# Beyond the Wealth of Nations: The Effect of Renewable Energy Policy in the Netherlands on Welfare in a Broad Sense

**Master Thesis**

Master Policy Economics

Erasmus University Rotterdam

Erasmus School of Economics

Author Hidde Schaap (447856)

Supervision by Gloria Moroni

Assessment by Dinand Webbink

**Abstract**

To assess the effect of renewable energy policy on welfare in the Netherlands, this thesis is composed as a diptych. First, the Monitor on Well-being, a unique instrument available in the Dutch setting, is reviewed. Strong associations between economic progress and well-being are inferred whereas inverse relationships with subjective evaluations and environmental quality become apparent. This follows from correlation coefficients, cluster analysis and principal component analysis. Second, a renewable energy subsidy scheme is evaluated and its effect is linked to welfare in a broad sense where government policy appears to have positively affected renewable energy production and induced economic growth, abated greenhouse gas emissions, contributed to a rise in employment and a fall in labor costs. This thesis presents an innovative and coherent assessment of welfare effects of government policy and contributes to the academic literature on the crossroads of the Beyond GDP debate and renewable energy policy.

## Section 1. Introduction

Over the past decades, gross domestic product (GDP) has been increasingly equated to welfare and societal progress. Although GDP is an arguably robust indicator for the measurement of economic activity in the present, it was never intended to measure welfare in a broad sense. Simon Kuznets (1934) warned for this equalizing tendency at its inception by stating that welfare cannot be inferred from an aggregate composition of economic activity. It spurred a wide and fierce debate on GDP, the characteristics of welfare and alternative instruments of measurement. More recently, the influential publication by Stiglitz et al. (2009) has intensified the study and measurement of welfare in a broad sense, defined as the quality of life in the present and the degree to which this affects future generations and communities abroad. The discussion became more popularly known as the debate on Beyond GDP where the OECD Better Life Initiative (OECD, 2011) and the UN Sustainable Development Goals (UN, 2016) are perhaps the most visible and established outcomes.

More recently, Statistics Netherlands, a frontrunner in advancing welfare statistics and the study of welfare in a broad sense, has developed the Monitor on Well-being and Sustainable Development Goals (henceforth the Monitor). This initiative, being the first full implementation of the CES Recommendations (UNECE/Eurostat/OECD, 2014), comprises a dashboard with a wide variety of carefully selected indicators that measure welfare in the dimensions “here and now” (i.e. factors contributing to welfare in the present), “later” (i.e. capital stocks available to future generations) and “elsewhere” (i.e. cross-border impacts of Dutch developments in welfare). Moreover, it maps progress towards the sustainable development goals (henceforth SDGs) with indicators relating to the availability of means and realisation of (perceived) outcomes (Statistics Netherlands, 2018; 2019; 2020). In other words, the Monitor provides a comprehensive overview of the state and development of various aspects of welfare in the Netherlands across temporal (i.e. for current and future generations) and spatial (i.e. within the Netherlands and abroad) dimensions. To illustrate, it contains information on well-being, health status, housing, social trust, physical safety and environmental quality, among others. Moreover, it measures capital stocks in economic, environmental, human and social terms even as monetary and resource flows between the Netherlands and other nations. With 66 indicators classified into 14 aspects across 3 dimensions, the Monitor provides a much richer perspective of welfare than one can infer from the System of National Accounts (SNA), serving as the foundation of GDP, alone.

However, despite the wealth of information and valuable insights provided, the impact of the Monitor (as well as other Beyond GDP intitiatives) has thus far been limited compared to GDP (Hoekstra, 2019). More generally, this can be attributed to limited tractability and lack of harmonization. Although a statistical account of individual trends in welfare in the Netherlands can be provided from the Monitor, a more complete portrayal of the relationships and associations between various aspects and dimensions of welfare are intricate and largely unexplored (Statistics Netherlands, 2018; 2019; 2020). Until now, this has not been subject to systematic mensuration and remains subsistently obscured. This also prohibits the evaluation of government policy on criteria of welfare (Horlings and Smits, 2019; Van de Ven, 2019; Hoekstra, 2019). This limits the relevance of the Monitor in public even as political debate and renders it less conducive to policy-making. A more complete conspectus and thorough understanding of the apparent associations and relationships would remedy these issues and allow academics and policy-makers alike to move beyond singular (economic) indicators in studying welfare and evaluating government policy.

This thesis aims to accommodate such an empirical assessment of associations and relationships between aspects and dimensions of welfare even as the evaluation of the impact of government policy. The Dutch setting provides scope for such an original dissertation. The Monitor can be utilized to extract and present a copious variety of associations. This serves as a bold and innovative attempt to demonstrate potential structural relationships between aspects and dimensions of welfare in the Dutch context. What is more, it is a vital exploration of this active area of research and constitutes a contribution to the advancement of the Beyond GDP debate. Moreover, the resulting insights can be utilized to subsequently analyse government policy on several criteria of welfare in a broad sense. A renewable energy subsidy scheme in the Netherlands serves as a prime example.

Due to the low emission intensity of renewable resources (such as wind, solar and water), renewable energy is widely regarded as an adequate means to reduce greenhouse gas emissions in energy production (Hill et al., 2006). Besides, the transition to renewable energy production is also believed (and advocated) to induce substantial welfare gains through potential increases in economic activity and employment, a more pristine and healthier environment even as a cleaner and more secure energy supply (Van der Ree et al., 2019). As a consequence, the government of the Netherlands has resided to incentivizing and promoting the use of renewable resources in energy production. Due to the potentially broader effects of renewable energy subsidies on welfare, it makes for an exemplary subject for the exploration of the impact of government policy on welfare in a broad sense.

To recapitulate, the associations and relationships between various aspects and dimensions of welfare even as how these are affected by government policy have not been subject to extensive empirical research to date. It remains largely unclear how various aspects and dimensions of welfare are associated, whether these are affected by government policy and, if so, by what magnitude. In other words, a more unified and cohesive approach combining these elements is lacking. Moreover, while empirical work has focussed on the U.S. or pan-European setting, focus on a country-specific case is rare. It remains ambiguous what effects identified in the literature persist in the Netherlands and, if they do, by what magnitude. Perhaps most importantly, the utilization of the Monitor is also a unique undertaking to harness a novel tool on welfare in a broad sense. The exploration constitutes a valuable addition to a largely undivulged area of research with both substantial social and scientific relevance. Finally, evaluating a particular type of government policy and linking this to welfare in a broad sense is a bold attempt to provide new insights and evaluate policy aimed at one particular goal on multiple dimensions, both temporaly and spatially. All in all, there is ample room to extend on and contribute to the active debate on Beyond GDP.

The objective of this thesis is to assess the effects of government policy in the Netherlands on welfare in a broad sense using the Monitor. Thereto, it evaluates a major renewable energy subsidy scheme on economic, environmental, labour market and social dimensions of welfare across temporal and spatial dimensions, empirically. The research question central to this thesis is, hence, the following:

*Research Question: What is the effect of renewable energy subsidies in the Netherlands on economic, environmental, labour market and social aspects of welfare across temporal and spatial dimensions?*

As follows from the above paragraphs, the central aim of this paper is, in essence, twofold. Thereto, this thesis is composed as a diptych. First, the associations between a wide variety of welfare indicators are evaluated. Pearson product-moment and Spearman rank correlation coefficients are employed to this end while cluster analysis allows for a more meticulous appraisal of associations between indicators as well as enhanced interpretation. Principal component analysis serves to effectuate data reduction for the purpose of tractability of the Monitor in subsequent inquiries. Second, the effect of renewable energy policy on welfare indicators in a broad sense is assessed using dynamic multivariate ordinary least squares regression even as instrumented regression techniques on a variety of outcome variables following from both satellite accounts, the SDGs and the Monitor.

The inquiry into the associations in the Monitor points towards the presence of strong statistical relationships between a wide variety of indicators. Moreover, within and across each dimension, there appears to be groups of similarly associated indicators, providing scope for cluster analysis and principal component analysis. A thorough review of the large number of associations shows that many indicators are strongly associated with economic progress, in general. These comprise indicators with positive associations related to material welfare, health, education, social trust, economic, human and social capital even as trade relationships. Subjective well-being appears to be strongly correlated with economic progress too. Subjective evaluations of employment, social contacts and housing even as environmental indicators tend to negatively relate to economic progress, however. These associations are persistent across types of correlation coefficients and clustering technique.

The assessment of the renewable energy subsidy scheme in the Netherlands provides evidence for a statistically significant impact on renewable energy production. The normal and instrumented regression equations suggest that an increase in subsidy payments by 1 percentage point results in an increase in renewable energy production by 0.334 percentage points. Moreover, subsidy payments also seem to positively affect measures of economic activity and employment, decreases labor costs and contributes to the abatement of greenhouse gas emissions in the energy sector, specifically. Regression on the principal components indicates a significant impact on renewable energy production, economic growth, imports (of raw materials and fossil fuels) and the accumulation of physical and knowledge capital. Moreover, nitrogen emission and nitrogen deposition seem to be limited whereas biodiversity on land appears to increase. Although the effects identified appear plausible and can be unified with economic intuition, caution must be exercised in the interpretation of the results. Limitations arise with respect to potential confounding factors, reverse causality and spurious regression. The findings in this thesis hopefully induce a further inquiry into the associations identified in the Monitor and new contributions to the Beyond GDP debate.

The rest of this thesis is constructed as follows. Literature that serves as the context and building blocks of the analysis is introduced in Section 2. The setting of a subsidy measure in the Netherlands is illustrated in Section 3. Section 4 describes the data and introduces the methodology. Section 5 contains a presentation of the results along with a discussion of the limitations and suggestions for future research. Section 6 concludes.

## Section 2. Literature Review

It is expedient to place this thesis in the appropriate context. As in the previous section, the debate on Beyond GDP takes a central position. Firstly, the shortcomings of GDP are discussed and, secondly, alternatives are highlighted. Thirdly, the Monitor is introduced in more detail. Literature on the effects of renewable energy policy (on welfare in a broad sense) and a set of hypotheses concludes. This section claims little innovation but provides a necessary foundation for discussions in subsequent sections.

### 2.1 Shortcomings of GDP

GDP is defined as the market value in monetary terms of all final goods and services produced in a country over a period of a year. As mentioned in Section 1, it is not intended to measure welfare but rather reflect the size of an economy or the scope of economic activity. Over the past decades, however, it has been persistently used as a synonym for "quality of life" implying it reflects much more than economic activity alone. Moreover, it is employed to judge the development and position of a nation in terms of welfare with respect to others. Before discussing alternative measures of welfare a brief account of the shortcomings of GDP as a measure of welfare is provided.[1]

A survey of the literature by Van den Berg (2009) is followed to reflect on the main issues relating to GDP as a measure of welfare. Firstly, in contrast to proper accounting rules, GDP measures on a cost basis without squaring accompanying benefits. To illustrate, expenditures to repair a broken window add to GDP without constituting a real welfare gain. Hoekstra (2019) adds to this by highlighting the importance of price, quantity and quality in quantifying GDP. As it is a market valuation in monetary terms, these three aspects crucially affect how it is calculated. For example, globalization and digitalization came in no small part with increases in product quality and free provision of services. Moreover, developed economies experienced a rapid expansion of government services over the past decades. All these aspects (arguably) improved welfare but are not (accurately) comprised by GDP. Besides, Aitken (2019) notes that the informal economy is substantial in many (developing) countries. However, is not included in the calculation of GDP.

[1] To emphasize, note that this is not a critique of GDP in itself (this is beyond the scope of this thesis). The shortcomings of GDP discussed in this section merely relate to its (mis)representation of the concept of welfare.

Secondly, GDP is a one-dimensional measure of economic activities performed in a certain country. Current levels and developments do not take into account effects on future generations, populations elsewhere in the world nor aspects such as inequality or environmental degradation while these are of importance to the welfare of individuals (i.e. it is a flow-based rather than a stock-based measure). Besides, GDP does not incorporate tipping points or limits to substitutability between goods and services, foregoing important dimensions of welfare. Finally, GDP has shown to be related to welfare to only a limited extent. For example, prominent publications by Easterlin (1974), Dolan et al. (2008) and, more recently, Gallardo-Albarrán (2019) highlight the disconnect between GDP and alternative measures of welfare.

### 2.2 Beyond GDP

Though informative, a full survey of alternatives to move Beyond GDP is outside the scope of this thesis. A good overview can be found in Hoekstra (2019). To briefly illustrate, he draws a comparison between the GDP Multinational and the Beyond GDP Cottage Industry. GDP, on the one hand, is based on the SNA and, with that, is integrated into accounting standards worldwide. This makes the indicator robust, intuitive and comparable across nations. Beyond GDP initiatives, on the other hand, are often loosely founded, rely on particular data and lack international coordination. This has severely limited their interpretability and use to date. However, significant advances have been made recently.

As mentioned in the introduction, Stiglitz et al. (2009) is a leading dissertation with a pivotal function in the debate on Beyond GDP. Taking a more technical approach towards the measurement of welfare, they review the role of GDP in public and political debate and (recommend to) erect a framework to capture and quantify the concept of welfare. The authors stress the importance of accurate measurement and a good understanding of (statistical) concepts.[2] As the collective pursuit of goals both forms and follows from the measurement of economic growth and societal progress, the measures one employs have serious implications for public and political debate. In other words, if measures themselves (or our understanding) are flawed, the decision-making process will be distorted, too. To this end, the authors provide several recommendations on the measurement of welfare which have been broadly adopted by social and scientific communities since.

[2] "The report is about measurement rather than policies, thus it does not discuss how best our societies could advance through collective actions in the pursuit of various goals. However, as what we measure shapes what we collectively strive to pursue - and what we pursue determines what we measure - the report and its implementation may have a significant impact on the way in which our societies looks at themselves and, therefore, on the way in which policies are designed, implemented and assessed." – Stiglitz et al. (2009).

As the concept of welfare is by definition plural, one should aim to capture as many relevant aspects as possible. The capability approach developed by Sen (1999) serves as a useful conceptual approach underlying this notion. It states that welfare is determined by an individuals' opportunities and freedoms (i.e. capabilities), their state and the activities they participate in (i.e. functionings) even as their personal assessment of these capabilities and functionings (i.e. subjective evaluation). In that regard, the framework of actionable intelligence developed by Patton (2002) can be considered useful to approach the mensuration of inputs, outputs and outcomes, respectively. Based on a thorough review of the (economic) literature, aspects relevant to the welfare of individuals comprise material living standards (i.e. measured through consumption rather than production concepts), health, education, personal activities, governance, social connections, the environment and insecurity.

What is more, for an accurate measurement of well-being, current well-being should be considered separately from sustainability. The latter comprises the potential to maintain a certain rate or level of welfare (with a particular focus on environmental sustainability).[3] The Brundtland-report (WCED, 1987) provided a formal definition of sustainable development (i.e. meeting the needs of the present without compromising the ability of future generations (and, commonly added, communities abroad) to meet their needs) underlying this notion.

To recapitulate, welfare in a broad sense takes into account subjective outcomes (e.g. contrary to measures of happiness) even as relevant objective inputs and outputs. It furthermore implies a human-centric approach to welfare. Put differently, it takes all aspects into account that contribute directly to human welfare whereas it disregards the interests of governments, institutions and corporations even as intrinsic valuations. Finally, as functionings and subjective evaluations per the capability approach are inherently linked to such functionings and subjective evaluations of future generations and communities abroad, these must also be incorporated in our evaluation.

The CES Recommendations (UNECE/Eurostat/OECD, 2014) further operationalize these advancements in the Beyond GDP debate and introduce a list of welfare indicators that adhere to the conceptual framework outlined above. In other words, it serves as a practical guideline to construct an instrument of measurement for welfare in broad sense of which the Monitor is a first in this regard.

[3] "The assessment of sustainability is complementary to the question of current well-being or economic performance, and must be examined separately. (…) To take an analogy, when driving a car, a meter that added up in one single number the current speed of the vehicle and the remaining level of gasoline would not be of any help to the driver. Both pieces of information are critical and need to be displayed in distinct, clearly visible areas of the dashboard." – Stiglitz et al. (2009).

### 2.3 Monitor on Well-being and Sustainable Development Goals

The previous paragraphs accommodate a more coherent debate on welfare in a broad sense and, to that extent, the Monitor. The Monitor on Well-being by Statistics Netherlands (2018; 2019; 2020) is aligned with the recommendations by Stiglitz et al. (2009) and constitutes the first full implementation of the CES Recommendations (UNECE/Eurostat/OECD, 2014) for measuring sustainable development in the world. This section encompasses a more complete description of this specific tool.

Concretely, the Monitor includes measures of well-being, earnings, health, employment status, housing, social contacts, safety and environmental quality. Moreover, the capital approach is used to quantify economic, natural, human and social capital available to future generations to assess the temporal dimension of welfare. Finally, resource extraction even as trade relationships and development aid are included to evaluate the consequences of welfare in the Netherlands on communities abroad. All these aspects are quantified by several indicators. These indicators are statistical measures that are representative of a particular aspect. In the case of a multifaceted and multidimensional phenomenon like welfare, every indicator will reflect only (part of) an aspect that contributes to welfare in a broad sense. As long as every indicator is valid for the aspect it is intended to measure, the combination of indicators will provide a complete and cohesive image of the phenomenon. Table 1 provides an overview of all 66 indicators, 14 aspects and 3 dimensions covered by the Monitor.

Note that the Monitor provides a balanced and coherent set of reliable and timely indicators to support public and political debate on welfare and (potentially) the effectiveness of government policy (Horlings and Smits, 2019). So far all publications of the Monitor have highlighted several developments in welfare in the Netherlands. Whereas well-being, material welfare, social cohesion and safety in the present are among the highest in Europe and largely improving over time, there have been declining trends in the domains of health, housing and the environment. Moreover, there appears to be sufficient economic, human and social capital available to satisfy the needs and wants of future generations whereas natural capital, most notably fossil fuel reserves, carbon dioxide emissions and diversity of fauna, has deteriorated substantially. Lastly, Dutch welfare has spurred economic development elsewhere in the world as trade flows from mainly Asia and Oceania have increased over the past years. However, it also imposed a weighty claim on natural capital abroad by inducing a further depletion of foreign resources and greenhouse gas emissions (Statistics Netherlands, 2018; 2019; 2020).

