrate	6.2440916	5.8543694
labourshare	.7107	.7097463
labprodhour	11.371661	10.838507
tradeopen	.91772874	.28564217
youthshare	41.946171	41.039872

Table 2: Predictor balance in the 1970 GDP model

depends on the size of the country specific shock and the size that country's assigned weight in the synthetic control. Small shocks or a small weight will lead to a small bias, while large shocks or a large weight may cause a large bias. There is no formal way of examining these biases, so to control for them I will have to find economic events specific to the countries in the weight pool for the period 1970-1980 and assess the combined importance of these events and the weight assigned to each country.

The weights chosen by the estimation procedure is given in the first column of table B6 in the appendix. Five countries have been chosen, and Australia, Canada, Germany and Japan are the most important with weights at approximately 0.3, 0.25, 0.23 and 0.13 respectively. Switzerland is also included, but weighted below 0.1, and any shock specific to the Swiss economy will therefore carry little effect over to the synthetic Netherlands. Determining what types of events should be considered large enough to bias my estimate is difficult. I have therefore studied the period 1970-1980 extensively for these countries. The only event large enough to consider during this period in these countries is the summer Olympics in Canada held in 1976. The effect of hosting the summer Olympics has been studied by sev-

eral articles<sup>16</sup> and they seem to indicate some positive effect on the GDP of the host country. These effects are on the other hand rather small, and considering that Canada only constitutes 25% of the synthetic control, the potential bias from the summer Olympics will be trivial. Canada has some petroleum production, but since this production accounts for such a small portion of the economy, and since I have not found any reference to Dutch disease effects in Canada for this period, I will ignore this and trust the estimates obtained with the aforementioned weights.

### 6.1.2 1979 GDP model

As mentioned in section 4.1, I will also construct a synthetic control under the assumption that the Dutch disease was contracted in 1979. In contrast to the 1970 model, there seems to be a negative effect of the disease in this model. The dashed line of the synthetic Netherlands in figure 9 seems to follow the trend from before 1979, while the actual Netherlands suffered from a mild recession. This negative causal effect is in line with the predictions from the theory of endogenous productivity and booming sector models, but before jumping to conclusions there are some issues to address.

Since the actual date when the Netherlands contracted the Dutch disease is unknown, the effect I have found here might be the result of some other event that happened in 1979. An obvious candidate for such an event is the oil crisis of 1979. The Iranian revolution and the following Iran-Iraq war led to a sharp reduction in oil production, which again drove up the oil price. Oil price changes are of course events that affect all countries, but an argument has been made that small, open and trade dependent economies such as the Netherlands were hit particularly hard. The reason for this is that the oil crisis of 1979 led to a large decrease in world trade activities due to higher fuel costs, an activity the Dutch economy is very dependent of. The results from the 1979 GDP model is given by figure 9. The effect here is clearly visible, and amounts to approximately USD -1 150 in 1989, which

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<sup>16</sup>For a summary of these studies, see Zhang and Zhao (2007)

is a reduction in GDP per capita of almost 7%.

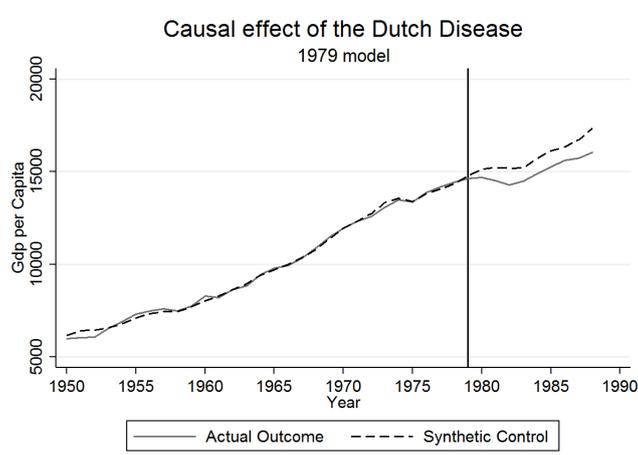


Figure 9: Causal effect of the Dutch Disease on GDP per capita in 1979

I have included a variable for trade-openness in my predictors, so the synthetic control should capture the vulnerability to reduced trade. However, as can be seen from table 3, the trade variable *tradeopen* is not very well replicated in the synthetic control. This means that the GDP reduction from reduced trade may not be properly captured in the counterfactual outcome, and the estimated effect may just be the recession caused by reduced world trade after the oil crisis. The reason for the poor match between the synthetic and actual trade predictor may be the restriction put on the weights in the optimization routine (Abadie et al. 2010). Since none of the  $J$  weights may be larger than one, it will be impossible to replicate a predictor if the actual value of that predictor is one of the largest in the donor pool. If the Netherlands is the most open economy, meaning it has the largest value for the variable *tradeopen*, no linear combination of other countries may replicate this value as long as the weights are restricted to be less than or equal to one.

The weights chosen by this model are given in column 2 of table B6. The synthetic control mainly consists of Australia, Belgium, France, Japan and Switzerland, with weights 0.23, 0.303, 0.131, 0.11 and 0.137 respectively. While both Canada and United states are also weighted positively, these

	Actual	Synthetic
capshare	254.71585	253.23315
govconsshare	.15720555	.13654159
humcapindex	2.6272846	2.6269361
inflation	6.6538462	6.6872538
investrate	5.6322151	5.0633981
labourshare	.7107	.6825023
labprohour	16.882759	15.135254
tradeopen	.92605954	.55101329
youthshare	42.86915	40.415854

Table 3: Predictor balance in the 1979 GDP model

weights are so small that any shock to these countries will carry very small effects onto the synthetic control, meaning they will lead to very small biases. I therefore ignore these countries here. I have been unable to identify any shocks to these countries that would not have affected the Netherlands in the period 1979-1990.

### 6.1.3 Placebo tests

Abadie et al. 2010 suggest a number of inference techniques to validate the results of the synthetic control method. The first, the time placebo test, is of particular interest, since the treatment period is difficult to set. The time-placebo test is done by changing the treatment period to a date before treatment actually takes place. If the model is able to construct a proper counterfactual, changing the treatment period should not change the period in which the treatment effect occurs. Put differently, if the treatment effect is found at any random treatment period before the intervention, then the effect is spurious and should not be interpreted as the actual causal effect of the treatment. The results of the time-placebo is given in figure 10. Here I have graphed the difference between the actual and the synthetic outcomes of GDP per capita, meaning a negative value on the graph indicates a negative

effect of the Dutch disease on GDP per capita. The solid black line is the 1970 model, while the dashed line is the 1979 model. The grey lines are the causal effects from the model when the treatment period is changed iteratively from 1965 to 1980, meaning one grey line indicates the results when the treatment period is set to 1965, another when the treatment period is set to 1966 and so on for every year up to 1980.

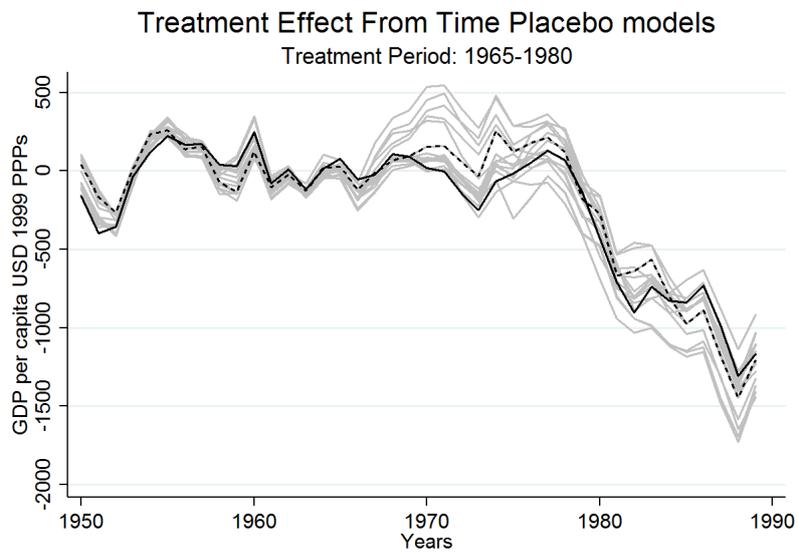


Figure 10: Time Placebo iterations of the GDP model, changing the treatment period iteratively from 1965-1980

From the figure it is evident that changing the treatment period does little for the resulting causal effect. I find no significant effect during the 1970s for any treatment period before or during that decade, but all treatment periods lead to a drop in GDP per capita in 1979. This means the model is robust to changes in the treatment period, which speaks in favour of the reliability of my results.

Another inference technique is to conduct what Abadie et al. (2010) call a space-placebo test. This means changing the treated unit, i.e. country, iteratively for the whole donor pool and compare the effects with the one found for the Netherlands. If the effect found in the Netherlands is well inside

the interval of effects found in the other countries that have not contracted the Dutch disease, then the effect I have found is likely to be insignificant or spurious. The results from the 1970 and 1979 models are given in figure 11 and 12 respectively. Once again these figures display the difference between the actual and the synthetic outcome of GDP per capita. The black line is the causal effect in the Netherlands, while the grey lines are the effect on the countries in the donor pool. Following Abadie et al. 2010 I have removed all countries with a pre-treatment RMSPE twice as large as that of the Netherlands. RMSPE<sup>17</sup> is the average deviation between the synthetic outcome and the actual outcome. If this deviation is large during the pre-treatment period, the assumptions outlined in equation 1 will be violated and the estimates are invalid. Removing all results with a RMPSE larger than twice that of the Netherlands will ensure I only compare valid estimates<sup>18</sup>.

The space-placebo test for the 1970 model further confirms the conclusion that the Dutch disease has had no significant effect on GDP per capita. The effect found in the Netherlands is negligible compared to the effect found in the placebo countries.