Table 1 Overview of the dimensions, aspects and indicators in the Monitor (Statistics Netherlands (2020).

| **Dimension of Welfare** | **Aspect of Welfare** | **Indicator** |
|---|---|---|
| **Here and Now** | **Well-being** | Life Satisfaction |
| | | Personal Well-being Index (PWI) |
| | | Sense of Command over Life |
| | **Material Welfare** | Median Disposable Income |
| | | Individual Consumption |
| | **Health** | Healthy Life Expectancy Men |
| | | Healthy Life Expectancy Women |
| | | Overweight |
| | **Labour and Leisure** | Long-term Unemployment |
| | | Labor Force Participation |
| | | Highly Educated Population |
| | | Free Time Satisfaction |
| | | Time Loss in Traffic |
| | | Work Satisfaction |
| | **Housing** | Quality of Housing |
| | | Satisfaction with Housing |
| | **Society** | Social Contact |
| | | Voice and Accountability |
| | | Trust in Institutions |
| | | Trust in People |
| | | Norms and Values |
| | | Voluntary Work |
| | **Safety** | Feeling Unsafe (Neighbourhood) |
| | | Victim of Crime |
| | **Environment** | Nature in NNN |
| | | Quality of Water |
| | | Fauna in Water and Marshland |
| | | Fauna on Land |
| | | Nitrogen Deposition |
| | | PM2.5 Exposure |
| | | Environmental Issues |
| **Later** | **Economic Capital** | Physical Capital Stock |
| | | Human Capital Stock |
| | | Average Household Debt |
| | | Median Household Capital |

| | | |
|---|---|---|
| | **Natural Capital** | Fossil Fuel Reserves |
| | | Renewable Energy Capacity |
| | | Nature in NNN |
| | | Phosphorus in Excess |
| | | Nitrogen in Excess |
| | | Fauna in Water and Marshland |
| | | Fauna on Land |
| | | Water Extraction |
| | | PM2.5 Exposure |
| | | Cumulative CO2 Emission |
| | **Human Capital** | Hours Worked |
| | | Highly Educated Population |
| | | Healthy Life Expectancy Men |
| | | Healthy Life Expectancy Women |
| | **Social Capital** | Trust in Institutions |
| | | Trust in People |
| | | Feeling of Discrimination |
| **Elsewhere** | **Trade and Aid** | Import Total |
| | | Import Europe |
| | | Import Africa |
| | | Import America |
| | | Import Asia |
| | | Import Oceania |
| | | Import LDC's |
| | | Development Aid |
| | | Foreign Transfers |
| | **Environment and Resources** | Import Fossil Fuel |
| | | Import Fossil Fuel from LDC's |
| | | Import Metal |
| | | Import Metal from LDC's |
| | | Import Non-Metal |
| | | Import Non-Metal from LDC's |
| | | Import Biomass |
| | | Import Biomass from LDC's |
| | | Carbon Footprint |

### 2.4 Renewable Energy Subsidies

Having reflected on (influential publications on) Beyond GDP, renewable energy policy is discussed here. To the best of my knowledge, a comprehensive evaluation of the effect of renewable energy policy on a broad definition of welfare has not been attempted so far. To provide guidance on an analysis of the effectiveness of government policy using the Monitor, a major scheme for renewable energy subsidies (RES), being the main instrument to promote renewable energy production in the Netherlands, is assessed.

Van der Ree et al. (2019) state that the transition to renewable energy production can contribute to economic growth, job creation, emission abatement and improvements in environmental quality and health outcomes. These positive side effects of such a transition are also widely noted in public and political debate (The Economist, 2017; 2018; 2020). While the effectiveness of RES in promoting renewable energy production or abating emissions is discussed in academic literature, fewer publications direct attention towards the relationship between energy production and other aspects of welfare. By linking both strands of literature and taking a more cohesive approach, this thesis adds to the available literature.

From a theoretical perspective, there have been several critical evaluations of RES. In the absence of a first-best uniform global carbon tax or permit trading scheme to internalize the costs of pollution, governments have resided to second-best alternatives such as regional carbon taxes, local permit trading schemes and RES schemes with debatable effectiveness (Ostrom, 2012). What is more, RES schemes come at high costs that marginalize welfare gains and can lead to unintended side effects (Stern, 2007; Sinn, 2008; Böhringer et al., 2013; Kalkuhl et al., 2013; Horshig and Thran, 2017). Although these models point towards small to negligible welfare gains (or even welfare losses), it is ultimately an empirical question.

Firstly, the literature on the determinants of renewable energy production is surveyed. Besides renewable energy policy, several other factors play a prominent role. Carley (2009) uses a fixed-effects model for states in the U.S. and finds that resource endowments, economic developments and energy prices have significant impacts on renewable energy production. Marquis and Fuinhas (2012) highlight the importance of lobbying and (overall) $CO_2$ emissions which is in line with Aguirre and Ibikunle (2014) who also point towards the importance of environmental concerns among the population. Both are the result of Panel Corrected Standard Estimators on a global dataset. More recently, Kilinc-Ata (2016) and Papiez et al. (2018) confirmed the importance of resource endowments, economic growth and fossil fuel prices. These factors should, hence, be accounted for when evaluating renewable energy production.

Secondly, studies that compare various renewable energy policies in both the U.S. and Europe tend to reach consensus on the effectiveness of RES. Mainly feed-in tariff or premium systems (like the RES scheme in the Netherlands) tend to be effective, especially when compared to quotas, tax incentives and portfolio standards in renewable energy production (Haas et al., 2011; Keyuraphan et al., 2012; Murray et al., 2014; Nicolini and Tavoni, 2017; Liu et al., 2019). Most notably, Frondel et al. (2010) evaluate the German RES feed-in tariff system on several (welfare) dimensions. Not only do they look at policy effectiveness and efficiency, they also focus on job creation and climate protection. They find that energy policy has not harnessed progress in any of these dimensions resulting in massive expenditures with little economic, environmental or social returns.

Thirdly, there is evidence that, in line with Van der Ree et al. (2019), renewable energy policy spurred economic growth and job creation. Fang (2011) focusses on the case for China and finds a significant impact of energy consumption on various income measures. He points towards a strong role of government policy and regulation. Tugcu et al. (2012) find a similar relationship between energy consumption and economic growth (as measured by GDP) in the world's largest economies. They also confirm bi-directional causality. This is in line with the findings of Al-Mulali et al. (2013).

There have also been two policy reports on the RES scheme in the Netherlands. These review the effectiveness and efficiency of the RES scheme and provide valuable insights for further discussions. As Section 3 provides more details on the specific functioning of the RES scheme in the Netherlands, the policy reports are presented there for the sake of clarity. Based on the literature on RES, a hypothesis can be constructed to better concentrate the analyses on welfare in a broad sense even as review the impact of government policy.

*Hypothesis 1: Renewable energy subsidies in the Netherlands have positively impacted renewable energy production (i.e. have effectively realized their primary aim).*

*Hypothesis 2: Renewable energy subsidies in the Netherlands have fostered improvements in economic, employment and environmental aspects of welfare in a broad sense.*

The next section further elaborates on the renewable energy subsidy scheme studied in this thesis and highlights several trends of interest in the energy sector in the Netherlands. This is subsequently linked to the literature, the data and the methodology to accommodate a clear and coherent answer to the research question.

**Section 3. The Dutch Setting**

On January 1st, 2003, the Dutch government introduced a new renewable energy subsidy scheme, named Milieukwaliteit van de Elektriciteitsproductie (MEP), to incentivize private investors and firms to produce renewable energy from sources such as wind, solar, water and biofuels. The subsidy was based on the (capped) average market-costs (in Euros per kWh) of production of one unit of energy from a renewable source in excess of the ongoing market price (in Euros per kWh). In other words, the government subsidized the costs that could not be earned back by producing and selling a unit of renewable energy, also known as the unprofitable top. This enabled private investors and firms to compete with incumbent fossil fuel energy producers and, hence, bring renewable energy to the market. However, the MEP was abandoned in 2006 due to excessive expenditures. Only previously allocated subsidy payments for ongoing projects were continued (Algemene Rekenkamer, 2015).

On January 1st, 2008, the Dutch government implemented a successor, the Stimulering Duurzame Energieproductie (SDE). Though similar to the MEP, the structure and design of the subsidy request system was altered to address the issues resulting in excessive expenditures under the MEP. Firstly, subsidy payments (formerly allocated on fixed market prices for energy) became subject to yearly reviews to incorporate altering market prices for energy. Secondly, a budget ceiling (absent under the MEP) for each type of renewable energy production (i.e. wind, solar, water and biofuels) was installed to prevent expenditures over and above the pre-defined maximum. Whereas this resolved the issues under the MEP, the strict division of the available budget under separate budget ceilings triggered a new efficiency loss. As the division prevented transfers between budgets, there was no form of "efficient rationing". To illustrate, if the budget for wind energy was depleted before the budget for biofuels, subsidies for the production of wind energy, having become very cost-efficient, was foregone for the production of biofuels, being far less cost-efficient (Algemene Rekenkamer, 2015).

To comply with the EU Renewable Energy Directive (2009) and address the efficiency loss under the SDE, the government introduced the Stimulering Duurzame Energieproductie+ (SDE+) in 2011. It discarded the strict division of the budget and, instead, created a single budget ceiling. Moreover, it introduced a phased allocation of the budget aimed at enhancing efficiency and effectiveness. CE Delft and SEO (2016) conclude this was successful. The budget ceiling induced sufficient competition between renewable energy producers through the credible admonition of budget depletion whereas the phased approach allows for a more efficient allocation of subsidy payments. Based on financial statements and survey data, the authors conclude that 85% to 95% of all financed renewable energy production would not have occurred in the absence of subsidy payments. Compared to other types of renewable energy policies (where this is below 50%) this is a remarkably low deadweight loss. Moreover, the allocation of subsidies is deemed efficient through a low administrative burden relative to the amount of subsidies received. These findings on the effectiveness and efficiency of the MEP, SDE and SDE+ are a solid foundation to further explore the relationship between RES and renewable energy production.

On a practical note, the allocation and provision of subsidy payments for the MEP, SDE and SDE+ were administered by EnerQ (a subsidiary of national grid provider TenneT) until 2009 after which the responsibility was transferred to the Netherlands Enterprise Agency (RVO) which performs this task until the present. To prevent fraud, the government introduced Guarantees of Origin (GvO). These are certificates issued by CertiQ (another subsidiary of national grid provider TenneT) per 1000 MJ of renewable energy produced. Renewable energy producers are legally required to apply for such a certificate in case they wish to receive subsidy payments. Besides, through such a certificate consumers can confirm the source of energy purchased. These certificates can be used for part of the analysis as will be discussed along with the methodology in Section 4.

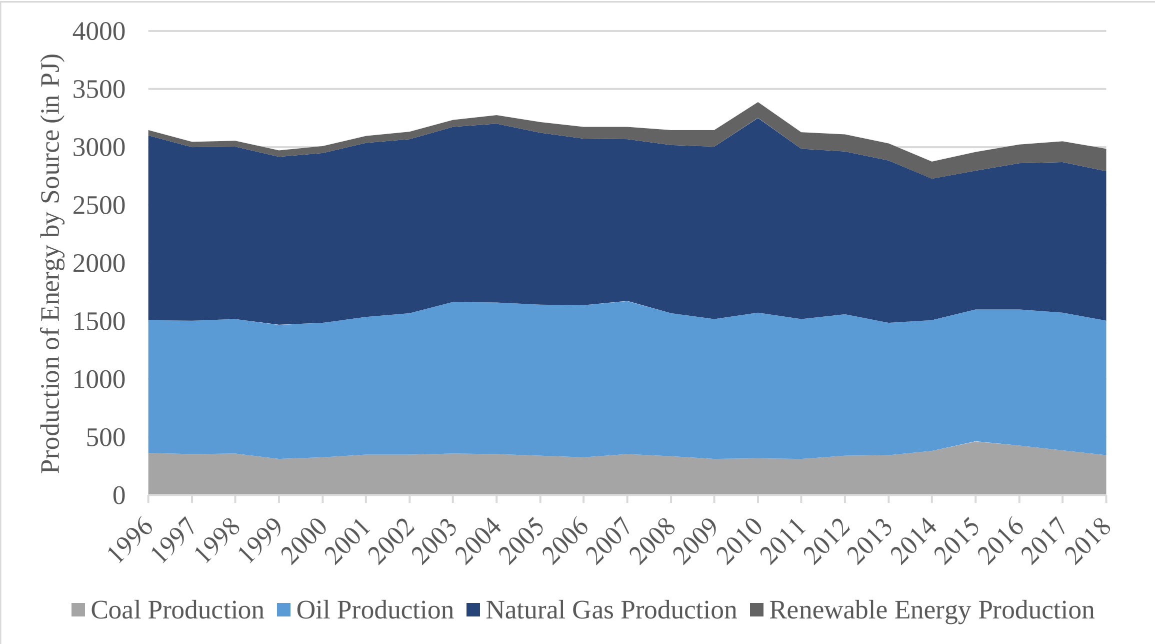


Figure 1 Energy Production by Source in the Netherlands from 1996 through 2018. Source: Statistics Netherlands.

To the end of an increased understanding of the context and selection of the data and methodology, several aspects of the Dutch energy market are presented. The Netherlands is a resource-abundant country when it comes to natural gas and, to a lesser extent, oil. Being the second-largest natural gas producer in Europe, it extracts natural gas and oil for energy production, household consumption and export. Due to earthquakes in the Groningen region (where over 50% of the gas shales is located) induced by natural gas extraction, the government capped and reduced natural gas production from 2013 onwards.

Figure 1 shows energy production by source in the Netherlands over the period 1996 through 2018. All in all, energy production appears to be rather stable over the period under consideration, fluctuating between 3000 PJ and 3500 PJ. Energy usage peaks around 2010 and reaches a low in 2014. These fluctuations appear to be driven by the average temperature in these years. Notably, natural gas production shows a decrease from approximately 2013 onwards, in line with the reduction in natural gas extraction from the Groningen gas shale in that same year. Usage of coal and oil appears to remain stable throughout the entire time span with a slight increase in coal and oil production after 2013. Renewable energy, on the other hand, shows an increasing trend throughout the entire period under consideration. However, the Dutch energy market should not be viewed in isolation.

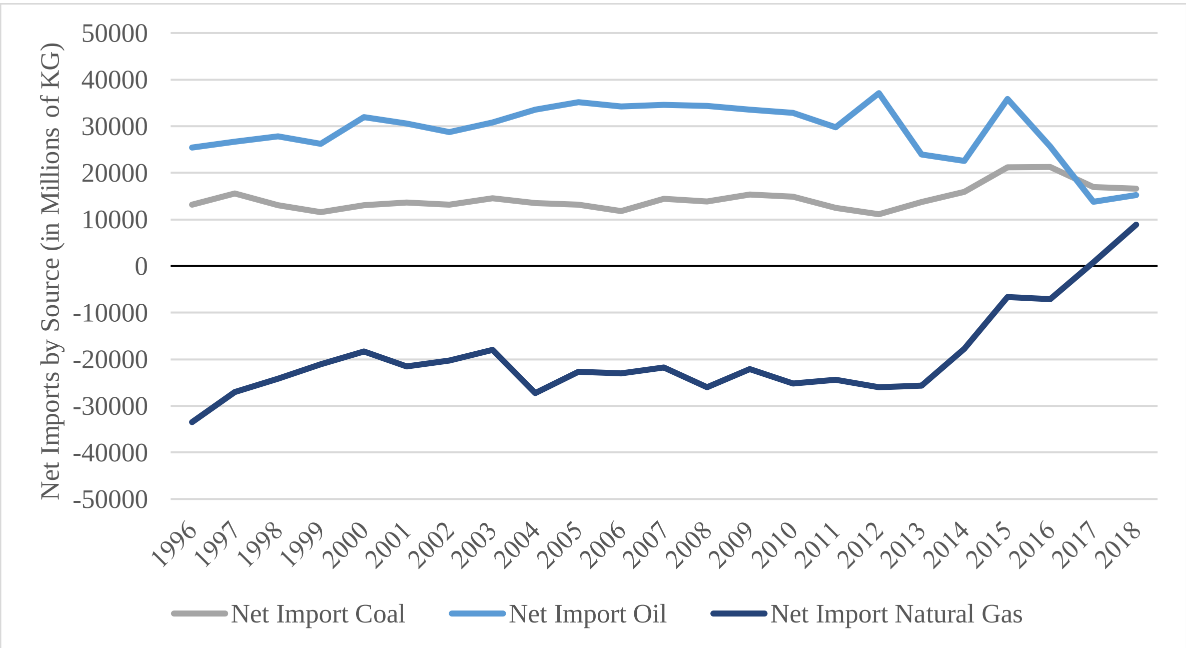


Figure 2 Net Import by Source in the Netherlands from 1996 through 2018.
Source: Statistics Netherlands.

Figure 2, showing net imports of coal, oil and natural gas, provides a broader perspective on the the international energy market. As the European energy market is strongly interconnected, shifts in imports and exports of fossil fuels might signal effects of changes in production, export and imports of energy produced from other sources. The image mainly aligns with the findings in Figure 1. It confirms a stark reduction in domestic natural gas production from 2013 onwards. For the first time in history, the Netherlands imported more natural gas than it exported in 2018. Coal and oil appear to be rather stable, though an increase in net imports of coal and a decrease in the net exports of oil seems evident from 2013 onwards. This signals that the fall in natural gas production is compensated by additional coal imports (even as coal production) whereas revenue losses from reduced natural gas exports are somewhat offset by additional oil exports (Statistics Netherlands, 2018). However, no substantial impact of RES seems evident from the visualisations above.

Finally, Figure 3 shows energy consumption by sector. Again, no marked changes are visible. Each sector appears to consume approximately the same share of energy throughout the period of interest. In other words, there appears to be no substantial change in the consumption of energy. This is comforting in further assessing the effect of RES as potential shifts in energy consumption do not appear to drive the results one finds nor play a pivotal role in the interpretation of the results.

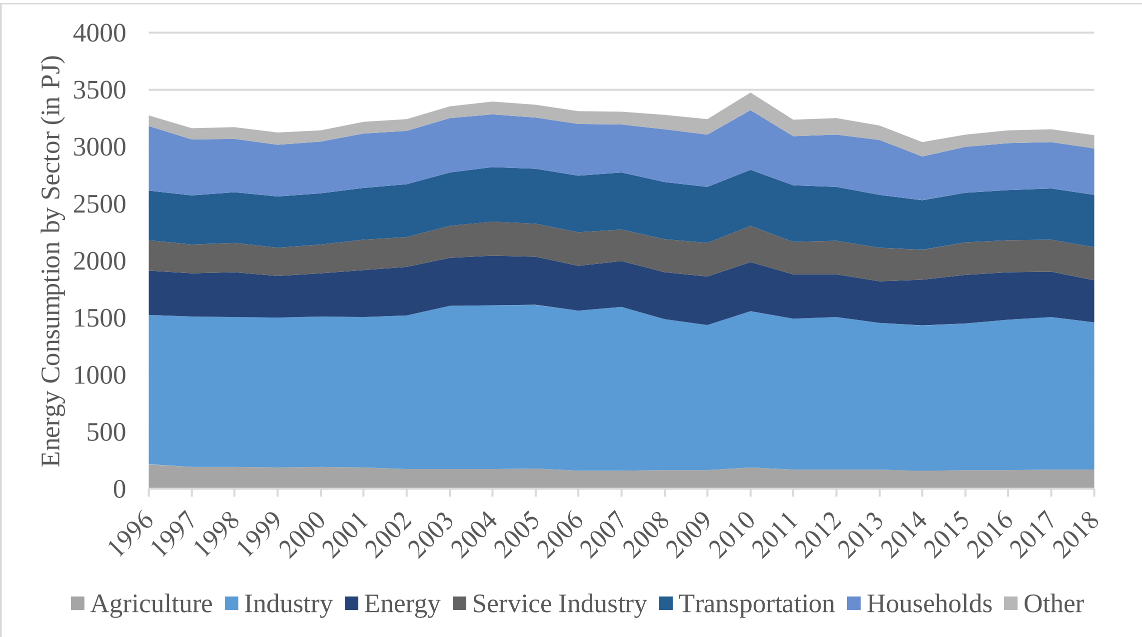


Figure 3 Energy Consumption by Sector in the Netherlands from 1996 through 2018. Source: Statistics Netherlands.