For the 1979 model the results are more interesting. The black line indicating the Netherlands is on the lower extremity of the effect distribution. Without any formal significance test it is difficult to assess if this effect is large enough to be significant. While a formal test for this does not exist, I may approximate such a test by using RMSPE ratios. The RMSPE ratio is defined as the post treatment RMSPE divided by the pre treatment RMSPE, or more formally

$$RMSPE_{ratio} = \frac{RMSPE_{t>T_0}}{RMSPE_{t\leq T_0}} \quad (6)$$

Comparing the RMSPE ratio for all the countries in the donor pool will

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<sup>17</sup>The Root Mean Square (Prediction) Error is a measure of deviation between a predicted time series and the actual values of the same series, given by  $RMSPE = \sqrt{\frac{\sum_{t=1}^n (Y_t - \hat{Y}_t)^2}{n}}$ . The formula for this statistic is available from any book on time series analysis.

<sup>18</sup>This process is discussed in detail in Abadie et al. (2010)

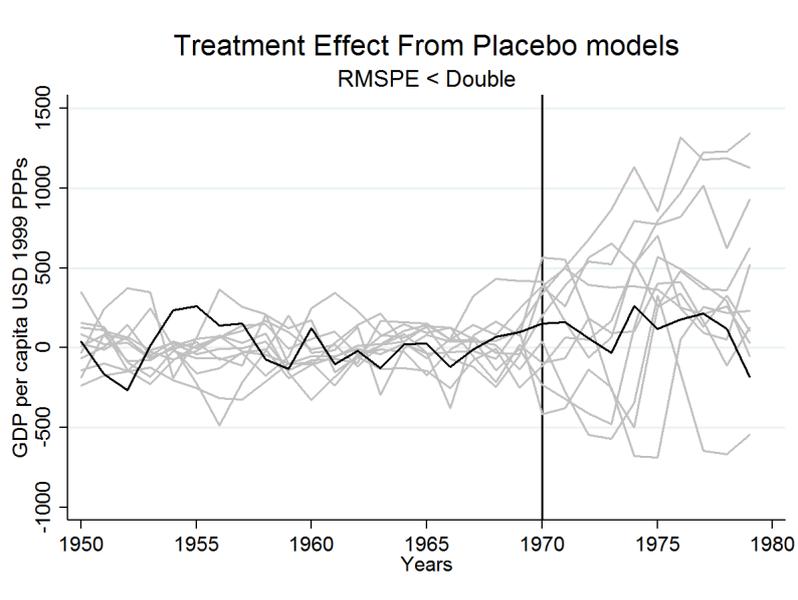


Figure 11: Placebo iterations of the 1970 GDP model, running on all countries in the donor pool. Pre-treatment RMSPE less than 200% of the Netherlands

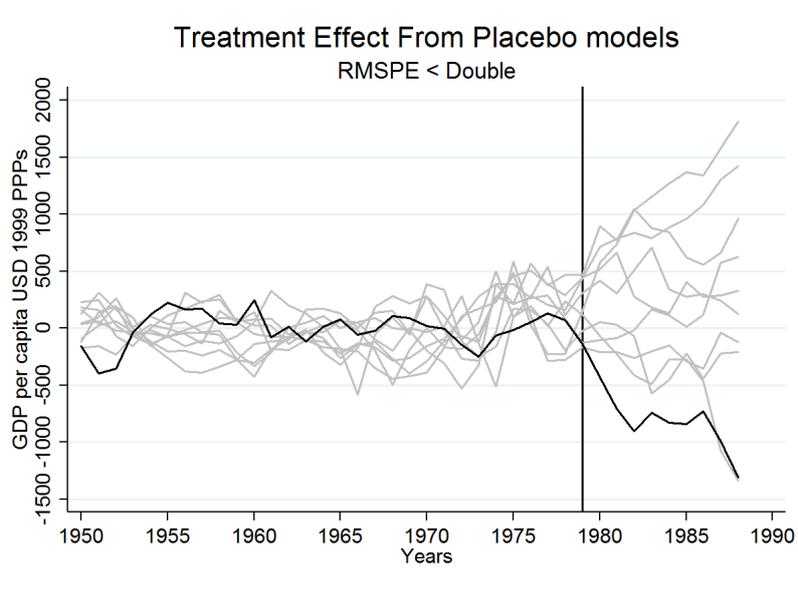


Figure 12: Placebo iterations of the 1979 GDP model, running on all countries in the donor pool. Pre-treatment RMSPE less than 200% of the Netherlands

tell me whether the effect of the treatment is large relative to the goodness of fit of the synthetic control. The advantage of this test compared to the space placebo is that I do not need to assign any a priori cut off point for the pre treatment RMSPE when choosing which placebo countries have a good enough fit of their synthetic control.

The RMSPE ratios are plotted in figure B18 and B19. The 1970 RMSPE ratio for the Netherlands is one of the smallest in the whole placebo sample, further affirming the conclusion that the Dutch disease had no effect on GDP per capita in the 1970s. For the 1979 model the space placebo test was somewhat inconclusive, but the RMSPE ratio gives some evidence towards rejecting the effect I have found. The Netherlands has the second highest RMPSE ratio in the sample, a little behind Finland, and 3 other countries have ratios of almost the same magnitude. The fact that 4 out of 19 countries have almost the same RMSPE ratios means that the effect found for the Netherlands should be interpreted with caution.

## **6.2 Effects on productivity - The size of externalities**

While the main purpose of this thesis is to study the cost of the Dutch disease and therefore the effect on GDP per capita, it is also of interest to estimate the effect it may have had on productivity. As discussed earlier in this paper, the main channel through which the Dutch disease can lead to a cost is reduced productivity. I have not yet found solid evidence of any cost by studying GDP directly, so to check the robustness of these findings it may be fruitful to study the effect on productivity. The results will be reported in the same way as I have for GDP and I will use the same inference techniques as above.

### **6.2.1 1970 productivity model**

The results from the 1970 productivity model are given in figure 13. The rather surprising results show that the Dutch disease may have contributed to an increase in GDP per person employed of 2200 USD in 1979, an increase

in productivity of almost 6.3%. This result is the opposite of what is expected according to the theories of the Dutch disease, but will of course need to be checked for potential biases and significance.

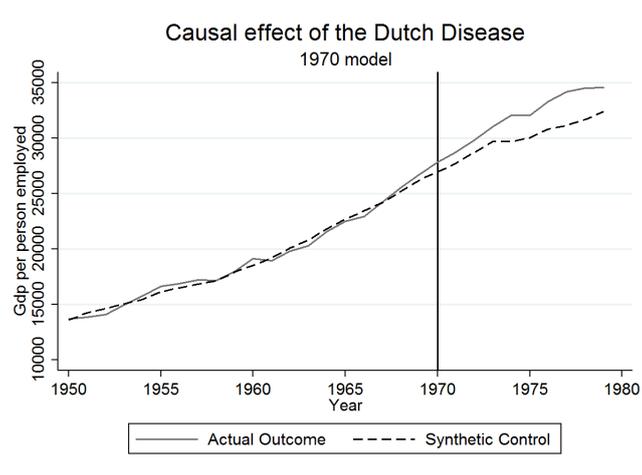


Figure 13: Causal effect of the Dutch Disease on GDP per person employed in 1970

The predictors are given in table 4, and the synthetic predictors are quite close to the actual predictors. The only problematic predictor is once again the variable for trade openness, but since removing this does little to alter the results I conclude that the predictors are close enough.

As it was with the GDD results, checking for shocks to the weight countries is necessary to avoid potential biases. The weights are given in column 3 in table B6. The synthetic control consists of Japan, Sweden and the United States with weights 0.239, 0.22 and 0.233 respectively. Australia, Canada, Finland and Germany is also used, but with weights smaller than 0.1. Since I have been unable to find any economic event large enough to significantly alter the GDP per capita in these countries I have no reason to believe these results are biased.

	Actual	Synthetic
capshare	232.21225	232.35187
gdppcPPP	9127.7661	9038.4767
govconsshare	.17074895	.15674979
humcapindex	2.3099846	2.5273066
inflation	3.3212945	3.3252379
investrate	6.2440916	6.2467601
labourshare	.7107	.66760836
tradeopen	.91772874	.28682334
youthshare	41.946171	41.142124

Table 4: Predictor balance in the 1970 productivity model

### 6.2.2 1979 productivity model

Results from the 1979 productivity model are reported in figure 14. This result is quite similar to the results in the 1979 GDP model and the effect seems substantial. The treatment effect is close to -4100 USD in 1989, which amounts to a decrease in labour productivity of almost 11%. The productivity measure GDP per person employed shares much in common with GDP per capita, and the potential causality problems found in the discussion of the 1979 oil crisis effect will apply here as well.

From table 5 it is evident that for the first time the trade-predictor, along with all the others, is replicated well by the synthetic control. This means the argument for these results being caused by reduced world trade is severely weakened, as any such effect should also affect the synthetic control to the same degree as the actual Netherlands.

The weights for this model is given by column 4 in table B6. The synthetic control is mostly made up of Belgium and Switzerland with weights 0.731 and 0.171. Finland, Japan and Sweden is also chosen, but with weights too small to cause any sizeable bias. Again I find no economic events large enough to cause any bias to this result.

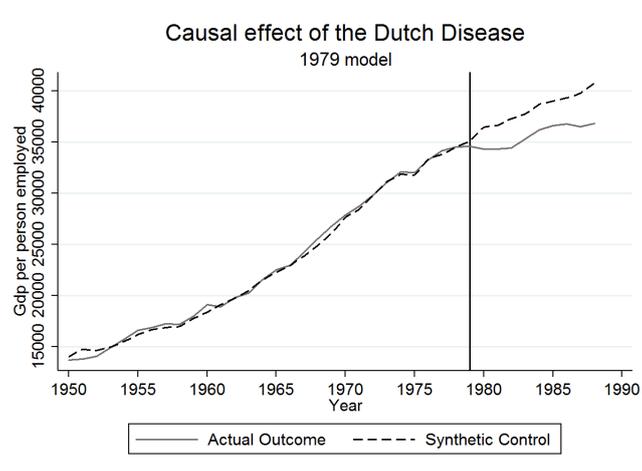


Figure 14: Causal effect of the Dutch Disease on GDP per person employed in 1979

	Actual	Synthetic
capshare	254.71585	241.23931
gdppcPPP	12458.108	12268.088
govconsshare	.15720555	.15603874
humcapindex	2.6272846	2.558012
inflation	6.6538462	6.0809077
investrate	5.6322151	4.5991549
labourshare	.7107	.64344115
tradeopen	.92605954	.91085732
youthshare	42.86915	37.938795