**Section 4. Data and Methodology**

To assess the effects of RES on broad aspects of welfare, the presentation of the data and the methodology are both subdivided into two parts. Firstly, the data in the Monitor is discussed. Then, associations and relationships are identified using Pearson product-moment and Spearman rank correlation coefficients. Cluster analysis (and a visualisation thereof) accommodates a comprehensive review and more intuitive presentation of the findings. Thereafter, principal component analysis is employed to reduce the data dimensions for subsequent analyses. Secondly, the effects of RES in the Netherlands are investigated using indicators retrieved from the Monitor as well as the System of National Accunts (SNA) and the Sustainable Development Goals (SDGs). Dynamic multivariate ordinary least squares and instrumented regression techniques are employed to evaluate the effects of interest. Assumptions and limitations for each method are briefly presented and reflected on throughout this section. They will be subject to further elaboration with the presentation of the results.

The Monitor is central to assessing associations between and across aspects and dimensions of welfare in the Netherlands. Due to the large number of indicators a brief account is provided. Table 2 presents descriptive statistics of all indicators adopted from the Monitor. For many of the indicators, data is available on a yearly basis from 1995 to 2019. However, there are differences among indicators. Some are measured once every two years, some are gathered for only the last decade and still others have not been updated till 2019, leading to certain discrepancies in the number of observations (i.e. variations from 5 to 25 observations). To address these discrepancies, linear interpolation for several indicators is applied when deemed appropriate.[4] This allows for a more complete utilization of the available information. Moreover, for the sake of interpretation in PCA and regression estimates, all indicators are converted as to have a positive impact on welfare.[5] In general, subjective indicators are based on survey responses where individuals expressed their (dis)satisfaction on a scale from 1 to 10. This is thereafter converted into a percentage of the population with a score above a threshold value. Objective measures take many forms. Most frequently they are population shares or per capita measures in terms of EUR, emission quantities or indices.

[4] Indicators fit for interpolation are Sense of Command over Life, Voice and Accountability, Norms and Values, Feeling Unsafe, Victim of Crime, Feeling of Discrimination and Carbonfootprint. The use of interpolated values will be mentioned at each stage of the analysis. Moreover, their use is made explicit when reporting model outcomes by adding a daggar (†) to these variables in tables.

[5] Indicators converted for a positive impact on welfare are Overweight, Long-term Unemployment, Time Loss in Traffic, Feeling Unsafe, Victim of Crime, Nitrogen Deposition, PM2.5 Exposure, Environmental Issues, Household Debt, Phosphorus in Excess, Nitrogen in Excess, Cumulative CO2 Emissions, Feeling of Discrimination, Import of Material and Carbon Footprint.

Table 2 Descriptive Statistics of all key indicators adopted from the Monitor (Statistics Netherlands, 2020).

| Indicator | Observations | Mean | Standard Dev. | Minimum | Maximum | Unit of Measurement |
|---|---|---|---|---|---|---|
| GDP | 25 | 574314 | 136021 | 329547 | 812051 | Million of EUR |
| Life Satisfaction | 23 | 84.9 | .9 | 83.6 | 87.3 | Percentage of the Population |
| Personal Well-being Index | 7 | 60.1 | 3.4 | 55.6 | 64.7 | Percentage of the Population |
| Sense of Command over Life † | 9 | 48.3 | 0.8 | 47.2 | 49.6 | Percentage of the Population |
| Median Disposable Income | 8 | 24540 | 738 | 23573 | 25620 | EUR per Capita |
| Individual Consumption | 25 | 24235 | 1907 | 19428 | 26289 | EUR per Capita |
| Healthy Life Expectancy M | 25 | 63.3 | 1.5 | 60.8 | 65.3 | Years |
| Healthy Life Expectancy W | 25 | 62.5 | 1.0 | 60.4 | 64 | Years |
| Overweight | 25 | 46.2 | 3.7 | 38 | 51.1 | Percentage of the Population |
| Long-term Unemployment | 17 | 1.8 | .6 | 1 | 3 | Percentage of the Population |
| Laborforce Participation | 25 | 65.2 | 2.2 | 59.4 | 68.8 | Percentage of the Population |
| Highly Educated Population | 24 | 29.9 | 5.6 | 21.8 | 39.7 | Percentage of the Population |
| Free Time Satisfaction | 7 | 74.5 | .7 | 73.9 | 75.7 | Percentage of the Population |
| Time Loss in Traffic | 15 | 3.5 | .5 | 2.6 | 4.2 | Hours per Capita (VVU100) |
| Work Satisfaction | 13 | 77.47 | .9 | 76 | 78.8 | Percentage of the Population |
| Quality of Housing | 15 | 84.2 | 1.3 | 81.7 | 86.5 | Percentage without Def. |
| Satisfaction with Housing | 7 | 87.4 | .5 | 86.5 | 88 | Percentage of the Population |
| Social Contact | 8 | 73.7 | 1.2 | 72.2 | 76.2 | Percentage with Contact |
| Voice and Accountability † | 23 | 1.5 | .1 | 1.5 | 1.7 | Score from -2.5 to 2.5 |
| Trust in Institutions | 8 | 59.5 | 3.0 | 56 | 63.1 | Percentage of the Population |
| Trust in People | 8 | 60.0 | 1.7 | 57.9 | 62.2 | Percentage of the Population |
| Norms and Values † | 23 | 37.0 | 4.2 | 30.5 | 46.7 | Percentage of the Population |
| Voluntary Work | 8 | 48.6 | 1.2 | 46.7 | 50.5 | Percentage of the Population |
| Feeling Unsafe † | 12 | 1.6 | .1 | 1.4 | 1.8 | Percentage of the Population |
| Victim of Crime † | 15 | 20.0 | 4.0 | 13.7 | 27.5 | Percentage of the Population |
| Nature in NNN | 8 | 18.3 | 1.4 | 17.3 | 20.6 | Percentage of Surface |
| Quality of Water | 10 | 66.1 | 11.4 | 44.4 | 74 | Percentage Certified as Exc. |
| Fauna in Water and Marshland | 24 | 133.4 | 12.0 | 108 | 143 | Index (1990 = 100) |
| Fauna on Land | 24 | 85.9 | 1.0 | 85 | 89 | Index (1990 = 100) |
| Nitrogen Deposition | 24 | 72.2 | 2.3 | 67.8 | 74.9 | Percentage of Nature Excess |
| PM2.5 Exposure | 11 | 14.1 | 2.5 | 11.2 | 17.4 | Microgram per SM3 |
| Environmental Issues | 15 | 14.2 | .9 | 12.9 | 16 | Percentage with Problem |
| Physical Capital Stock | 24 | 141.4 | 8.7 | 129 | 153 | EUR per Hour Worked |
| Human Capital Stock | 24 | 8.3 | 1.7 | 6.1 | 11.3 | EUR per Hour Worked |
| Average Household Debt | 24 | 78968 | 24342 | 31787 | 101702 | EUR per Household |
| Median Household Capital | 13 | 30854 | 10025 | 16800 | 46900 | EUR per Household |
| Fossil Fuel Reserves | 25 | 2.9 | 1.1 | .5 | 4.5 | TJ per Capita |
| Renewable Energy Capacity | 25 | 163.1 | 168.4 | 18.7 | 656.2 | MWH per Million Capita |
| Nature in NNN | 8 | 18.3 | 1.4 | 17.3 | 20.6 | Percentage of Surface |
| Phosphorus in Excess | 20 | 10.1 | 6.4 | 1.6 | 22.8 | KG per Acre |
| Nitrogen in Excess | 20 | 182.7 | 24.8 | 151.7 | 243 | KG per Acre |
| Fauna in Water and Marshland | 24 | 133.4 | 12.0 | 108 | 143 | Index (1990 = 100) |
| Fauna on Land | 24 | 85.9 | 1.0 | 85 | 89 | Index (1990 = 100) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Water Extraction | 18 | 598.6 | 95.0 | 419 | 717 | SM3 per Capita |
| PM2.5 Exposure | 11 | 14.1 | 2.5 | 11.2 | 17.4 | Microgram per SM3 |
| Cumulative CO2 Emission | 20 | 7.3 | .2 | 6.9 | 7.7 | Tons CO2 per Capita per Year |
| Hours Worked | 25 | 747.6 | 19.7 | 696.6 | 788.2 | Hours per Capita per Year |
| Highly Educated Population | 24 | 29.9 | 5.6 | 21.8 | 39.7 | Percentage of the Population |
| Healthy Life Expectancy M | 25 | 63.3 | 1.5 | 60.8 | 65.3 | Years |
| Healthy Life Expectancy W | 25 | 62.5 | 1.0 | 60.4 | 64 | Years |
| Trust in Insitutions | 8 | 59.5 | 3.0 | 56 | 63.1 | Percentage of the Population |
| Trust in People | 8 | 60.0 | 1.7 | 57.9 | 62.2 | Percentage of the Population |
| Feeling of Discrimination † | 17 | 7.7 | 0.7 | 6.8 | 9.2 | Percentage of the Population |
| Import Total | 25 | 17401 | 5546 | 8370 | 26515 | EUR per Capita |
| Import Europe | 25 | 11046 | 3244 | 6048 | 16199 | EUR per Capita |
| Import Africa | 25 | 489 | 246 | 165 | 976 | EUR per Capita |
| Import America | 25 | 2069 | 623 | 942 | 3136 | EUR per Capita |
| Import Asia | 25 | 3695 | 1407 | 1193 | 6165 | EUR per Capita |
| Import Oceania | 25 | 65 | 31 | 21 | 130 | EUR per Capita |
| Import LDC's | 16 | 131.7 | 49.6 | 38 | 185 | EUR per Capita |
| Development Aid | 24 | .75 | .08 | .6 | .8 | Percentage of GNI |
| Foreign Transfers | 24 | .82 | .44 | .3 | 1.5 | Percentage of GDP |
| Import Fossil Fuel | 24 | 11.2 | 1.8 | 8 | 14.2 | Tons per Capita |
| Import Fossil Fuel from LDC's | 16 | 126.3 | 57.3 | 13.9 | 209.3 | KG per Capita |
| Import Metal | 24 | 2.1 | .2 | 1.8 | 2.6 | Tons per Capita |
| Import Metal from LDC's | 16 | 10.4 | 9.4 | 1.1 | 31.6 | KG per Capita |
| Import Non-Metal | 24 | 3.2 | .5 | 2.3 | 4.2 | Tons per Capita |
| Import Non-Metal from LDC's | 16 | 3.2 | 1.3 | 1.7 | 7 | KG per Capita |
| Import Biomass | 24 | 4.2 | .5 | 3.3 | 5.1 | Tons per Capita |
| Import Biomass from LDC's | 16 | 14.2 | 4.6 | 9.3 | 23.2 | KG per Capita |
| Carbon Footprint † | 12 | 17.0 | 1.5 | 14.9 | 19.9 | Tons CO2 Equiv. per Capita |

To assess the effect of RES on welfare in a broad sense, the data in the Monitor are complemented with several outcome indicators from national accounts and satellite accounts. These data are provided by Statistics Netherlands on the years 1995 through 2018 and concern observations for the energy sector (SBI-code: 4), specifically. This comprises renewable energy production in million MJ, GDP of the energy sector in million EUR, employment in the energy sector in thousands of jobs, hours worked in the energy sector in thousands of hours worked, labor costs in the energy sector in million EUR, employment in the environmental sector in thousands of jobs and greenhouse gas emissions in millions of CO2-equivalent units. Moreover, output indicators for the Netherlands relating to SDG 7 on affordable and clean energy as well as SDG 13 on climate action are adopted and comprise installed capacity for renewable energy production measured in MWh per capita, fossil fuel import measured in thousand KG and emission intensity measured in thousand KG of CO2-equivalent units per EUR of GDP.

As in any type of regression analysis, omitted variable bias and reverse causality potentially impact the relationship of interest. Although a more elaborate discussion follows at a later stage, several indicators are included to address factors potentially confounding the relationship of interest. Annual commodity prices for the European market are collected from the FRED for the years 1995 through 2018. Prices are reported in US$ per barrel for Brent crude oil, US$ per million British thermal units for natural gas and US$ per metric ton for coal. Moreover, the effect of lobbying (as indicated in the literature) is addressed. Since there are no direct measures of lobbying activities available for the Netherlands, an index of the Worldwide Governance Indicators (WGI) for the Netherlands is constructed as an approximation of the potential effectiveness of lobbying. The data is provided by the Worldbank on the years 1996 through 2018 and measured on a scale from -2.5 to 2.5. The original indicators include control of corruption, government effectiveness, political stability, regulatory quality, rule of law and voice and accountability (note that the latter is also adopted in the Monitor by itself) and are subsequently converted into a single index.[6] This serves as a proxy for the power of the (energy) lobby in general. Annual subsidy data in million EUR from RVO on the years 2003 through 2018 is used. This serves as the main variable of interest. Finally, data on the number of Guarantees of Origin issued by CertiQ on the years 2003 through 2018 is deployed.

Table 3 displays descriptive statistics of the data used for the evaluation of RES. Note the wide range in renewable energy production with a minimum of 1423 million MJ to 21844 million MJ. This implies a stark increase in the level of renewable energy production. Similarly, RES range from 0 million EUR to 1173 million EUR. Also GDP in the energy sector, employment in the environmental sector in the energy sector, GDP, the coal price, the oil price and the fossil fuel reserve have large standard deviations compared to their means, indicating substantial variation over the period under consideration. Cumulative CO2 emissions and the World Governance Indicators appear to exhibit little variation over time.

Data in both Table 2 and 3 originates mainly from Statistics Netherlands even as SCP, RIVM, Eurostat, OECD, Worldbank and several other government institutions. Due to the rigurous data standards and trustworthy character of thes sources, the data used in this thesis can be deemed reliable and accurate for the objective at hand.

[6] Note that the the index constructed for WGI applies equal-weighting.

Table 3 Descriptive Statistics of all key variables included in the RES evaluation.

| Indicator | Observations | Mean | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|---|
| Renewable Energy Production | 25 | 8690 | 5763 | 1423 | 21844 |
| GDP Energy Sector | 24 | 6159 | 1511 | 4262 | 8182 |
| Employment in the Energy Sector | 24 | 26 | 1 | 23 | 29 |
| Hours Worked in the Energy Sector | 24 | 44 | 3 | 39 | 52 |
| Labor Costs in the Energy Sector | 24 | 1718 | 250 | 1394 | 2104 |
| Environmental Sector in the Energy Sector | 16 | 773 | 426 | 76 | 1391 |
| Greenhouse Gas Emissions in the Energy Sector | 25 | 49878 | 9001 | 9065 | 56869 |
| Installed Capacity for Renewable Energy Production | 25 | 163 | 168 | 18.7 | 656.2 |
| Fossil Fuel Import | 24 | 11 | 1.78 | 8 | 14.2 |
| Emission Intensity | 25 | 0.39 | 0.07 | 0.29 | 0.54 |
| RES | 25 | 438 | 390 | 0 | 1173 |
| GDP | 25 | 574314 | 136021 | 329547 | 812051 |
| Coal Price | 25 | 66 | 34 | 26 | 138 |
| Gas Price | 25 | 6 | 3 | 2 | 13 |
| Oil Price | 25 | 55 | 32 | 13 | 112 |
| Fossil Fuel Reserve | 24 | 1472 | 375 | 836 | 1997 |
| Cumulative CO2 Emissions † | 25 | 7.2 | 0.3 | 6.6 | 7.7 |
| Control of Corruption † | 23 | 2.1 | 0.1 | 1.9 | 2.2 |
| Government Effectiveness † | 23 | 1.9 | 0.1 | 1.7 | 2.1 |
| Political Stability † | 23 | 1.2 | 0.3 | 0.8 | 1.8 |
| Regulatory Quality † | 23 | 1.8 | 0.1 | 1.7 | 2.1 |
| Rule of Law † | 23 | 1.8 | 0.1 | 1.7 | 2.0 |
| Voice and Accountability † | 23 | 1.5 | 0.1 | 1.5 | 1.7 |

As the Monitor consists of a diffuse set of indicators measured for multiple time periods for the Netherlands only, it is said to be in a longitudinal format. In other words, the data under consideration is time series data. Naturally, the number of observations in time series data is important for the consistency of statistical estimates retrieved from that data. The number of observations in the Monitor exceeds 20 observations for the majority of variables. This also holds true for data retrieved from the SDGs and the SNA. Although a larger sample size is favourable for the purpose of increased precision, the number of observations in the Monitor can be deemed sufficient to produce unbiased and consistent correlation coefficients and also assures reliable cluster analysis (Bonett and Wright, 2000). Although some issues with the data structure are discussed at a later stage, the number of observations is no reason for direct concern regarding principal component analysis in the low-sample-size high-dimensional data set either (Afifi et al., 2012). Finally, time series regression also produces unbiased and consistent estimators with the number of observations available (Stock and Watson, 2015).

## 4.1 Methodology for the Monitor

As stated above, the Monitor consists of 66 indicators spread over 14 aspects covering 3 dimensions. To effectively evaluate the relationships and associations between these indicators several methods are deployed.

### 4.1.1 Correlation Coefficients

Firstly, correlation coefficients are used to quantify associations between variables within and across aspects and dimensions. Thereto, Pearson product-moment correlation coefficients and Spearman rank correlation coefficients are used. The Pearson product-moment correlation coefficients are used as a primary and intuitive measure of association. The Spearman rank correlation coefficients are included to address the effect of scaling of individual indicators (i.e. the distribution of the observations). As all observations are converted into ranks, the characteristics of and variation in scaling is rescinded through standardization. In the absence of outliers, a quantitative representation of variables and (approximately) linear relationships, the conditions for producing correlation coefficients are satisfied. More formally, the Pearson product-moment correlation coefficient $\rho_P$ for two indicators, say, X and Y, is defined as;

$$\rho_P = \frac{cov(X,Y)}{\sigma(X)\sigma(Y)}$$

where $cov(X,Y)$ is the covariance between X and Y and $\sigma(X)$ and $\sigma(Y)$ are the standard deviations of X and Y, respectively. The Spearman rank correlation coefficient $\rho_S$ based on the ranks $r_i$ and $s_i$ for indicators, say, X and Y, respectively, is defined as;

$$\rho_S = \frac{\sum_i (r_i - \bar{r})(s_i - \bar{s})}{\sqrt{\sum_i (r_i - \bar{r})(s_i - \bar{s})^2}\sqrt{\sum_i (r_i - \bar{r})(s_i - \bar{s})^2}}$$

To utilise all available information, pairwise correlation estimates are presented (i.e. casewise rather than listwise deletion is applied). To better evaluate these associations, the correlation coefficients are subsequently visualised. Histograms provide insight on how correlations are distributed on a -1 to 1 scale and indicate to what extent indicators included in the Monitor are complements or substitutes. Cluster analysis allows for the identification of similar groupings of association across indicators. Heatmaps visualize these clusters of association and allow for a comprehensive overview of the relationships in the Monitor.