Table 5: Predictor balance in the 1979 productivity model

### 6.2.3 Placebo tests

As with the GDP model, I need to run placebo tests to determine whether my results are spurious or not. The time placebo test is given in figure 15. The choice of treatment period clearly matters in this case and there seems to be two patterns emerging from the different treatment periods. Setting the treatment period to any year between 1965 and 1970 gives a positive effect on productivity as was found in the 1970 model, while setting the period to any year from 1971 to 1980 gives the same results as was found in the 1979 model.

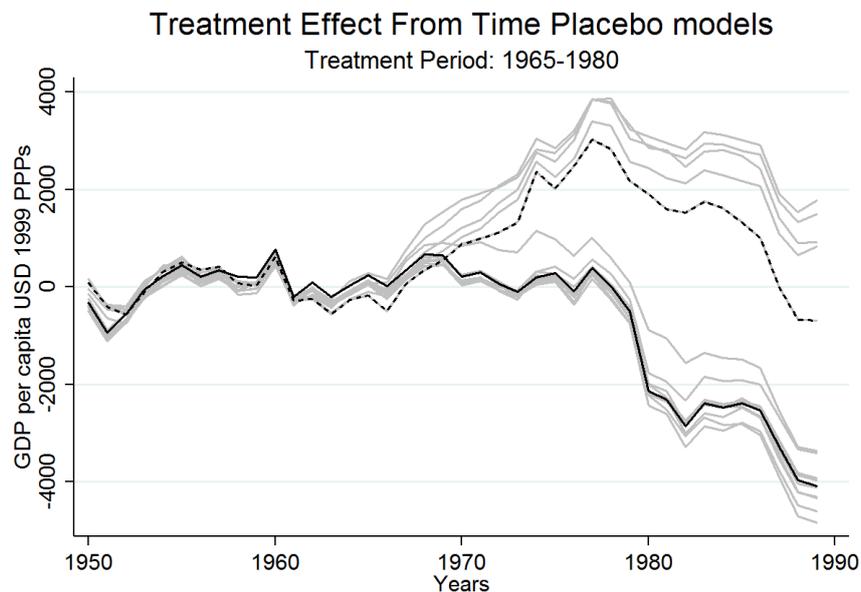


Figure 15: Time Placebo iterations of the model, changing the treatment period iteratively from 1965-1980 for the Netherlands

The results from the space placebo test on the 1970 model are given in figure 16. The effect I found was positive, but it is by no means largely different from the effect I found in the placebo countries. The effect is therefore not likely to be significant, and looking at the RMSPE ratios in figure B20 confirms this. The ratio for the Netherlands is well inside the distribution

of the ratios and I will therefore conclude that there is no evidence of the Dutch disease having any effect on productivity during the 1970s.

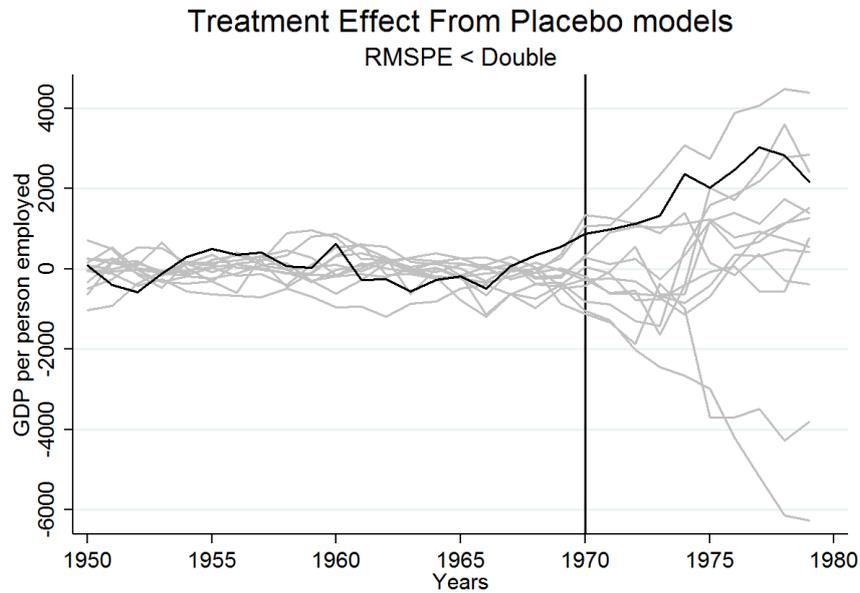


Figure 16: Placebo iterations of the 1970 productivity model, running on all countries in the donor pool. Pre-treatment RMSPE less than 200 percent of the Netherlands

In the 1979 productivity model I found a large negative effect, but, as shown in figure 17, the effect is on the edge of the placebo distribution. The RMSPE ratios for this space placebo tells the same story. The Netherlands has the second largest RMSPE ratio after Belgium, closely followed by Spain. 3 out of 19 countries have more or less identical RMSPE ratios, meaning I cannot conclude that there is any causal effect of the Dutch disease on the Netherlands.