### 4.1.2 Principal Component Analysis

Secondly, the relationships between various indicators are compressed using more technically grounded data reduction techniques (beyond heatmaps), specifically principal component analysis (PCA). The eigenvalues, eigenvectors and loading scores are presented even as the explained variation of all indicators. These are linked to the associations derived earlier and can be utilised in the analysis of RES. Using PCA, similarity of indicators can be exploited to reduce the number of indicators while retaining all available information. Any analysis on over 70 outcome variables would be difficult to present and interpret. Reducing the number of variables whilst retaining all information through PCA is a useful way to evaluate effects on welfare in a broad sense. Moreover, it reduces the variance in subsequent regression estimates yielding enhanced precision. Finally, PCA is also useful for evaluating the variance across indicator sets and for assessing systematic relationships. A short elaboration on the technique as employed in this thesis follows below.

By demeaning the data, all observations are clustered around the origin without affecting the relative position of the observations. A line of best fit, through the origin and all other observations, is derived by maximizing the distance of the observations to the origin in Euclidian space, known as singular value decomposition (SVD). The slope of this line of best fit is a linear combination of the observations of each indicator and elucidates the relative importance of each variable. These linear combinations are commonly referred to as eigenvalues. The slope (i.e. the ratio of eigenvalues) is then scaled to unity to obtain the eigenvector. The converted units are known as loading scores. These properties are summarized by a principal component. This procedure can be repeated by constructing lines of best fit that are perpendicular to each previously determined eigenvector and, hence, principal components for at most the number of observations or variables, whichever is smallest.

The variation around the principal components derived from the eigenvalues is visualised in a Scree Plot. Using the Kaiser Criterion, only components with an eigenvalue larger than unity are retained. Components with an eigenvalue lower than unity are discarded as they capture too little variation to allow for meaningful interpretation. In case significant jumps between eigenvalues materialize, it might be appropriate to deviate from the Kaiser Criterion. This is ultimately an empirical matter and, therefore, assessed in Section 5. To evaluate simple structures, orthogonal and oblique rotation is considered. This way the loading of indicators on principal components becomes more explicit and can be better interpreted. Whereas the former technique allows for more straightforward interpretation, it strictly retains the uncorrelatedness of principal components. As this is undesirable from a theoretical standpoint (i.e. indicators loaded on different components are likely to be correlated), the latter relaxes this uncorrelatedness. It provides additional freedom in generating a simple structure but complicates the potential for interpretation. Finally, Bartlett's Test of Sphericity is used to formally test the appropriateness of PCA on the data. For a more theoretical disquisition of PCA, I refer to the original work of Pearson (1901) and Hotelling (1933) or the later contribution of Afifi et al. (2012).

Note that the use of correlation coefficients, cluster analysis and PCA is primarily concerned with the identification of associations even as potential structural relationships. It is a unique attempt to analyse a wider variety of welfare indicators in a coherent framework and constitutes a valuable contribution to the public and academic debate on welfare in a broad sense. Moreover, it serves as a foundation for further inquiries into the active debate on Beyond GDP, in general, and the Monitor, specifically. However, it is exploratory by nature and provides no unconditional basis for causal inference. Therefore, these estimates must be evaluated with caution and be considered in their appropriate context.

### 4.2 Methodology for RES

To evaluate the effect of RES, this thesis proceeds in several steps. Firstly, the association between RES and renewable energy production are investigated using Pearson product-moment and Spearman rank correlation coefficients.

#### 4.2.1 Dynamic Ordinary Least Squares Regression

Secondly, a dynamic ordinary least squares (OLS) regression model is fit to estimate the effect of the variable of interest. As noted above, the data is said to be time series data. Time series regression can be employed and will return unbiased and consistent estimates in case the requirements of conditional mean independence, weak dependence, the absence of outliers and no multicollinearity are satisfied. Moreover, the time series is required to be stationary (i.e. the probability distribution should not change over time) to prevent bias, inefficiency and misleading inference to arise. The assumptions are reviewed after the introduction of the regression equation and, if needed, describe how potential violations are addressed. More formally, the regression equation reads;

$$\begin{aligned} RE\_Production_t &= \alpha + \beta_1 RES_t + \beta_2 RES_{t-1} + \beta_3 GDP_t + \beta_4 Gas\_Price_t + \beta_5 Oil\_Price_t \\ &+ \beta_6 Coal\_Price_t + \beta_7 Fossil\_Fuel\_Stock_t + \beta_8 Cumulative\_CO2_t + \beta_9 WGI_t + \varepsilon_t \end{aligned}$$

where renewable energy production in million MJ is the dependent variable. RES is measured in millions of EUR, GDP of the Netherlands is measured in millions of EUR, the gas price is measured in US$ per million British thermal units, the oil price is measured in US$ per Brent crude oil barrel, the coal price is measured in US$ per metric ton, fossil fuel stocks are reflected in million standard cubic metres of natural gas reserves in the Netherlands, cumulative CO2 emissions include the average emissions of CO2 per capita since 1860 and WGI is an index constructed from the World Governance Indicators measured on a scale from -2.5 to 2.5.

Based on the literature reviewed in Section 2, seven variables are identified as potential confounding factors. These are included in the regression equation to (better) satisfy the conditional mean independence assumption. GDP of the Netherlands is included to control for broader trends in economic development as increasing affluence in the Netherlands might affect both subsidy payments and renewable energy production. The natural gas stock in the Netherlands is taken as an approximation of the resource endowment. As per Section 3, the Netherlands is relatively abundant when it comes to natural gas. This makes the natural gas stock an appropriate measure of the endowment effects identified in the literature. Cumulative CO2 emissions are included to address environmental concerns and the salience of abatement for the general public. Emissions of CO2 are integrated and anchored in the Sustainable Development Goals (UN, 2016) even as the National Climate Agreement (2019) and can, hence, be seen as an appropriate indicator for the urgency to take action for government and public alike. World Governance Indicators (WGI) are used as a proxy for the impact of lobbying. In the absence of structural breaks over the period under consideration these are likely to absorb little variation. Nonetheless, as the effect of lobbying is identified in the literature, they are a valuable inclusion. Finally, commodity prices (i.e. prices of gas, oil and coal) are included to address a broad array of confounding factors. Following from the efficient market hypothesis (Malkiel, 1989), these control for a diffuse set of factors impacting renewable energy production beyond the variable of interest, such as market expectations and speculations, price and income elasticities, even as political tensions and societal pressures. Since observed market prices are the result of an equilibrium process, including commodity prices controls for a large array of confounding variables affecting (or even constituting) the equilibrium outcome. By including the variables in this section, a whole array of (un)observed potential confounders are absorbed. However, even though all potential confounders identified in the literature are included, as in any multivariate OLS regression framework, one must remain cautious of other factors confounding the relationship of interest when interpreting model outcomes.

Weak dependence can reasonably be assumed, as observations over long periods of time are likely to be unrelated. Moreover, outliers as well as multicollinearity appear to be absent in the data and regression specification, respectively. Stationarity, however, might be reason for concern. Figure 4 graphically represents the development of renewable energy production and RES. Note that the time period under consideration is 1995 through 2019, the level of production is in kWh and subsidy payments are in million EUR. These time series exhibit a persistent long-term movement and, hence, point towards the presence of an underlying (deterministic or stochastic) trend. As mentioned above, this might result in bias in regression coefficients and misleading inference (both through adjusted statistical distributions and spurious regression). The following paragraphs outline the strategy of this thesis for detecting and addressing the presence of an underlying trend.

Firstly, as a graphical evaluation of time series data is insufficient for the detection of underlying trends, Augmented Dickey-Fuller tests are employed (Dickey and Fuller, 1979). These will infer into non-stationarity (i.e. the presence of a unit root process). The null hypothesis indicates non-stationarity and the alternative hypothesis indicates either stationarity or, alternatively, stationarity around a deterministic trend. If the null hypothesis is rejected, non-stationarity can be deemed irrelevant and the time series requires no further adjustments. If the null hypothesis is not rejected for stationarity around a deterministic trend, the specification above will be contrasted with an identical specification to which a linear time trend is added. This time trend then also controls for the influence of altering demographic, social and meteorological factors beyond the control variables that might drive the time series to exhibit non-stationarity. Moreover, if the null hypothesis is rejected for both the test on stationarity and stationarity around a deterministic trend, first differencing will be applied to ensure a stationary process. Note the nature of the Dickey-Fuller test by which failure to reject the null hypothesis does not necessarily mean the null hypothesis holds true. Therefore, the regression specification without and with a time trend might still contain important information and serve as a valuable reference point. Therefore, these will be presented even if non-stationarity cannot be rejected. To decide on the appropriate lag length for the regression specification, the Bayesian information criterion (BIC) and Lütkepohl (2005) information criterion are employed. Trading off increased precision and statistical power, both information criteria indicate first-order (out of third-order) lagged variables are optimal (see Table A1). [7]

[7] The maximum of third-order lagged variables in the regression model is motivated by both data concerns (i.e. the required pre-sample) and administrative information (i.e. this is the maximum time allowed for renewable energy producers to initiate energy production after having been assigned a subsidy).

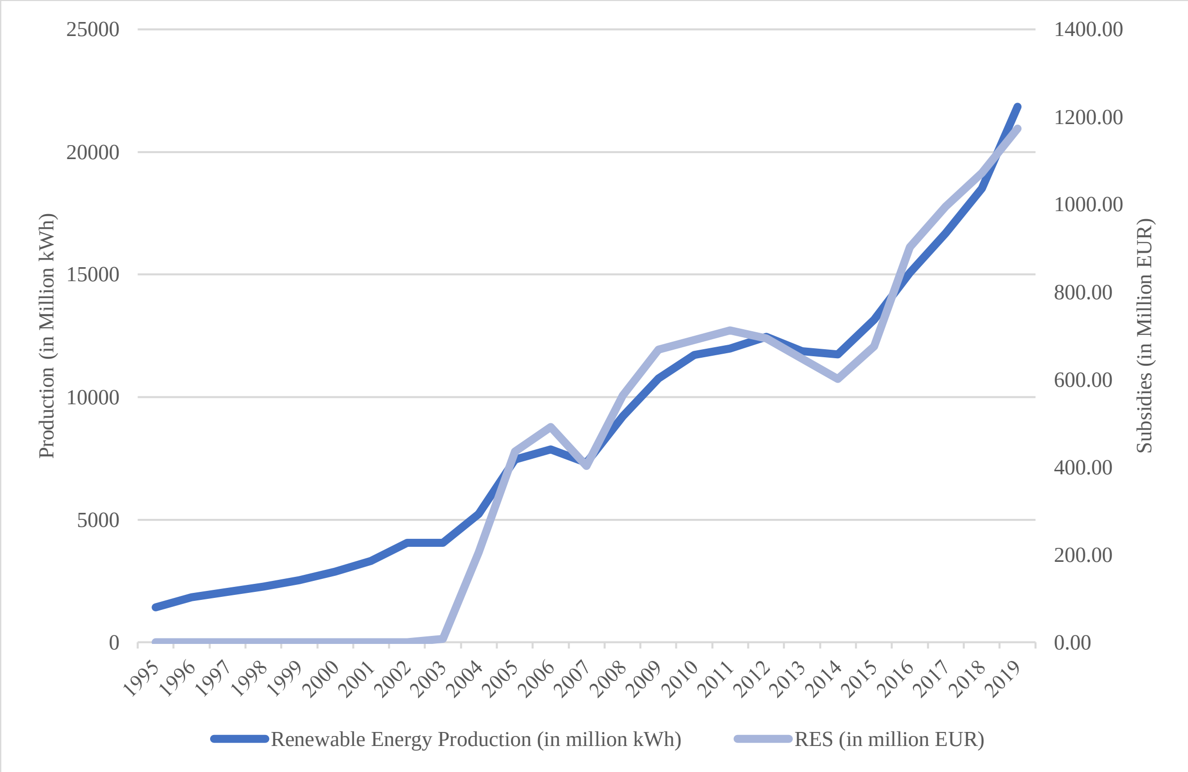


Figure 4 The relationship between renewable energy production and RES.

Secondly, in case a stochastic trend is detected by the Augmented Dickey-Fuller tests, one might consider these stochastic trends to be the same for the variables under consideration. Based on Figure 4, this might be a reasonable assumption as both time series move closely together. This implies that the time series can be modelled as a linear combination. This phenomenon is referred to as cointegration. As the cointegrating coefficient is unknown from economic theory, an Engle-Granger Augmented Dickey-Fuller test can be employed to test for cointegrated time series (Engle and Granger, 1987). In case the series appear to be cointegrated, the error correction term can be adopted in the model specification (similar to the time trend) to better assess the relationship of interest.

Furthermore, Figure 4 does not provide a definitive answer on the direction of the effect under consideration. To clarify, it is not necessarily clear whether subsidy payments increased renewable energy production or vice versa. Especially the pre-2003 period might substantiate such a claim. To address this concern, a test of predictive content, also known as a Granger causality test, is employed (Granger, 1969).[8] This will provide further intuition on the direction of the relationship of interest which is particularly important in assessing dynamic effects.

[8] Again, a maximum of third-order lagged variables is allowed in the Granger causality test, motivated by the same data concerns and administrative information as under the information criteria.

### 4.2.2 Instrumented Variable Regression

Although a test of predictive content yields important information on the direction of the effect under consideration, one might still be concerned about reverse causality under the allocation of RES under the MEP, SDE and SDE+ subsidy schemes. Recall that subsidies are paid out based on the unprofitable top, being the difference between the cost of producing energy from renewable sources (i.e. average market-cost) and the ongoing market price of energy. This means that subsidies are inherently linked to the market price of energy. As subsidies are expected to promote the production of renewable energy which, in turn, affect market prices which, in turn, affect subsidy payments, reverse causality could bias the estimates upwards (i.e. increased energy supply suppresses market prices and (mechanically) increases subsidy payments). To circumvent this issue, Guarantees of Origin can be used as an instrument. As discussed in Section 3, the purpose of these certificates is to request subsidy payments. Guarantees of Origin are, hence, issued for every unit of renewable energy for which subsidy payments are requested in the Netherlands. Though these Guarantees of Origin are strongly related to RES, the certificates are independent of market prices. This thus circumvents the issue of reverse causality through the market price of energy. This also means first-order lag of RES need not be instrumented. As renewable energy production in the present does not affect the market price of energy in the previous period, RES in the previous period will not be affected by this type of reverse causality.

Note that employing Guarantees of Origin as an instrument only resolves the particular issue of reverse causality through market prices of energy. Although this mechanism is expected to impact the regression estimates, other issues regarding reverse causality (as well as confounding factors) might not be resolved. To be explicit, the instrument does not (aim to) resolve all reverse causality or potential endogeneity issues. Formally, the first stage is represented by the following equation;

$$RES_t = \delta + \gamma Certificates_t + \pi_1 RES_{t-1} + \pi_2 GDP_t + \pi_3 Gas\_Price_t + \pi_4 Oil\_Price_t + \pi_5 Coal\_Price_t + \pi_6 Fossil\_Fuel\_Stock_t + \pi_7 Cumulative\_CO2_t + \pi_8 WGI_t + \mu_t$$

The power of this first stage will be assessed using a formal F-test. The reduced form is formally represented by the following equation;

$$RE\_Production_t = \theta + \tau Certificates_t + \varphi_1 RES_{t-1} + \varphi_2 GDP_t + \varphi_3 Gas\_Price_t + \varphi_4 Oil\_Price_t + \varphi_5 Coal\_Price_t + \varphi_6 Fossil\_Fuel\_Stock_t + \varphi_7 Cumulative\_CO2_t + \varphi_8 WGI_t + \omega_t$$

The entire procedure will be performed using two-staged least squares estimation. Postestimation will infer into a sufficiently strong first stage even as endogeneity of RES through the Woolridge (1995) robust regression-based test. The latter sheds some light on the sign and magnitude of potential omitted variable bias.

### 4.2.3 Broader Effects of RES

Finally, once the effect of RES on renewable energy production is evaluated, the effects of RES can be assessed more broadly using a wider variety of dependent variables, such as economic, environmental, labour market and social dimensions of welfare for the energy sector (SBI-code: 4), specifically. To clarify, here the outcome variables extracted from the SNA (particularly satellite accounts) and SDGs are employed. Thereafter, the principal components derived from the Monitor can be included to extend the findings. This accommodates a comprehensive and more coherent evaluation of broad welfare effects. Again, dynamic multivariate OLS regression is employed. The regression of interest reads;

$$Y_{zt} = \alpha + \beta_1 RES_t + \beta_2 RES_{t-1} + \beta_3 GDP_t + \beta_4 Gas\_Price_t + \beta_5 Oil\_Price_t + \beta_6 Coal\_Price_t + \beta_7 Fossil\_Fuel\_Stock_t + \beta_8 Cumulative\_CO2_t + \beta_9 WGI_t + \varepsilon_t$$

where $Y_z$ is a vector of nine outcome variables with z representing (1) GDP for the energy sector as measured in millions of EUR, (2) greenhouse gas emissions in the energy sector as measured in millions of CO2-equivalent units, (3) employment in the energy sector as measured in thousands of individuals, (4) hours worked in the energy sector as measured in thousands of hours, (5) costs of labour in the energy sector as measured in millions of EUR, (6) production of the environmental sector in the energy sector in millions of EUR, (7) installed renewable energy capacity as measured in MWh per capita, (8) fossil fuel import as measured in thousand KG and (9) emission intensity as measured in thousand KG of CO2-equivalent units per EUR of GDP. Finally, the principal components derived from the Monitor are also included in the vector $Y_z$.

On a final note, two issues will be briefly addressed. Correlated error terms over time might cause an incorrect estimate of the parameter variances. Thereto, heteroscedasticity and autocorrelated consistent (HAC) estimators are used. To ensure linearity and provide for more intuitive interpretation of the results, a logarithmic transformation is considered in addition to the linear outcomes. To assess functional form misspecification, link tests and augmented partial residual plots are employed. Partial regression leverage plots are employed to assess potential outliers.

## Section 5. Results and Discussion

To recapitulate, the presentation of the results is subdivided among two parts. Firstly, the associations in the Monitor are presented. Thereto, (1) the distribution of correlation coefficients is displayed, (2) groupings of similarly related indicators derived from cluster analysis are combined with heatmaps and (3) the principal component analysis (PCA) is reviewed. Secondly, the results of the time series regression of renewable energy production on RES is provided. Here, (1) stationarity, (2) cointegration and (3) reverse causality are reflected upon. Finally, broader effects even as limitations and suggestions for further research are discussed. All parts will be deliberated upon in turn.

### 5.1 Results for the Monitor

To assess the associations within the Monitor, Pearson product-moment and Spearman rank correlation coefficients are produced using casewise deletion to utilize all available data. Due to the sheer number of pairwise correlation coefficients (i.e. over 4000 coefficients), the individual coefficients are not disclosed explicitly in this thesis. To more intuitively present and interpret the associations reflected by these coefficients, several visualisations are provided instead. After a brief dissertation of these representations, their implications are discussed more elaborately, before turning to principal component analysis.

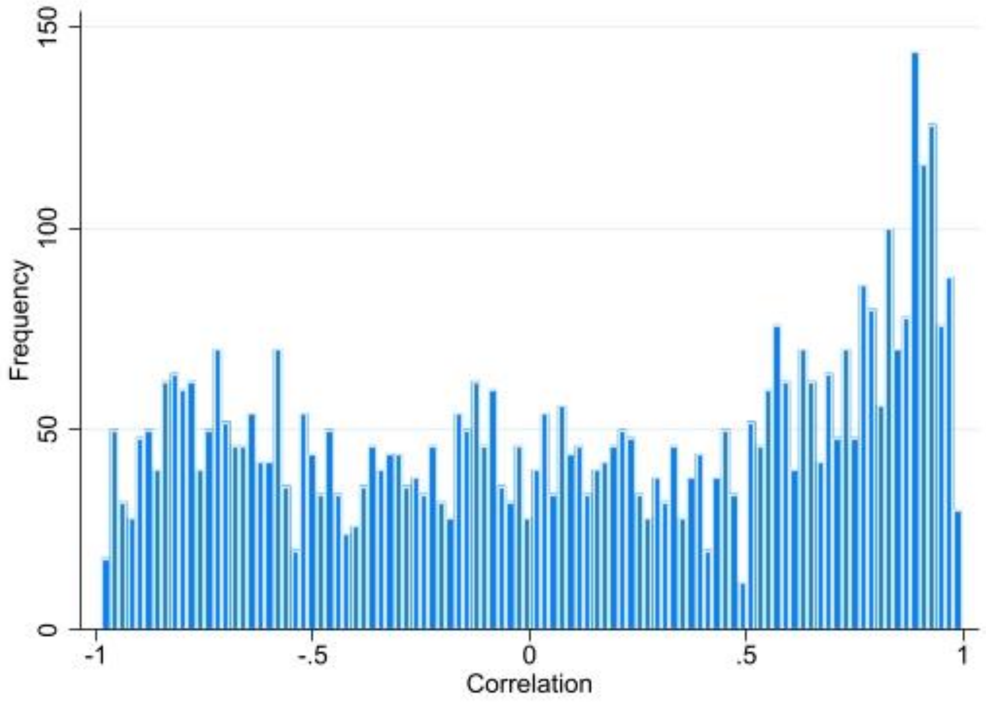


Figure 5 The distribution of Pearson product-moment correlation coefficients.

### 5.1.1 Correlation Coefficients

Figure 5 displays the distribution of Pearson product-moment correlation coefficients and Figure 6 presents the spread of Spearman Rank correlation coefficients as a histogram on a -1 to 1 scale with an 0.020 bin width. The distribution of correlation coefficients is also presented separately for each of the dimensions in the Appendix, where Figures A5.1, A5.2 and A5.3 show Pearson product-moment correlation coefficients and Figures A6.1, A6.2 and A6.3 display Spearman rank correlation coefficients. The dimension "here and now" contains an 0.040 bin width whereas the dimensions "later" and "elsewhere" contain an 0.066 bin width. The purpose of the histograms is assess to what extent indicators included in the Monitor are complements (i.e. a correlations around 0) or substitutes (i.e. a correlations close to -1 or 1).

All figures are remarkably similar and indicate that correlation coefficients are spread out rather evenly across the -1 to 1 scale. In addition, an increase in observation density for correlation coefficients towards positive 1 can be observed. This also holds for separate dimensions, where the dimension "later" exhibits disproportionately many strongly correlated indicators. This implies many of the indicators in the Monitor tend to exhibit similar patterns over time and, therefore, serve as substitutes. Although this is an outcome of significance by itself, it also underscores the scope for the detection of clusters of association within the Monitor as well as the potential for data reduction techniques.

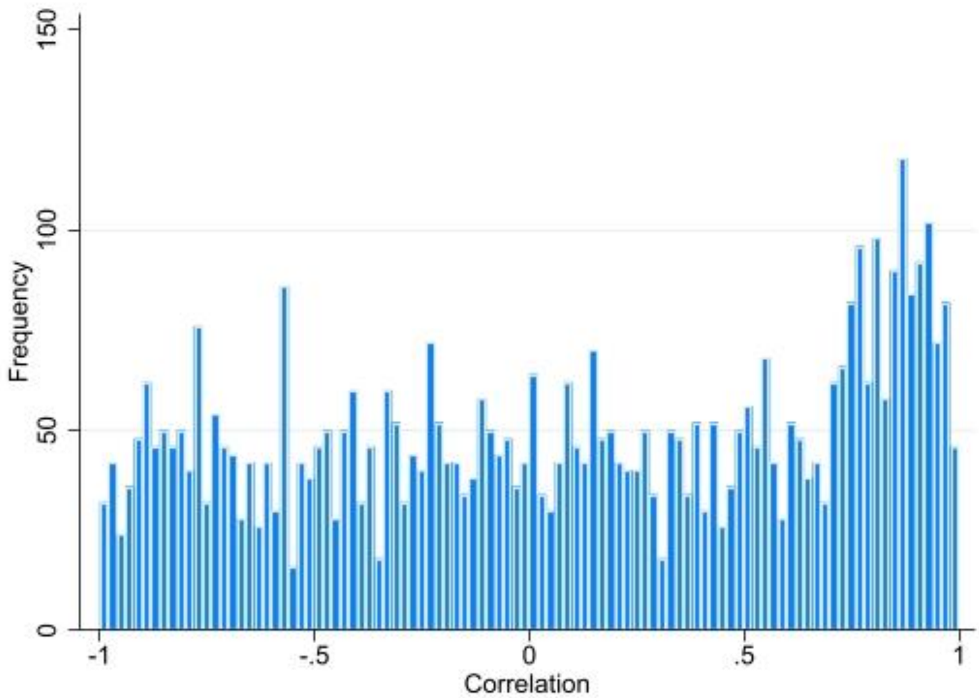


Figure 6 The distribution of Spearman rank correlation coefficients.

The distribution of correlation coefficients yields valuable insights into the data structure but tells little about the underlying qualitative relationships. To better present the content of the associations in the Monitor, heatmaps are regarded a powerful visualisation tool. Here, the strength of associations between individual indicators is portrayed through colour-coding of correlation coefficients. This yields the most straightforward presentation of all associations in the Monitor as it preserves the complete correlation coefficient matrices, capturing over 4000 correlation coefficients in a single figure.

Moreover, to better confer all associations within the Monitor in a heatmap, a more efficient ordering of indicators is considered. Whereas the thematic categorisation of the Monitor is useful for cultivating awareness of trends and outcomes of separate aspects of welfare, it is less fit for the purpose of statistical analysis and inference (as per this thesis). Alternatively, categorizing the indicators on basis of their statistical relationships is deemed expedient. Firstly, this allows for a more thorough reflection upon the data. By identifying groups of indicators that exhibit similar developments across temporal and spatial dimensions, the interpretation of associations and identification of potential trade-offs becomes more explicit. Secondly, it substantially reduces the dimensions of the data. Whereas taking into account all 66 indicators as potential variables of interest limits tractability, creating groups of similarly associated indicators allows for a more comprehensive and concise presentation even as interpretation of the results.

To realize the efficient ordering of indicators, cluster analysis is employed. Clustering is based on the Pearson product-moment and Spearman rank correlation coefficient matrices using hierarchical average linkage dissimilarities in Euclidian space. Hence, the clustering is based on the (dis)similarity of associations between all individual indicators.[9] Adjusting the order of indicators based on these criteria accommodates a more intuitive reflection upon the associations across several aspects, within separate dimensions as well as for the Monitor as a whole. All in all, it substantially improves the meaning of the heatmaps.

Figure 7 presents a heatmap for Pearson product-moment correlation coefficients whereas Figure 8 provides a heatmap for Spearman rank correlation coefficients. Heatmaps for the dimensions “here and now”, “later” and “elsewhere” are presented in the Appendix where Figures A7.1.1, A7.2.1 and A7.3.1 use Pearson product-moment correlation coefficients and

[9] Note that correlation coefficients are a type of similarity measure by themselves. Since one is interested in the resemblance of associations between a wide variety of indicators (rather than the similarity between individual indicators, as this is already captured by correlation coefficients), similarities (or dissimilarities in this case) of a similarity measure are evaluated for each individual indicator.

Figures A8.1.1, A8.2.1 and A8.3.1 use Spearman rank correlation coefficients, respectively. The clustering in these heatmaps can be visualized by dendrograms where the length of a line to a node is instructive of the association (or disassociation) between indicators or clusters of indicators. Dendrograms for the dimensions “here and now”, “later” and “elsewhere” are presented in Figures A7.1.2, A7.2.2 and A7.3.2 for Pearson product-moment correlation coefficients and Figures A8.1.2, A8.2.2 and A8.3.2 for Spearman rank correlation coefficients in the Appendix, respectively. A dendrogram for the entire Monitor is generated but not presented due to the size and clarity of the figure.

A careful reading of the heatmaps referred to above provides a rather consistent image of the associations and relationships in the Monitor. Both Pearson product-moment and Spearman rank correlation coefficients are of almost identical sign and magnitude. Also the clusters of association appear to be minimally affected by the choice of correlation coefficient. The clustering of indicators is also robust to the choice of clustering method. Similar groupings of indicators arise from hierarchical single linkage clustering and Ward’s linkage clustering. This provides confidence in the correct estimation of both correlation coefficients and clusters of association. Moreover, it allows for more meaningful interpretation of the heatmaps. To be complete, heatmaps for Pearson product-moment correlation coefficients (in Figure 7) are discussed in text and, hence, serve as the benchmark case. This is motivated by the more straightforward interpretation and wider use of Pearson product-moment correlation coefficients. Note that a discussion of Spearman rank correlation coefficients (in Figure 8), however, would produce the same outcomes and qualitative implications.

From Figure 7, five clusters of association can be identified for the Monitor. Reading from top to bottom (or, as the correlation coefficient matrix is symmetric, from left to right), Cluster 1 comprises 34 indicators ranging from GDP up to biomass imports from least developed countries, Cluster 2 comprises 8 indicators ranging from the Personal Well-being Index (PWI) up to life satisfaction, Cluster 3 comprises 7 indicators ranging from time lost in traffic up to metal imports from least developed countries, Cluster 4 comprises 13 indicators ranging from sense of control up to non-metal imports from least developed countries and, finally, Cluster 5 comprises 9 indicators ranging from employment satisfaction up to carbon footprint. To elaborate on the associations these clusters contain and provide them with more qualitative meaning, they will be highlighted in turn and are subsequently referred to under a name that represents the most intuitive associations they comprise. Moreover, the relationships between the various clusters are also deliberated upon.

The first cluster, being the largest by a substantial margin, comprises indicators that are (intuitively) related to economic development and exhibit a strong association with GDP. Hence, this can be referred to as a cluster on “economic progress”. The cluster comprises indicators of consumption, employment, education, capital accumulation, imports (of raw materials and fossil fuels) and emissions. Moreover, associations concerning improvements in norms and values and an increased sense of discrimination are also included in this cluster. These might constitute higher-order effects (i.e. indirect consequences of economic progress) by which expanded focus or a broader platform are a consequense of increased economic activity. However, the associations by no means represent causal relationships and must be handled with caution. Nonetheless, they are informative of the comovement of indicators across time in the Netherlands.

The second cluster comprises indicators such as the Personal Well-being Index (PWI), life satisfaction, disposable income even as trust in people as well as institutions. One might want to refer to this group of indicators as a cluster on “well-being”. Remarkably, this cluster is closely related to the cluster on “economic progress”, implying that indicators relating to both “well-being” and “economic progress” have very similar characteristics. This might imply that “well-being” is (partially or, perhaps, even mainly) driven by indicators (associated with) “economic progress”. This is subject to substantive discussion in the debate on Beyond GDP.[10] For the Netherlands it appears as if, at least to some extent, “well-being” and “economic progress” share an intimate connection.

The third cluster includes nitrogen deposition, nitrogen excess, phosphorus excess, time lost in traffic, household capital and metal imports from least developed countries. While small in size, the indicators are much more dispersed. Contrary to before, the indicators it comprises appear to have less intuitive associations among themselves. However, the indicators do exhibit an overall negative association with the cluster on “economic progress”. This signals that “economic progress” might play a role in reducing emissions of harmful pollutants (from a long-term perspective).[11] Moreover, it reduces household savings and reduces imports of metal from less developed nations. On the contrary, it exhibits no relationship with “well-being”, implying the indicators in this cluster might not affect nor be affected by the subjective well-being of individuals. One might refer to this cluster as “externalities”.

[10] Boarini et al. (2006), Dolan et al. (2008) and Van Zanden et al. (2014), for example, provide various accounts of the relationship between economic development and measures of well-being.
[11] Grossman and Krueger (1991) and Brock and Taylor (2010) provide an account of the potential for Green Growth as implied by the Environmental Kuznets Curve.

The fourth cluster, contrary to all other clusters, shows only moderately strong associations among the indicators it comprises. It includes indicators such as sense of command over life, satisfaction with free time, housing and social contacts, voice and accountability, volunteering, sense of security and environmental issues. This might be referred to as a cluster on "subjective evaluations" (of outcomes). Although these indicators seem to have no intuitive connection with one another directly, they are (weakly) negatively correlated with the cluster on "economic progress" and (strongly) negatively correlated with the cluster on "well-being". Although one might expect these "subjective evaluations" to contribute to "well-being" of individuals, the associations between these clusters point towards a potential trade-off between economic prosperity and other dimensions of welfare. To illustrate, "economic progress" is likely to affect how individuals allocate their time which is subsequently reflected in subjective measures relating to leisure, time loss and contacts. Also competition on the housing market limits the degree to which individuals can find appropriate housing and, through "subjective evaluations", impact "well-being".[12]

Finally, the fifth cluster contains indicators that are, again, more dispersed. Satisfaction with employment, victim of crime, exposure to PM2.5, non-metal imports and carbon footprint are grouped together here. This final cluster can be referred to as "other indicators". The cluster exhibits a strong inverse relationship with "economic progress" as well as "subjective well-being". This implies that economic activity reduces the levels of the indicators in this final cluster, for example through a tighter labor market or increased abatement efforts. Moreover, these might be aspects of well-being that, in contrast to the third cluster, suppress "subjective well-being". [13] Again, it is important to stress that these relationships are by no means causal but provide valuable insights in the comovements of aspects of welfare in the Netherlands.

In conclusion, the Monitor contains a wide variety of associations that can be effectively evaluated using cluster analysis and comprehensively presented using heatmaps. Relationships between economic development, well-being, subjective evaluations and externalities are detected and briefly reconciled with theory. Though several of the associations noted are discussed in academic literature, several other aspects could be subject to further deliberation. Especially converting simple associations (of higher-order effects) into empirically grounded assessments of (causal) relationships would be of interest.

[12] Some of these relationships are also noted in the original Monitor (CBS, 2020). A more elaborate account of such potential effects is provided there.
[13] Statistics Netherlands (2020) provides a more elaborate account of such potential effects.

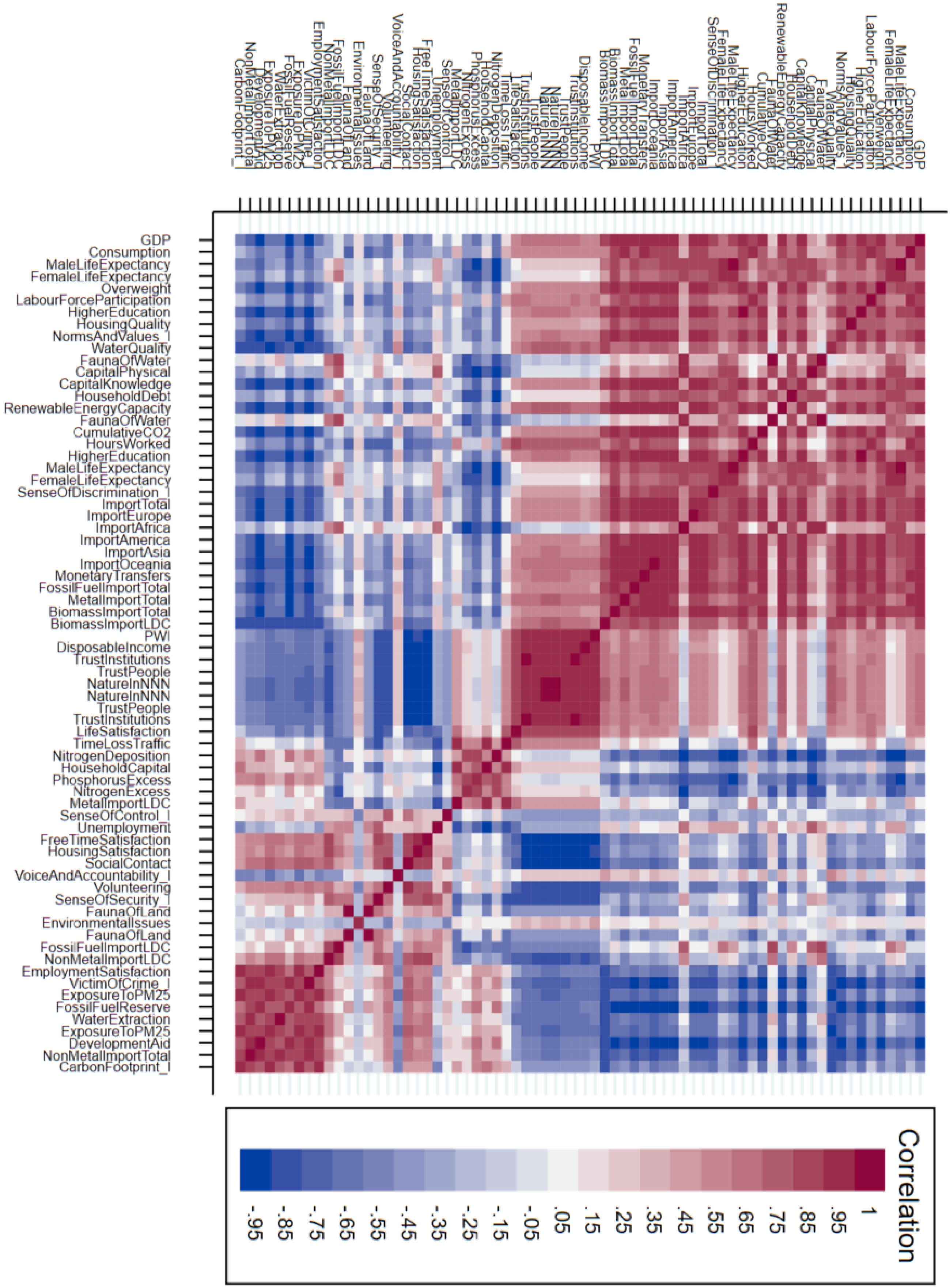


Figure 7 Heatmap of the Pearson product-moment correlation coefficients.