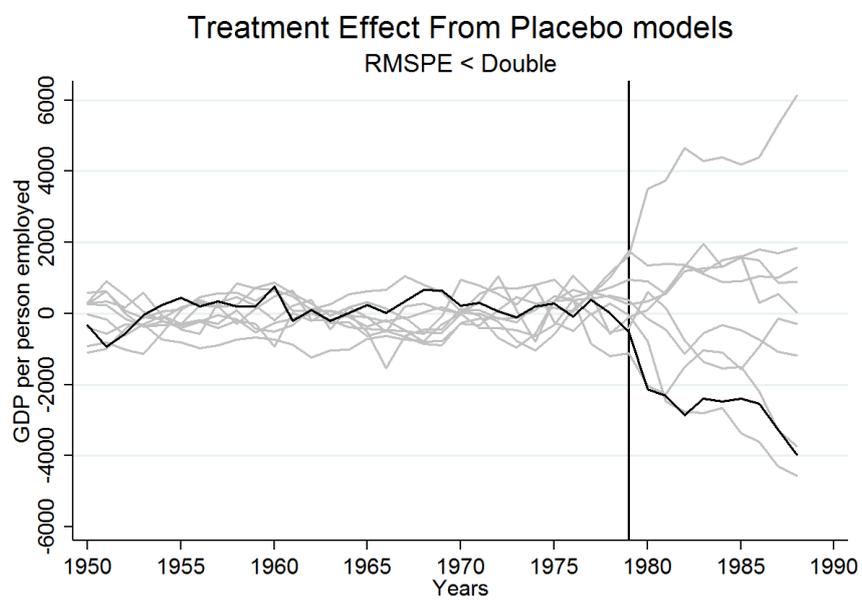


Figure 17: Placebo iterations of the 1979 productivity model, running on all countries in the donor pool. Pre-treatment RMSPE less than 200 percent of the Netherlands

## 7 Conclusions

Contracting the Dutch disease has been a concern for countries discovering natural resources or receiving foreign exchange gifts since the troubles of the Dutch economy in the 1970s and 1980s. Using the Synthetic control method as an empirical strategy, this thesis shows how these concerns might have been exaggerated

Assuming that the Dutch disease was contracted by the Netherlands in 1970, I find no proof that this has had any effect on neither GDP per capita or labour productivity, the opposite of what most of the theoretical literature predicts. This leaves two possible conclusions.

First, it is possible that the Dutch manufacturing sector suffered severely from the discovery of gas, but this has no consequence for overall economic performance without the existence of externalities. The results I have found will then be evidence that these externalities do not prevail to the extent that losing them hurts the economy.

Secondly, the conclusion may be that the gas discoveries in the Netherlands did not hurt the Dutch manufacturing sector. The existence of the resource movement and spending effects has been confirmed in some cases in other countries, but I have not been able to find any studies of these effects in the Netherlands. Given the evidence found in other countries, this conclusion is less likely in my opinion, but a proper empirical study on the effect of the gas discovery on the manufacturing sector in the Netherlands is needed to draw a final conclusion and should be the focus of future research on the Dutch disease in the Netherlands.

Since there is no general agreement on the exact period of the Dutch disease, I have run the same analysis under the assumption that the Dutch disease was contracted in 1979. The results are not as clear cut as under the 1970 assumption. There seems to be a negative impulse to both GDP per capita and productivity in 1979, but the placebo tests I run show that this effect may just be spurious. The other problem with the possible effect is that it may be a result of the 1979 oil crisis, and not a consequence of any

Dutch disease. International trade has always been very important to the Netherlands, and the oil crisis led to a collapse in world trade. The results I have found may therefore very well be the effect of the oil crisis rather than the discovery of natural gas.

The policy implications of these findings are clear, but due to the lack of empirical analysis of the subject they should be treated with great care. Without any externalities, any argument for subsidies of the manufacturing sector is of course invalid. Furthermore, the role of sovereign wealth funds such as the Norwegian pension fund may need to be revised. In Norway, an important argument for the 4% budgetary rule is to protect the non-oil related manufacturing sector from exchange rate appreciations (Thøgersen et al. 2015). The downside of this activity is ineffective allocation of investments between the private and public sector. The results found in this thesis challenge this argument for foreign investments of sovereign wealth funds.