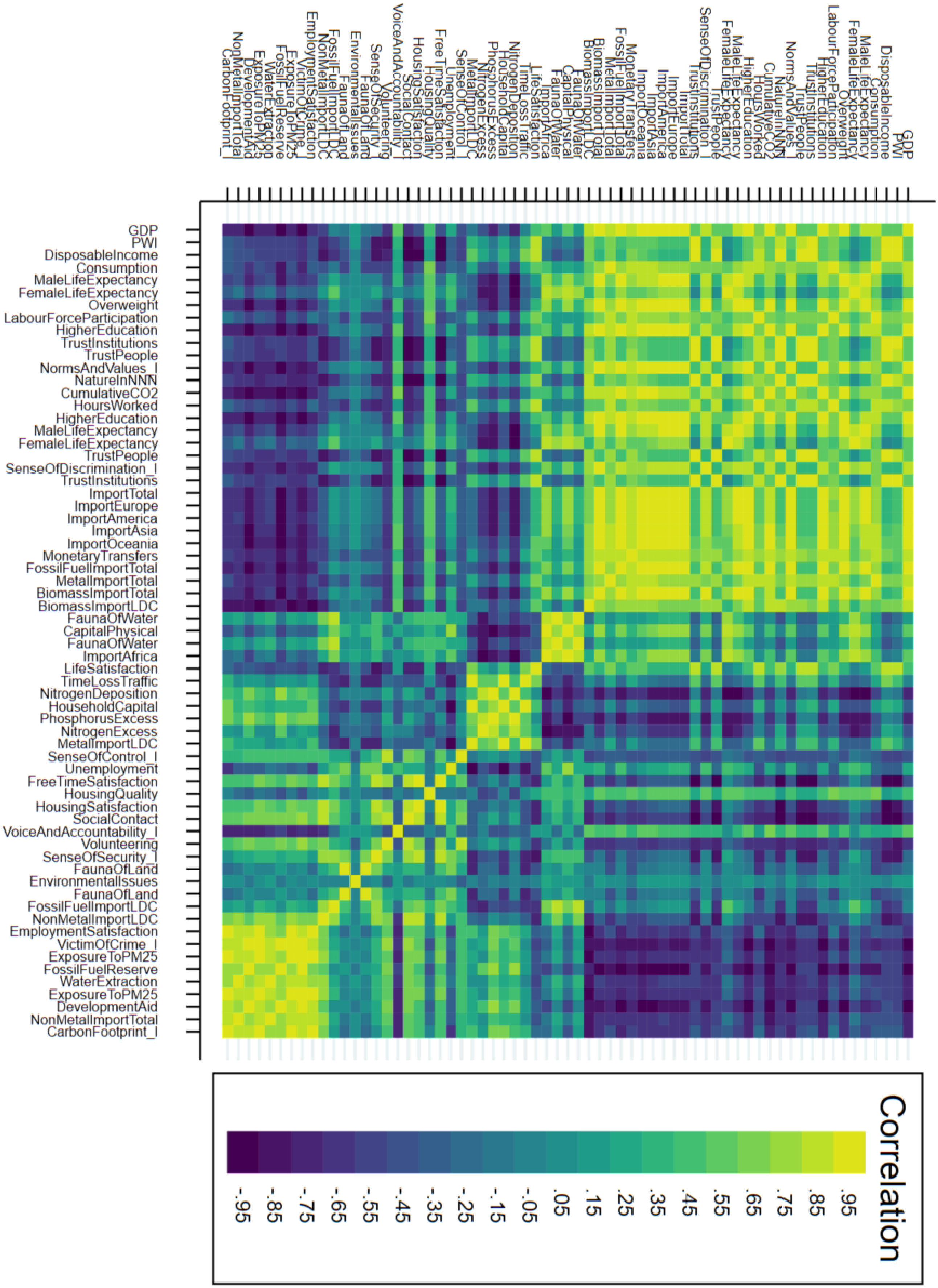


Figure 8 Heatmap of the Spearman rank correlation coefficients.

### 5.1.2 Principal Component Analysis

The clusters of (strongly) associated indicators identified in the Monitor presents an auspicious characteristic of the data. A more technical approach utilizing such associations is introduced with principal component analysis (PCA) allowing for a comprehensive and tractable evaluation of government policy. However, in the construction of principal components, some features of the data appeared problematic. As indicated in Section 4, the number of observations of indicators differed between indicators, resulting in missing values throughout the Monitor. When producing correlation coefficient matrices, casewise deletion was applied (i.e. pairwise correlation estimates were constructed) to address this issue. This gave a primary indication of the association between variables while utilizing all available information between variable pairs. For PCA, however, listwise deletion is forced, reducing the number of observations drastically.[14] This could not be addressed effectively through additional interpolation or extrapolation. However, two alternative solutions have been identified and employed to the end of performing PCA in a robust and meaningful way.

Firstly, the number of indicators included in the PCA could be reduced by leaving out those indicators with (many) missing observations. This yields longer time series (notably from 1997 to 2018) of 39 indicators without missing values in the Monitor. The maximum number of components is limited 22 as per the number of included observations. Secondly, one could reduce the number of observations, reducing the length of the time series to 2013 through 2018 while retaining all 66 indicators in the Monitor. This means the maximum number of components is limited to 6 as per the number of included observations. For the sake of completeness, both options have been explored. The former option, though leaving out some of the indicators in the Monitor, appeared most appropriate and is presented in this thesis. The latter option retained too few observations. This led to a lack of statistical power, preventing meaningful interpretation of the PCA, and is, hence, omitted.

The output of the PCA is summarized in Table 4. Component 1 explains a substantive 67% of the variation. Taking into account the Kaiser Criterion, all components up to Component 5 should be included, capturing 94% of all variation in the data. This is also indicated by the Scree Plot depicted in Figure A9 in the Appendix. Hence, PCA reduced the dimensions of the data to only five components while capturing almost all variation.[15]

[14] For the sake of clarity, listwise deletion means that in case one missing observation in one of the indicators in one year appears to be missing, all observations of all indicators of that particular year are discarded.

[15] Note that Component 1 to Component 18 are presented in Table 4, omitting Component 19 to Component 22. As eigenvalues were zero, these components were wholly uninstructive.

Table 4 PCA Output with Eigenvalues and Explained Variation.

| Component | Eigenvalue | Proportion | Cumulative |
|---|---|---|---|
| Component 1 | 26.05 | 0.67 | 0.67 |
| Component 2 | 3.93 | 0.10 | 0.77 |
| Component 3 | 3.18 | 0.08 | 0.85 |
| Component 4 | 2.37 | 0.06 | 0.91 |
| Component 5 | 1.11 | 0.03 | 0.94 |
| Component 6 | 0.68 | 0.02 | 0.96 |
| Component 7 | 0.48 | 0.01 | 0.97 |
| Component 8 | 0.34 | 0.01 | 0.98 |
| Component 9 | 0.26 | 0.01 | 0.98 |
| Component 10 | 0.18 | 0 | 0.99 |
| Component 11 | 0.12 | 0 | 0.99 |
| Component 12 | 0.10 | 0 | 1 |
| Component 13 | 0.07 | 0 | 1 |
| Component 14 | 0.05 | 0 | 1 |
| Component 15 | 0.04 | 0 | 1 |
| Component 16 | 0.02 | 0 | 1 |
| Component 17 | 0.01 | 0 | 1 |
| Component 18 | 0.01 | 0 | 1 |

As noted in Section 4, simple structures can be employed to clarify variable loading scores and (potentially) eliminate double loadings. Following from Table 4, there is a rather substantial difference between eigenvalues for each component. Component 1 captures a marked 67% of variation in the entire dataset. Components 2 through 5 capture 10%, 8%, 6% and 3%, respectively. Due to this particular data structure, rotation is considered but concluded to be inadvisable. All variation now comprised by Component 1 becomes spread out over a vast larger number of components (i.e. 18 in total) which nullifies the aim of PCA. As this hinders effective interpretation, unrotated variable loadings are considered instead.

Table 5 presents the variable loading scores. Using five components, the unexplained variation of the variables is low, showing most of the variation is captured by the included components. By reading the table row-wise, the loading of each indicator on each component can be determined. Although the purpose of PCA in this setting is analytical by nature, it can also be used as a more exploratory tool. Clusters of association can be identified from the variable loadings on each of the principal components. Although all indicators somehow load on each principal component, it is the primary loadings that one is (most) interested in. These are presented in bold in Table 6 for the sake of clarity. Component 1 loads 22 indicators, Component 2 loads 10 indicators, Component 3 loads 4 indicators, Component 4 loads 5 indicators and Component 5 loads 10 indicators.

Table 5 Unrotated Variable Loadings for each component following from the PCA.

| Indicator | Component 1 | Component 2 | Component 3 | Component 4 | Component 5 | Unexplained |
|---|---|---|---|---|---|---|
| GDP | **0.19** | -0.01 | 0.05 | -0.05 | -0.04 | 0.01 |
| Life Satisfaction | -0.01 | -0.08 | **0.50** | 0.08 | 0.08 | 0.16 |
| Consumption | 0.17 | **0.20** | 0.11 | 0.00 | -0.03 | 0.04 |
| Male Life Exp. | **0.18** | 0.11 | -0.05 | 0.04 | -0.16 | 0.09 |
| Female Life Exp. | **0.17** | **0.18** | -0.05 | 0.11 | -0.11 | 0.11 |
| Overweight | **-0.18** | 0.12 | 0.02 | 0.07 | **0.16** | 0.08 |
| Labor Force Part. | 0.11 | 0.16 | **0.35** | 0.23 | -0.02 | 0.08 |
| Higher Education | **0.19** | -0.08 | 0.00 | -0.07 | -0.09 | 0.01 |
| Voice and Account. † | 0.01 | -0.17 | -0.14 | **-0.51** | 0.31 | 0.11 |
| Norms and Values † | **0.18** | -0.04 | 0.07 | -0.10 | 0.05 | 0.09 |
| Fauna in Water | 0.16 | **0.24** | -0.15 | -0.09 | 0.03 | 0.01 |
| Fauna on Land | 0.04 | -0.31 | -0.14 | **0.44** | 0.17 | 0.03 |
| Nitrogen Deposition | 0.15 | 0.04 | **-0.18** | **0.18** | **-0.18** | 0.18 |
| Physical Capital | **0.18** | 0.03 | -0.22 | -0.03 | -0.01 | 0.02 |
| Knowledge Capital | **0.18** | -0.12 | 0.02 | -0.02 | **-0.17** | 0.04 |
| Av. Household Debt | **-0.18** | -0.15 | 0.08 | 0.00 | -0.02 | 0.02 |
| Fossil Fuel Reserve | **-0.18** | 0.13 | -0.07 | 0.14 | 0.04 | 0.03 |
| Renewable Energy | **0.17** | **-0.18** | 0.15 | -0.13 | **-0.18** | 0.02 |
| Phosphorus in Excess | **0.18** | 0.00 | -0.09 | 0.08 | -0.01 | 0.13 |
| Nitrogen in Excess | **0.16** | **0.16** | -0.13 | **0.15** | 0.08 | 0.14 |
| Fauna on Land | 0.04 | -0.31 | -0.14 | **0.44** | 0.17 | 0.03 |
| Fauna in Water | 0.16 | **0.24** | -0.15 | -0.09 | 0.03 | 0.01 |
| CO2 Emissions | **-0.19** | 0.04 | 0.03 | 0.04 | 0.05 | 0.01 |
| Hours Worked | 0.05 | 0.08 | **0.52** | 0.11 | -0.04 | 0.03 |
| Higher Education | **0.19** | -0.08 | 0.00 | -0.07 | -0.09 | 0.01 |
| Male Life Expectancy | **0.18** | 0.11 | -0.05 | 0.04 | -0.16 | 0.09 |
| Female Life Expectancy | **0.17** | **0.18** | -0.05 | 0.11 | -0.11 | 0.11 |
| Import Total | 0.19 | -0.05 | 0.03 | 0.01 | **0.21** | 0.01 |
| Import from Europe | **0.19** | -0.04 | 0.03 | 0.01 | **0.20** | 0.02 |
| Import from Africa | 0.16 | 0.04 | -0.13 | 0.16 | **0.36** | 0.09 |
| Import from America | 0.18 | -0.01 | 0.07 | 0.08 | **0.23** | 0.03 |
| Import from Asia | **0.19** | -0.08 | 0.03 | -0.03 | **0.20** | 0.02 |
| Import from Oceania | 0.16 | **-0.24** | 0.16 | -0.03 | 0.08 | 0.04 |
| Development Aid | -0.14 | **0.28** | -0.01 | 0.18 | 0.08 | 0.13 |
| Foreign Transfers | **0.18** | 0.12 | 0.11 | -0.02 | -0.07 | 0.05 |
| Import Fossil Fuel | **-0.18** | 0.14 | -0.04 | 0.01 | 0.09 | 0.07 |
| Import Metal Import | -0.12 | -0.12 | -0.14 | 0.19 | **-0.46** | 0.17 |
| Import Non-Metal | 0.10 | **-0.39** | -0.06 | -0.03 | -0.25 | 0.05 |
| Import Biomass | **-0.19** | 0.00 | -0.03 | -0.06 | -0.08 | 0.03 |

Notably, Component 1 loads a vast array of indicators across all dimensions. Some of the associations identified through cluster analysis also appear here. One can see that GDP, consumption, life expectancy, overweight, education, physical capital, knowledge capital and several import indicators load on Component 1, as was the case for the cluster on “economic progress”. Component 2 is scattered throughout and presents a less coherent image. Component 3 loads life satisfaction and emission indicators whereas Component 4 loads fauna and fossil fuel stocks. Finally, Component 5 loads mainly import indicators. Though interestingly enough, one must exercise caution in drawing conclusions. As noted above, the purpose of PCA is technical (i.e. dimension reduction) and, by extension, exploratory. However, it is in no way a confirmatory analysis.

The principal components are, finally, predicted for every individual time period. This captures the overall comovement of similar indicators in a given year and allows for the evaluation of RES on the Monitor through only five outcome variables. To assess the appropriate use of PCA on the dataset, Bartlett’s Test of Sphericity is employed. The null hypothesis that the variables in the Monitor are unrelated is rejected at even the 1% significance level with a Chi-squared statistic of 3481.6. and a p-value of 0.000. This indicates the Monitor is suited for structure detection and PCA is warranted, both intuitively and formally.

### 5.2 Results for RES

The review of the Monitor shows a wide variety of associations and potential relationships. These are effectively captured by PCA and, furthermore, provide a helpful context for the assessment of effects of RES on welfare in a broad sense. However, per the methodology, the primary effects of RES on renewable energy production are assessed first. Here tests that infer into stationarity, cointegration and reverse causality are deployed. Secondly, broader effects of RES within the energy sector (SBI-code: 4) are evaluated. Finally, potential effects of RES on the Monitor are assessed.

#### 5.2.1 Dynamic Ordinary Least Squares Regression

To grasp the power of the association between renewable energy production and RES, Pearson product-moment as well as Spearman rank correlation coefficients can be produced. Satisfaction of the requirements of no outliers, quantitative measurement and linear relationships allow for meaningful interpretation. The correlation coefficients have values of 0.9841 and 0.9669, respectively, being significant at even the 1% level. However, as has been the case so far, correlation estimates do not provide a basis for causal inference.

Thereto, heteroskedasticity- and autocorrelation-consistent (HAC) estimators of the dynamic multivariate OLS regression of renewable energy production on RES are presented in Table 6. Column 1 shows the estimates of the model specification presented in Section 4.1.2. The Augmented Dickey-Fuller test for non-stationarity (against the alternative of stationarity) returned insignificant results (see Table A2 in the Appendix) meaning non-stationarity cannot be rejected. Therefore, a time trend is added to the model specification to address non-stationarity following from a deterministic trend. These estimates are presented in Column 2. Moreover, the Augmented Dickey-Fuller test against the alternative of stationarity around a deterministic trend also returned insignificant results (see Table A3 in the Appendix). Thereto, first differences are calculated for the model specification in Section 4.1.2 to address non-stationarity following from a stochastic trend. These estimates are presented in Column 3.

The Augmented Dickey-Fuller test for non-stationarity (against the alternative of stationarity) for the differnced model specification indicates that differencing was effective in addressing non-stationarity in the time series (see Table A4 in the Appendix).[16] This allows one to conclude that the time series are integrated of order one meaning that differencing coverts the time series into a stationary set of observations, which is a prerequisite for the production of unbiased and consistent estimates following dynamic multivariate OLS regression. Therefore, the model specification to which differencing is applied is taken as the benchmark case to assess the effect of RES on renewable energy production in the Netherlands.

As the Augmented Dickey-Fuller test could not reject the presence of a stochastic trend in the original time series data, an Engle-Granger Augmented Dickey-Fuller test is employed to detect whether the time series are cointegrated (i.e. whether the stochastic trends are common for RES and renewable energy production). Based on MacKinnon (1990, 2010) critical values, the null hypothesis for non-cointegrated time series is not rejected for the original nor the differenced time series (see Table A5 and A6 in the Appendix, respectively). This implies the stochastic trends for RES and renewable energy production are not identical. Hence, no error correction term needs to be included in the model specification. Note that this would have effectively resulted in a vector error correction model (VECM) which could have provided further insight on the predictive content of either time series. This will be discussed along with the issue of reverse causality.

[16] Note that in calculating first differences for the time series data in order to address non-stationarity, an observation is lost due to the required pre-sample.

Turning to the content of Table 6, one finds that the estimates are of similar sign and magnitude. The dynamic multivariate OLS regression indicates that RES increased renewable energy production over the time period studied. Based on the estimates in Column 1, an increase in subsidy payments of 1 million EUR results in a 5.999 million MJ increase in renewable energy production. Moreover, subsidy payments in a previous period also tend to increase renewable energy production. Here, a 1 million EUR increase in subsidy payments would yield a 2.862 million MJ increase in renewable energy production. As both effects are statistically significant at the 5% and 10% level, respectively, this provides evidence for an effect of RES on renewable energy production. However, as the time series in this model is non-stationary, these estimates must be handled with caution as these might follow from incorrect test statistics or spurious regression. When incorporating a time trend in Column 2 (absorbing a potential deterministic trend), a comparable image arises. An increase in subsidy payments of 1 million EUR results in a 6.940 million MJ increase in renewable energy production. On the contrary, subsidy payments in the previous period result in a -1.342 million MJ increase. This is a striking outcome which cannot be readily explained by intuition. However, whereas the former effect is significant at the 1% level, the latter is insignificant at even the 10% level. Hence, interpretation of the latter estimate would be infeasible as it is indistinguishable from zero. Note that the estimates for RES in Column 1 and 2 do not differ from a statistical viewpoint as the confidence intervals overlap with the point estimates. Hence, these imply similar effects of RES on renewable energy production. Finally, the differenced model (absorbing the stochastic trend) is considered in Column 3. Again, similar estimates appear. As the time series are converted into percentage changes, the interpretation also concerns percentage points. To be precise, a 1 percentage point increase in subsidy payments results in a 0.334 percentage point increase in renewable energy production. This estimate is significant at even the 1% level. As in Column 2, the lagged effect is negative. However, as it is insignificant at even the 10% level it cannot be provided with a meaningful interpretation.

All in all, the various estimates indicate a positive effect of renewable energy subsidies on renewable energy production. This provides evidence of the effectiveness of energy policy and points towards substantial primary effects of energy policy. However, as pointed out in Section 4, the issue of reverse causality needs to be addressed. Thereto, a statistical test even as instrumented regression technique is deployed to isolate potential (upwards) bias.

Table 6 HAC Estimates of renewable energy production on RES.

| | (1)<br>Renewable Energy Production | (2)<br>Renewable Energy Production (Trend) | (3)<br>Renewable Energy Production (Δ) |
|---|---|---|---|
| RES | 5.999** | 6.940*** | 0.334*** |
| | (2.061) | (1.073) | (0.069) |
| RES (in t – 1) | 2.862* | -1.342 | -0.036 |
| | (1.436) | (1.478) | (0.058) |
| GDP | -0.003 | 0.007 | -0.017 |
| | (0.013) | (0.007) | (1.129) |
| Coal Price | 14.70** | -1.019 | 0.082 |
| | (6.795) | (6.921) | (0.083) |
| Gas Price | -92.63 | 68.12 | -0.065 |
| | (114.2) | (97.13) | (0.108) |
| Oil Price | -13.23 | -3.871 | 0.014 |
| | (14.44) | (13.99) | (0.079) |
| Gas Reserve | -2.703** | 12.14** | 0.038 |
| | (1.155) | (4.805) | (0.841) |
| CO2 Emissions | 5,417 | -25,38** | 13.14 |
| | (6,109) | (9,810) | (16.30) |
| WGI | 3,524 | -2,875 | -0.332 |
| | (2,550) | (1,765) | (1.119) |
| Trend | | *** | |
| Constant | -34,533 | 145,07** | 0.209 |
| | (39,557) | (57,291) | (10.93) |
| Observations | 23 | 23 | 22 |

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

Note that, whereas Column 1 indicates a (marginally) statistically significant dynamic effect of RES on renewable energy production, Column 2 and 3 do not. This could have various causes. Firstly, there might be no dynamic effect of RES on renewable energy production. Column 1, hence, presents an effect that is likely to be driven by a stochastic trend. Secondly, the control variables included might not absorb all potential confounding variables. If variables that cause a negative bias are not controlled for, these can cause insignificant outcomes. Thirdly, the functional form might be non-linear and, therefore, misspecified. This causes an ordinary least squares regression to return inaccurate and insignificant outcomes. To assess the plausibility of these explanations, additional information is collected. The issue will be reintroduced at the end of this section for further elaboration.

### 5.2.2 Instrumented Variable Regression

To address potential reverse causality, a Granger causality test is employed. Constructing a VAR model, allowing for up to three lags in both RES and renewable energy production, one infers into Granger causal links.[17] As stationarity is required for a correct specification of the Granger causality F-statistic, the results follow from the differenced model specification. The Granger causality test (see Table A7 in the Appendix) implies that RES holds predictive content for (i.e. Granger-causes) renewable energy production whereas renewable energy production holds no predictive content for (i.e. does not Granger-cause) RES. This implies that the upwards sloping trend in Figure 4 follows from the potential impact of RES on renewable energy production, rather than vice versa. As this is a test of predictive content, it does not provide an exhaustive answer to the issue of reverse causality. However, it is deemed a useful aid in determining the direction of the effect which is, especially given Figure 4, of particular importance in this context.

As follows from economic intuition and information on the allocation of subsidy payments, a more specific issue of reverse causality needs to be addressed. To repeat, subsidies are paid out based on the unprofitable top. As market prices of energy fluctuate, by no small part due to the supply of (renewable) energy, the unprofitable top and, hence, subsidies fluctuate too. An increase in renewable energy production might suppress the market price of energy which might positively impact the unprofitable top and, hence, increase subsidy payments. To address the issue of reverse causality through this price mechanism, a measure independent of market prices but closely related to renewable energy subsidies is considered. The instrumented regression specification introduced in Section 4.2.2 incorporates Guarantees of Origin for this purpose. Moreover, all other control variables that account for potential confounding factors are retained in the model specification. The second-stage regression output is reported in Table 7 where Column 1 shows the original two-stage specification, Column 2 incorporates a time trend and Column 3 includes a differenced time series.

Note that the estimates in Column 1 and 2 are of similar sign and magnitude and closely resemble the dynamic multivariate OLS regression estimates. Although they appear somewhat smaller, the difference is not statistically significantly as the confidence intervals overlap. Column 1 indicates that a increase in subsidy payments of 1 million EUR results in a 4.641 million MJ increase in renewable energy production. Moreover, subsidy payments in a

[17] To be precise, this refers to the Granger causality F-statistic following from a test on the null hypothesis that the explanatory variable of interest holds no predictive content on the outcome variable of interest beyond the predictive content captured by all other regressors in the model (Granger, 1969; Stock and Watson, 2015).

previous period also tend to increase renewable energy production. Here, a 1 million EUR increase in subsidy payments would yield a 3.804 million MJ increase in renewable energy production. As both effects are statistically significant at the 10% and 5% level, respectively, this provides additional evidence for an effect of RES on renewable energy production. Similarly, Column 2 indicates that an increase in subsidy payments of 1 million EUR increases renewable energy production by 6.748 million MJ. On the contrary, subsidy payments in a previous period tend to decrease renewable energy production. Whereas the former is significant at even the 1% level and, hence, allows for a meaningful interpretation, the latter is insignificant at even the 10% level and should be discarded. Note that the R-squared for the estimates in both Column 1 and 2 is also substantial. As it approaches unity it implies that the regressors explain almost all variation in renewable energy production. Moreover, the F-statistic for a sufficient first-stage (practically) satisfies the rule of thumb for F-statistic > 10. This signals that the relationship between Guarantees of Origin and subsidy payments was sufficiently strong to attribute a purposeful outcome. What is more, the Woolridge (1995) robust regression-based test shows p-values of 0,528 for Column 1 and 0,160 for Column 2. This indicates the variable of interest (i.e. RES) is reasonably exogenous and, hence, need not be treated as an endogenous regressor. Although the purpose of the instrument was to address reverse causality through the market price mechanism, this statistic provides additional confidence in appropriateness of the dynamic multivariate OLS estimates.

Compared to the instrumented regression estimates presented above, Column 3 shows a markedly different image. Estimates of subsidy payments in current and previous periods are negative and statistically insignificant. What is more, the R-squared is substantially lower and the F-statistic does not satisfy the rule of thumb for F-statistic > 10 for a sufficiently strong first stage. Although a meaningful interpretation is deterred, the insignificant estimates might induce doubt on the model characteristics or appropriate use of the instrument. Although differencing eliminates the stochastic trend in a time series integrated of order one, it also substantially reduces the variation in the original data. While the remaining variation sufficed for the dynamic multivariate OLS regression, it appears to impact the instrumented regression, requiring more statistical power, much more strongly. Therefore, the result in Column 3 might be driven by a mechanical effect in combination with a more demanding statistical test. This naturally also holds for the R-squared and the F-statistic as these are similarly affected by the variance in the data. Although one must exercise caution in putting to much weight on the implications of the instrumented regression, it does not render it inaccurate nor useless.

Table 7 Instrumented HAC estimates of renewable energy production on RES.

| | (1)<br>Renewable Energy<br>Production | (2)<br>Renewable Energy<br>Production (Trend) | (3)<br>Renewable Energy<br>Production (Δ) |
|---|---|---|---|
| RES | 4.641* | 6.748*** | -0.964 |
| | (2.372) | (1.228) | (4.275) |
| RES (in t – 1) | 3.804** | -1.183 | -0.279 |
| | (1.517) | (1.285) | (0.742) |
| GDP | -0.00449 | 0.00697 | -1.393 |
| | (0.0109) | (0.00490) | (5.157) |
| Gas Price | -85.92 | 67.85 | 0.414 |
| | (90.91) | (71.34) | (1.548) |
| Oil Price | -18.66 | -4.678 | 0.065 |
| | (14.73) | (8.669) | (0.240) |
| Coal Price | 18.88** | -0.335 | -0.055 |
| | (8.136) | (6.244) | (0.390) |
| Gas Reserve | -2.649*** | 12.04*** | 6.282 |
| | (0.899) | (3.657) | (19.76) |
| CO2 Emissions | 6,685 | -24,981*** | -52.08 |
| | (5,512) | (7,532) | (201.8) |
| WGI | 3,000 | -2,898** | -6.561 |
| | (2,096) | (1,283) | (19.30) |
| Trend | | *** | |
| Constant | -41,551 | 142,790*** | 79.90 |
| | (34,875) | (43,514) | (249.4) |
| Observations | 23 | 23 | 22 |
| R-squared | 0.995 | 0.998 | 0,370 |
| F-statistic | 12,763 | 9,359 | 0,055 |
| P-value | 0,528 | 0,160 | 0,170 |

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

To summarize, the dynamic multivariate OLS even as the instrumented regression provide evidence of a statistically significant impact of RES on renewable energy production. This is in line with Hypothesis 1 in Section 2. Although not unambiguous, an increase in subsidy payments in the current period tends to increase renewable energy production significantly and substantially across all but one specification. The inclusion of a time trend tends to increase the estimates of RES, implying these potentially suffered from downwards bias through a deterministic trend. What is more, the instrumented regression estimates are somewhat lower than the dynamic multivariate OLS regression estimates, implying a (small) positive effect of the price mechanism inducing reverse causality. However, as confidence intervals overlap this cannot be confirmed statistically. When a stochastic trend in the time series is addressed through differencing, the dynamic multivariate OLS regression estimates retain their sign, magnitude and statistical significance and remain comparable to the intial model specification as well as with the inclusion of a deterministic time trend.

### 5.2.3 Broader Effects of RES

Whereas the estimates above suggest that, in more general terms, energy policy in the Netherlands was effective in achieving its primary aim of inducing renewable energy production, broader welfare effects are yet to be explored. The rest of this section will reflect upon broader welfare effects of RES and concludes with a discussion on the limitations and suggestions for further research. Firstly, using HAC estimators, the effect of RES on different dimensions of welfare within the energy sector (SBI-code: 4), specifically, is evaluated. This should provide a first account of broader welfare effects of RES. Secondly, HAC estimates are produced for the principal components obtained earlier from the analysis on the Monitor. This should yield a final comprehensive assessment of welfare effects of energy policy in the Netherlands. Note that the purpose of this assessment is rather exploratory and the outcomes need to be interpreted with care as causal inference is not self-evident.

The evaluation of RES on broader aspects of welfare in the energy sector (SBI-code: 4) follows the same steps as the assessment of the primary effect of RES on renewable energy production. To elaborate, the model specification as presented in Section 4.2.3 is used to produce heteroskedasticity- and autocorrelation-consistent (HAC) estimates. Then Augmented Dickey-Fuller tests are employed to assess non-stationarity against the alternatives of stationarity and stationarity around a deterministic trend. Due to the extensive number of outcome variables these are not explicitly presented in this thesis. As all Augmented Dickey-Fuller tests could not reject non-stationarity, a time trend is added and, subsequently, differencing is applied to the model specification. This is made explicit for each of the indicators at the top of the columns. Note that, as before, the differenced model specification is selected as a benchmark case since stationarity is a prerequisite for the production of unbiased and consistent estimates following dynamic multivariate OLS regression. Cointegration is not considered. What is more, the issue of reverse causality is less prevalent for broad welfare effects and, hence, need not be addressed through an instrument.

Firstly, there appears to be a strong positive effect of RES on economic activity in the energy sector (as measured by GDP). The lagged effect is consistent across model specifications and significant at the 5% for Column 1 and 2 and even at the 1% level for Column 3. However, the current period effects of RES yields a less consistent image. Whereas the estimates are insignificant for the specifications in Column 1 and 2, it is marginally statistically significant (at the 10% level) for the differenced model specification. Nonetheless, as this the benchmark model, it provides evidence for a short-term effect of RES on economic growth (i.e. a 1 percentage point increase in RES induces an 0.145 percentange point increase in economic growth in the same period). What is more, there is more substantive evidence for long-term effect of subsidy payments on economic growth (i.e. a 1 percentage point increase in RES induces an 0.160 percentage point increase in economic growth). This is support for the notion of increased economic activity of a transition towards renewable energy production.

Secondly, RES seems to negatively impact greenhouse gas emissions in the energy sector. This points towards a positive effect of subsidy payments on the environmental aspect of welfare. Although of substantial magnitude, the estimates, presented in Columns 4 to 6, are not statistically significant. Only the lagged effect of RES in the differenced model specification is significant at the 5% level. As this is the benchmark model, it indicates a meaningful effect of RES on the abatement of greenhouse gas emissions (i.e. a 1 percentage point increase in RES leads to a reduction of 0.077 percentage points in greenhouse gas emissions). Again, this is in line with the notion of positive external effects of renewable energy policy in the Netherlands.

Thirdly, employment in the energy sector shows estimates of varying sign and magnitude across model specifications. Only the differenced model, being the benchmark model, provides significant estimates of RES on employment in the energy sector. Here, the estimates indicate that a 1 percentage point increase in RES in the current period induces additional employment (by 0.069 percentage points) whereas an identical increase in RES in a previous period might result in a reduction in employment (by 0.049 percentage points). Note that the magnitude of the estimates does not differ from a statistical perspective. This also follows from hours worked in the energy sector, being an alternative measure of employment. Whereas the short-term positive effect of RES on hours worked (by 0.004 percentage points) is insignificant, the long-term negative effect (by 0.037 percentage points) is significant at the 5% level. Overall, this signals potential positive short-term effects of RES on employment whereas in the long-term the effects might be negated.

What is more, labor costs appear to decrease as a result of RES. The different model specifications produce estimates of consistent sign and magnitude. Whereas model specifications in Column 13 and 14 imply a substantial negative effect of RES on current period labor costs that is significant at the 1% and 5% level, respectively, Column 15 indicates a negative yet insignificant effect of RES on labor costs. However, it does indicate a negative effect of RES in a previous period on current period labor costs (i.e. a 1 percentage point increase in RES induces a 0.039 percentage point decrease in labor costs). As this is the benchmark case, this final estimate is given most weight. Hence, subsidy payments appear to reduce labor costs in the energy sector. Note that this concerns overall labor costs. This might signal to long-term efficiency gains or cost reductions in energy production through, for example, increases in productivity.

Fourthly, a combination of the impact of RES on the environment and employment is represented more accurately by the effect of RES on the environmental sector. Note that, defined broadly, the environmental sector in the energy sector represents that part of the workforce in the energy sector (measured in thousand FTE) that contributes to a reduction in polluting activities. Here, yet again, estimates provide a consistent image of the impact of RES on employment in the environmental sector. To be specific, current period RES appears to induce employment in non-polluting activities in the energy sector which is both substantial and significant, at the 1% level (in Column 16 and 17) and at the 5% level (in Column 18). Taking the benchmark model, a 1 percentage point increase in RES results in a 1.331 percentage point increase in employment. This also sheds additional light on the general figures on employment and hours worked presented above. The short-term positive effect seems to be mainly driven by attraction in non-polluting activities. As a negative long-term effect is not detected here, it is plausible that the decrease in employment in the longer run results from those individuals in polluting activities. In other words, these combined estimates provide intuition for cleaner production in the energy sector (as was already signalled by Figure 1).

Finally, several outcome indicators from the Sustainable Development Goals (SDGs) are considered in Column 19 through 27. These relate to SDG 7 on affordable and clean energy as well as SDG 13 on climate action. Hence, these estimates are not specific to the energy sector but rather to the Netherlands as a whole. Only Column 20 and 25 include significant estimates for the installed renewable energy capacity and emission intensity, respectively. Neither constitute benchmark specifications.

Following from a detrended regression specification, installed renewable energy capacity appears to be positively affected by RES in the current period yet negatively affected by RES in a previous period. Whereas the former is in line with the expectation of the effect of RES, the latter is hard to reconcile with theory or intuition. Therefore, these are likely to be attributed to the stochastic trend. Once this is accounted for (in Column 21), the effects become indistinguishable from zero.

Emission intensity seems to fall significantly as a consequence of RES. Column 25 reports a marginally statistically significant effect at the 10% level for current period RES and a 1% statistically significant effect of last period RES. Hence, this signals a (weak) short-term and (strong) long-term downwards effect of RES on the emission intensity. When displaying three decimal places, the estimates are not different from zero. Although the significance shows they in fact are, the impact is very small. Moreover, the effect is absent in the benchmark model, implying it could suffer from non-stationarity.

In conclusion, the dynamic multivariate OLS regression estimates provide evidence of statistically significant effects of RES on broader aspects of welfare. This is in line with Hypothesis 2 in Section 2. As became apparent from Table 8, model specifications (i.e. initial, detrended and differenced) produced a wider spread in outcomes than was the case in the assessment of renewable energy production. Nonetheless, one may deduce that, for the energy sector, RES contribute to short-term and long-term economic growth, effectively reduce greenhouse gas emissions and boost employment (related to the environmental sector) in the short-term. For the latter, however, there appears to be a long-term negative effect of RES which might be attributed to efficiency and cost reduction in the transition to cleaner energy production. This notion is also supported by a fall in overall labor costs.

Thus far this thesis has deliberated upon (clusters of) associations in the Monitor and the effect of renewable energy policy on renewable energy production as well as broader aspects of welfare through industry-level and SDG data. This final section combines both strands by assessing the effect of RES on the Monitor, employing the principal components to this end.[18] Table 10 presents the estimates of the dynamic multivariate OLS regression of the PCA outcome on subsidy payments. As the principal components do not suffer from non-stationarity, no trend or differencing is applied.

[18] Remember that the principal components are constructed from a subset of 39 indicators of the Monitor.