Lastly some objections to these results may be given on empirical grounds. The synthetic control method is relatively new, and there are as of yet no formal inference techniques available to validate any results formally. Another objection is that the Dutch disease is not an event which may easily be attributed to a specific date, meaning it is hard to determine whether any effect I find is actually caused by the Dutch disease. This objection is mitigated by the fact that I do not find any effect, so the method may be better at disproving the existence of the disease than proving it. It is also worth mentioning that many of the theoretical predictions concerning the cost of the Dutch disease are focused on the time after the natural resource has been fully extracted. The gas production in the Netherlands levelled out in the 1980s and has remained at this level since, so the downside of the discovery may yet come. The evidence in this thesis nevertheless suggest that the term Dutch disease may be a fallacy on two accounts. Either the positive externalities believed to exist in the manufacturing sector are non-existent, and the Dutch disease is no disease, or the Netherlands never contracted the Dutch disease, and the Dutch disease was never Dutch.

## Appendix A Data Sources

The annual data used in this thesis has been gathered from a variety of sources. The original data is gathered from 23 OECD countries for the period 1946-2010. In this thesis I have excluded the countries Mexico, South Korea, Norway and the United Kingdom and the period 1946-1949. A list of the variables used and their sources follows below. They are sorted based on their use in the thesis.

### A.1 Main outcome variables

When these variables are not the outcome variable they are used as predictors.

- GDP Per Capita (PPP 1990 USD). Source: The Maddison Project 2013 version, found at <http://www.ggdcc.net/maddison/maddison-project/home.htm>
- Labour Productivity per person. Measure of productivity, GDP per person employed. Measured in 1990 USD. Source: The Conference Board (2015)

### A.2 Predictor variables in the final model

Variables used as predictors in the final model used to generate all results in this thesis

- Capital Stock. Value of capital stock at constant national 2005 prices. Used to create Capital share and Investment rate variables. Source: Feenstra et al. (2015)
- Government consumption Share. Government consumption as a share of GDP. Source: Feenstra et al. (2015)

- Human Capital Index. Index of human capital based on average years of schooling. Source: Feenstra et al. (2015)
- Inflation (Percentage change in CPI). Source: The OECD database for consumer prices, available at [stats.oecd.org](http://stats.oecd.org). as the OECD database is not complete, I have supplemented the variable using B.R Mitchels book series on International Historical Statistics 1750-2005. (Mitchell 2005)
- Labour input cost share. Share of GDP spent on wage compensation. Source: Feenstra et al. (2015)
- Merchandise Imports/Exports. Imports and exports of Merchandise as percent of gdp. Source: Feenstra et al. (2015)
- Population, used to calculate share of population under 30 years of age. Source: The Original Maddison project, found at <http://www.ggdcc.net/maddison/oriindex.htm>
- Population Groups. Population age groups in five-year intervals for persons aged 5 – 29. Used to calculate share of population under 30 years of age. Source: OECD database, available at [stats.oecd.org](http://stats.oecd.org)
- Real GDP. Real GDP at constant national 2005 prices in millions 2005 USD. Used to create capital share variable. Source: Feenstra et al. (2015)

### A.3 Other variables

Variables used for robustness check in the models or used for other graphs and figures.

- Country Size. Country Area in square kilometres. Source: OECD database, available at [stats.oecd.org](http://stats.oecd.org)

- Industry Share variables, Agriculture, Manufacturing, Commerce and Transportation. Source: Mitchell (2005). Agricultural shares for the period 1971-2001 is gathered from the World Banks World Development Indicator dataset from september 2005. This is available at <http://data.worldbank.org/products/data-books/WDI-2005>
- Labour Productivity per hour. Measure of productivity, GDP per hour worked in. Measured in 1990 USD. Source: The Conference Board (2015)
- Persons Employed. Number of person employed. Source: Feenstra et al. (2015)
- Petroleum aggregate production. Data for petroleum production in Norway, converted into oil equivalents. Source: Statistics Norways Statbank table 09319, avialable at <https://www.ssb.no/statistikkbanken>
- Pupils in secondary schools. Number of pupils registered in secondary schools. Source: Mitchell (2005)
- Secondary degree percentage. Percentage of population aged 15-64 with a secondary degree or higher. Source: Barro and Lees data set on long-term educational attainment by country, available at [http://barrolee.com/data/oup\\_download\\_b.htm](http://barrolee.com/data/oup_download_b.htm)
- Sectoral compositions of the Dutch economy are valued added at constant 2005 prices in local currencies and was gathered from the 10 sector database. Timmer et al. (2014)
- Students in universities. Number of Students registered in universities. Source: Mitchell (2005)
- Tertiary degree percentage. Percentage of population aged 15-64 with a tertiary degree or higher. Source: Barro and Lees data set on long-term educational attainment by country, available at [http://barrolee.com/data/oup\\_download\\_b.htm](http://barrolee.com/data/oup_download_b.htm)

- Unemployment (Percentage of civilian workforce). Source: Mitchell 2005. Contains holes for several countries that i was unable to mend with other sources.
- Working Hours. Average number of yearly working hours per person. Source: Feenstra et al. (2015)

## Appendix B Figures and Tables

Figures and tables not placed in the text

	Donor Pool Weights			
	GDP per capita	GDP per capita	Productivity	Productivity
	1970	1979	1970	1979
Australia	.308	.23	.073	0
Austria	0	0	0	0
Belgium	0	.303	0	.731
Canada	.251	.083	.069	0
Denmark	0	0	0	0
Finland	0	0	.084	.007
France	0	.131	0	0
Germany	.229	0	.092	0
Greece	0	0	0	0
Ireland	0	0	0	0
Italy	0	0	0	0
Japan	.134	.11	.239	.061
New Zealand	0	0	0	0
Portugal	0	0	0	0
Spain	0	0	0	0
Sweden	0	0	.22	.031
Switzerland	.077	.137	0	.171
United States	0	.006	.233	0

Table B6: Weights chosen for the synthetic Netherlands - All models

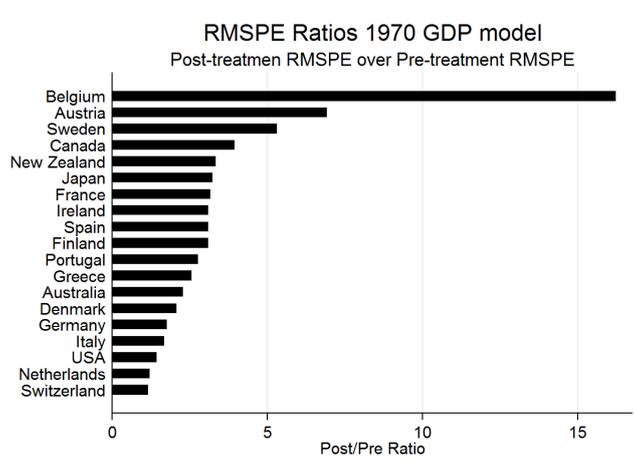


Figure B18: RMSPE ratio of all countries in the donor pool from the 1970 GDP model

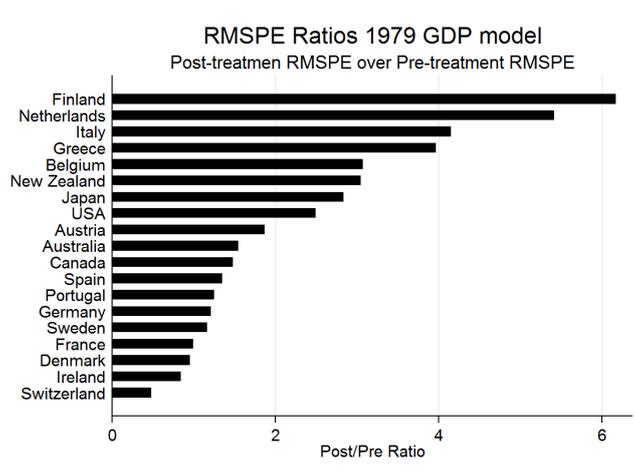


Figure B19: RMSPE ratio of all countries in the donor pool from the 1979 GDP model

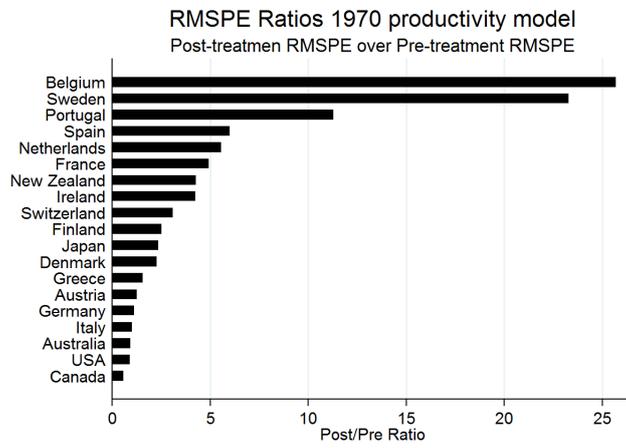


Figure B20: RMSPE ratio of all countries in the donor pool from the 1970 productivity model

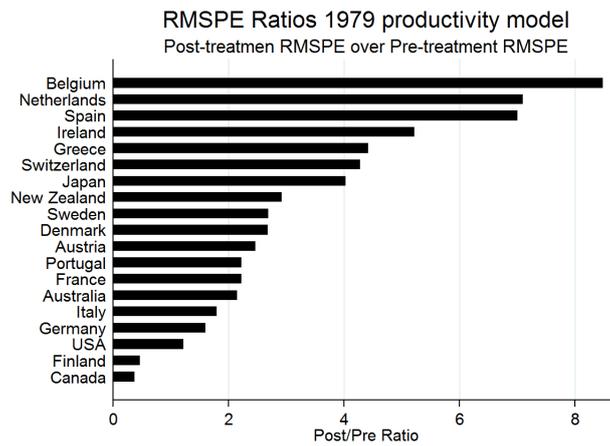


Figure B21: RMSPE ratio of all countries in the donor pool from the 1979 productivity model

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