Table 8 HAC estimates of RES on various outcome variables.

| | (1)<br>GDP in Energy Sector | (2)<br>GDP in Energy Sector (Trend) | (3)<br>GDP in Energy Sector (Δ) | (4)<br>GHG in Energy Sector | (5)<br>GHG in Energy Sector (Trend) | (6)<br>GHG in Energy Sector (Δ) |
|---|---|---|---|---|---|---|
| RES | -1.486 | -1.552 | 0.145* | -5.957 | -7.066 | -0.047 |
| | (1.232) | (1.298) | (0.067) | (6.197) | (5.880) | (0.044) |
| RES (t – 1) | 5.865*** | 6.159*** | 0.160** | -7.009 | -2.051 | -0.077** |
| | (0.967) | (1.645) | (0.059) | (4.691) | (6.284) | (0.026) |
| GDP | -0.0315*** | -0.032*** | -1.475 | -0.051** | -0.063*** | -0.090 |
| | (0.005) | (0.006) | (1.088) | (0.020) | (0.015) | (0.457) |
| Gas Price | 6.935 | 8.036 | -0.099** | 61.28** | 79.83*** | 0.029 |
| | (6.653) | (8.379) | (0.038) | (22.72) | (25.39) | (0.029) |
| Oil Price | 287.7** | 276.5** | 0.011 | -55.08 | -244.7 | 0.021 |
| | (119.1) | (121.3) | (0.060) | (348.5) | (310.4) | (0.057) |
| Coal Price | -41.08** | -41.73** | -0.088 | -108.4** | -119.4** | -0.110*** |
| | (13.88) | (15.17) | (0.084) | (44.70) | (42.36) | (0.0351) |
| Gas Reserve | 3.208*** | 2.167 | 0.066 | 15.45*** | -2.063 | 0.202 |
| | (1.030) | (3.789) | (0.827) | (4.018) | (13.81) | (0.657) |
| CO2 Em. | 16,305*** | 18,463* | 9.616 | 51,885*** | 88,209*** | 5.336 |
| | (2,560) | (8,658) | (16.99) | (10,914) | (24,096) | (7.255) |
| WGI | -744.9 | -296.5 | 0.140 | -27,365*** | -19,819* | -0.776 |
| | (1,106) | (2,175) | (0.796) | (6,252) | (9,228) | (0.440) |
| Trend | | *** | | | *** | |
| Constant | -98,168*** | -110,753* | 1.391 | -260,577*** | -472,409*** | -0.606 |
| | (17,707) | (52,202) | (12.20) | (68,619) | (146,135) | (6.867) |
| Observations | 23 | 23 | 22 | 23 | 23 | 22 |

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

Table 8 HAC estimates of RES on various outcome variables (continued).

| | (7) Employment in Energy Sector | (8) Employment in Energy Sector (Trend) | (9) Employment in Energy Sector (Δ) | (10) Hours Worked in Energy Sector | (11) Hours Worked in Energy Sector (Trend) | (12) Hours Worked in Energy Sector (Δ) |
|---|---|---|---|---|---|---|
| RES | -0.002 | -0.001 | 0.069** | -0.007 | -0.005 | 0.004 |
| | (0.002) | (0.002) | (0.023) | (0.005) | (0.003) | (0.030) |
| RES (t – 1) | 0.005 | 0.003 | -0.049*** | 0.013** | 0.003 | -0.037** |
| | (0.003) | (0.003) | (0.016) | (0.004) | (0.004) | (0.015) |
| GDP | 0.000*** | 0.000 | 0.431 | 0.000* | 0.000 | 0.437 |
| | (0.000) | (0.000) | (0.433) | (0.000) | (0.000) | (0.252) |
| Gas Price | 0.034** | 0.026 | 0.00385 | 0.058** | 0.019 | 0.001 |
| | (0.015) | (0.022) | (0.0283) | (0.025) | (0.020) | (0.026) |
| Oil Price | -0.035 | 0.050 | -0.0413 | -0.192 | 0.198 | -0.010 |
| | (0.217) | (0.245) | (0.0425) | (0.284) | (0.184) | (0.036) |
| Coal Price | -0.013 | -0.008 | 0.0454 | -0.017 | 0.006 | 0.044 |
| | (0.024) | (0.027) | (0.0610) | (0.041) | (0.031) | (0.034) |
| Gas Reserve | -0.008*** | -0.000 | 0.148 | -0.017*** | 0.019** | 0.684 |
| | (0.002) | (0.009) | (0.479) | (0.003) | (0.008) | (0.428) |
| CO2 Em. | -0.696 | -16.88 | -10.75 | -11.04 | -85.80*** | -19.69*** |
| | (5.103) | (23.22) | (8.311) | (11.36) | (18.09) | (5.159) |
| WGI | 0.291 | -3.071 | -0.452 | 1.625 | -13.91*** | -0.915** |
| | (2.084) | (3.862) | (0.403) | (4.588) | (4.023) | (0.373) |
| Trend | | *** | | | *** | |
| Constant | 57.86 | 152.2 | 5.205 | 166.0** | 602.0*** | 12.93** |
| | (34.01) | (135.6) | (5.981) | (73.02) | (106.5) | (4.816) |
| Observations | 23 | 23 | 22 | 23 | 23 | 22 |

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

Table 8 HAC estimates of RES on various outcome variables (continued).

| | (13)<br>Labor Costs in Energy Sector | (14)<br>Labor Costs in Energy Sector (Trend) | (15)<br>Labor Costs in Energy Sector (Δ) | (16)<br>Environmental Sector in Energy Sector | (17)<br>Environmental Sector in Energy Sector (Trend) | (18)<br>Environmental Sector in Energy Sector (Δ) |
|---|---|---|---|---|---|---|
| RES | -0.373*** | -0.294** | -0.033 | 1.040*** | 1.088*** | 1.331** |
| | (0.123) | (0.119) | (0.023) | (0.160) | (0.147) | (0.408) |
| RES (t – 1) | 0.466*** | 0.112 | -0.039*** | 0.056 | 0.028 | 0.252 |
| | (0.149) | (0.118) | (0.013) | (0.219) | (0.235) | (0.255) |
| GDP | -0.002** | -0.002** | 0.109 | 0.001 | 0.001 | -7.948 |
| | (0.001) | (0.001) | (0.366) | (0.001) | (0.001) | (5.042) |
| Gas Price | 2.267* | 0.947 | -0.010 | 0.147 | 0.326 | 0.528 |
| | (1.075) | (0.842) | (0.023) | (1.753) | (1.564) | (0.362) |
| Oil Price | 13.51 | 27.01* | 0.010 | 34.17 | 33.70 | -1.138 |
| | (15.95) | (14.51) | (0.027) | (20.23) | (21.29) | (0.771) |
| Coal Price | -2.630 | -1.844 | 0.038 | -4.366* | -3.669 | 0.792 |
| | (2.573) | (2.125) | (0.037) | (2.005) | (2.471) | (0.808) |
| Gas Reserve | -0.154 | 1.093** | 0.825*** | 0.536 | 0.785 | -9.974 |
| | (0.234) | (0.436) | (0.230) | (0.677) | (0.970) | (6.173) |
| CO2 Em. | 1,486** | -1,101 | -11.89** | 1,067 | -902.0 | 191.8 |
| | (590.0) | (731.9) | (4.608) | (835.2) | (2,702) | (109.8) |
| WGI | 128.7 | -408.7 | -0.689* | 631.8 | 167.0 | -0.895 |
| | (208.4) | (323.5) | (0.358) | (413.2) | (801.2) | (5.847) |
| Trend | | *** | | | *** | |
| Constant | -7,602* | 7,483 | 12.27*** | -9,970 | 3,544 | -132.1 |
| | (3,964) | (4,755) | (2.890) | (8,029) | (17,873) | (86.44) |
| Observations | 23 | 23 | 22 | 16 | 16 | 15 |

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

Table 8 HAC estimates of RES on various outcome variables (continued).

| | (19) RE Capacity | (20) RE Capacity (Trend) | (21) RE Capacity (Δ) | (22) Fossil Fuel Import | (23) Fossil Fuel Import (Trend) | (24) Fossil Fuel Import (Δ) | (25) Emission Intensity | (26) Emission Intensity (Trend) | (27) Emission Intensity (Δ) |
|---|---|---|---|---|---|---|---|---|---|
| RES | 0.137 | 0.186*** | -0.005 | 0.002 | 0.000 | 0.037 | 0.000* | 0.000 | 0.137 |
| | (0.095) | (0.048) | (0.124) | (0.001) | (0.001) | (0.058) | (0.000) | (0.000) | (0.095) |
| RES (t – 1) | 0.016 | -0.203*** | 0.000 | 0.000 | 0.002 | 0.034 | 0.000*** | 0.000 | 0.016 |
| | (0.059) | (0.058) | (0.078) | (0.000) | (0.001) | (0.025) | (0.000) | (0.000) | (0.059) |
| GDP | 0.001** | 0.002*** | 0.346 | 0.000 | 0.000 | 0.289 | 0.000*** | 0.000*** | 0.001** |
| | (0.001) | (0.000) | (1.397) | (0.000) | (0.000) | (0.464) | (0.000) | (0.000) | (0.001) |
| Gas Price | 0.225 | -0.594* | 0.024 | -0.005 | 0.001 | -0.007 | 0.001*** | 0.000*** | 0.225 |
| | (0.297) | (0.286) | (0.053) | (0.005) | (0.007) | (0.031) | (0.000) | (0.000) | (0.297) |
| Oil Price | -14.80** | -6.422*** | -0.065 | 0.127 | 0.063 | 0.076 | -0.001 | -0.000 | -14.80** |
| | (5.462) | (1.987) | (0.098) | (0.133) | (0.141) | (0.065) | (0.002) | (0.002) | (5.462) |
| Coal Price | 0.405 | 0.893** | 0.022 | -0.019 | -0.023 | -0.124* | 0.000** | -0.000** | 0.405 |
| | (0.805) | (0.383) | (0.125) | (0.018) | (0.018) | (0.059) | (0.000) | (0.000) | (0.805) |
| Gas Reserve | -0.539*** | 0.234 | -0.441 | -0.001 | -0.007** | -0.567 | -0.000*** | 0.000 | -0.539*** |
| | (0.052) | (0.138) | (1.127) | (0.002) | (0.002) | (0.687) | (0.000) | (0.000) | (0.052) |
| $CO_2$ Em. | -859.8*** | -2,465*** | -2.612 | 3.269 | 15.54 | 11.16 | 0.020 | -0.127 | -859.8*** |
| | (283.6) | (356.9) | (17.95) | (4.081) | (8.934) | (8.353) | (0.041) | (0.141) | (283.6) |
| WGI | 210.4* | -123.0 | -2.355* | 2.363 | 4.913** | 0.589 | -0.121*** | -0.151*** | 210.4* |
| | (112.0) | (74.61) | (1.289) | (1.572) | (2.024) | (0.511) | (0.020) | (0.046) | (112.0) |
| Trend | | *** | | | *** | | | | |
| Constant | 5,967*** | 15,325*** | 14.40 | -16.37 | -87.94 | -7.713 | 1.082*** | 1.941** | 2.153 |
| | (1,731) | (2,099) | (13.59) | (27.45) | (55.37) | (7.633) | (0.266) | (0.830) | (4.539) |
| Observations | 23 | 23 | 22 | 23 | 23 | 22 | 23 | 23 | 22 |

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

The dynamic multivariate OLS regression returns small and largely insignificant estimates for each of the components. Nonetheless, several effects of RES on welfare in a broad sense can be highlighted. Component 1, loading mainly indicators that are related to economic progress, appears to be positively affected by lagged RES. Although the estimate is only marginally statistically significant (at the 10% level), it implies a long-term effect of RES on, notably, renewable energy production, GDP, imports (of fossil fuels and raw materials) and the accumulation of physical capital and knowledge capital. Moreover, higher education, life expectancy, norms and values and the abatement of phosphorus and nitrogen excesses are included. On the contrary, fossil fuel reserves, CO2 emissions and household debt tend to rise too, constituting negative impacts on welfare in a broad sense. The most prominent outcome is the effect of RES on renewable energy production and GDP. This is a confirmation of the effects identified through regression analysis in the energy sector specifically and provides additional confidence in the broader welfare effects of RES in these domains. On the other hand, it also implies RES significantly affects the fossil fuel reserve and the imports of fossil fuels. As addressed in Section 3, this might point towards potential substitution effects or international dynamics and might require further investigation.[19] The effects of RES on abatement of pollutants can also be reconciled with cleaner energy production as was also indicated in the regression analysis in the energy sector. However, alternative positive impacts on higher education, life expectancy, development in norms and values as well as household debt are harder to explain. Though they provide interesting starting points for future research, their impact can be given less qualitative interpretation here. Nonetheless, the marginally statistically significant result of RES on Component 1 does provide evidence that is aligned with previous regression estimates and underscores the effect of government energy policy on welfare in a broad sense as per Hypothesis 2 in Section 2.

What is more, Component 4 indicates negative effect of current period RES (significant at the 5% level) and a positive effect of RES in the previous period (marginally statistically significant at the 10% level). As Component 4 captured nitrogen in excess, nitrogen deposition and fauna on land (all with positive loadings), RES seem to reduce these effects in the short-term but rather increases these effect in the long-term. This might be explained by a reduction in nitrogen emissions by the energy sector over this period. As it accounts for approximately 15% of all nitrogen emissions this is a reasonable explanation. Naturally, emission and deposition of nitrogen are closely linked. A reduction in emissions is likely to be accompanied

[19] Note, for example, potential Green Paradox effects as highlighted by Sinn (2008).

by a reduction in deposition. This also positively affects biodiversity as measured by fauna as it is in turn linked to nitrogen deposition.[20] Though this comprises circumstantial evidence, it might indicate a positive effect of RES on welfare in a broad sense. Moreover, note that voice and accountability load negatively on Component 4 and, therefore, seems to increase with RES. As was the case for several indicators loading on Component 1, a less qualitative interpretation can be provided. For now, this is hard to reconcile with intuition and economic theory and can be deemed an artefact of the data structure.

In conclusion, the dynamic multivariate OLS regression of principal components constructed from the Monitor on RES indicates small yet significant effects of RES on broader aspects of welfare. In line with previous estimates, RES seems to contribute to renewable energy production as well as economic development. What is more, abatement of pollutants (notably nitrogen and phosphorus) and their effect on fauna in the Netherlands is also detected. Finally, potential effects of RES on the fossil fuel reserve and import of fossil fuels is also detected. This points towards potential substitution effects or international dynamics that could be of relevance to further evaluate the broader effects of RES.

Note that the final part of this analysis is mainly exploratory by nature. Although one aims to accommodate all requirements for appropriate modelling and account for potential sources of bias and misspecification, it does not allow for straightforward causal interpretation. Nonetheless, it provides valuable information on the associations between a wider variety of welfare characteristics and how these are potentially affected by government policy. Combining the insights from the associations within the Monitor, the cluster analysis, PCA as well as dynamic multivariate OLS regression of RES on renewable energy production, outcomes in the energy sector and principal components, does provide for a more comprehensive and coherenet assessment of the Monitor, as was the aim of this thesis.

### 5.3 Discussion of the Limitations

As Section 5 provided a detailed description of the various relationships found, it is crucial to critically reflect on these findings and place them in the appropriate context. Once again, note that the analysis is (to a large extent) exploratory by nature. This holds not only for the correlation estimates, cluster analysis and PCA but also for the regression estimates. As is widely considered, causal inference of dynamic multivariate OLS regression might be hindered by several sources of which a more elaborate (and explicit) account is given in this final section.

[20] RIVM (2020) reflects on the sources and effects of nitrogen emission and deposition (on biodiversity).

Table 10 HAC Estimates of a regression of principal components on RES.

| | (1)<br>Component 1 | (2)<br>Component 2 | (3)<br>Component 3 | (4)<br>Component 4 | (5)<br>Component 5 |
|---|---|---|---|---|---|
| RES | -0.003 | -0.001 | 0.003 | -0.013** | 0.004 |
| | (0.002) | (0.003) | (0.002) | (0.004) | (0.002) |
| RES (t – 1) | 0.005* | 0.003 | -0.005 | 0.016* | -0.004 |
| | (0.003) | (0.004) | (0.003) | (0.009) | (0.004) |
| GDP | 0.000 | 0.000 | 0.000*** | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Gas Price | 0.020 | 0.011 | -0.031 | 0.067 | -0.006 |
| | (0.019) | (0.024) | (0.024) | (0.050) | (0.027) |
| Oil Price | 0.191 | 0.318 | 0.480** | 0.681* | -0.397 |
| | (0.132) | (0.312) | (0.181) | (0.332) | (0.365) |
| Coal Price | -0.016 | -0.021 | -0.048** | -0.135*** | 0.095* |
| | (0.018) | (0.037) | (0.021) | (0.031) | (0.045) |
| Gas Reserve | -0.006 | 0.003 | 0.016* | 0.002 | -0.006 |
| | (0.007) | (0.008) | (0.008) | (0.019) | (0.019) |
| CO2 Em. | 10.17 | -6.293 | -18.79** | 25.83 | -17.70 |
| | (7.747) | (10.50) | (7.344) | (18.92) | (12.40) |
| WGI | -3.310 | -23.33*** | 26.05*** | 1.186 | 4.321 |
| | (5.721) | (6.657) | (6.597) | (16.01) | (9.638) |
| Constant | -61.00 | 76.89 | -7.352 | -149.0 | 115.2 |
| | (79.98) | (102.4) | (83.58) | (206.9) | (131.1) |
| Observations | 19 | 19 | 19 | 19 | 19 |

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

Firstly, omitted variable bias is one of the principal concerns in multivariate OLS regression. Factors related to both RES and renewable energy production (or any other outcome variable for that matter) might confound the relationship of interest. Despite the inclusion of a set of theoretically grounded control variables as discussed in Section 2 and 4, the estimates might still capture variation due to other (unobservable) factors beyond the variable of interest. Such factors could affect the estimates both positively and negatively, depending on their relationship to both the explanatory variable and the outcome variable. To the best of my knowledge, the models under consideration accounted for all potential confounding factors identified in the literature. The inclusion of commodity prices, which follow from equilibrium processes, should account for a wide variety of potential confounding factors, too. Nonetheless, as endogeneity cannot be statistically tested, omitted variable bias must be considered in dynamic multivariate OLS regression. Moreover, as the instrument aims to address reverse causality rather than endogeneity, it does not provide for causal inference. Further research into more powerful identification strategies is, therefore, of interest.

Secondly, as in any time series model, deterministic or stochastic trends might jeopardize the outcomes. As was done at each stage of analysis, Augmented Dickey-Fuller tests inferred into non-stationarity and orders of integration. Thereto, potential deterministic trends were addressed by the inclusion of a time trend whereas potential stochastic trends were addressed by taking first differences of the regression specification. As all models that exhibited stochastic trends appeared to be integrated of order one, differencing effectively converted the data in stationary time series allowing for accurate and efficient estimation even as meaningful interpretation. As this was taken as the benchmark model in the interpretation of all model outcomes, the impact of (deterministic and stochastic) trends is minimal.

Thirdly, reverse causality could affect the model outcomes. Although a Granger causality test is employed and RES is instrumented by Guarantees of Origin, renewable energy production might drive RES. This would imply that RES would comprise deadweight loss subsidy payments as renewable energy production is not dependent on subsidy payments. However, this is deemed unlikely as a policy report on the MEP, SDE and SDE+ subsidy schemes estimated that the deadweight loss of RES was in the range of 5% to 15% due to an effective and efficient design of the subsidy allocation mechanism. Moreover, a Granger causality test allowing for up to three lags in both RES and renewable energy production implied that RES appeared to Granger-cause renewable energy production whereas renewable energy production appeared to not Granger-cause RES. Moreover, the price mechanism accounted for by the instrumented regression did not alter the regression estimates significantly. In conclusion, this provides confidence in the findings and negates the potential harm inflicted by reverse causality.

Fourthly, functional form misspecification is considered. Thereto, link tests and augmented partial residual plots to assess functional form misspecification and partial regression leverage plots to assess potential outliers are deployed. The linear models tended to fit the data well as they resulted in a constant and a consistent spread of residuals (i.e. the mean and variance appeared to be stable). As noted before, logarithmic transformation was considered to ensure linearity and for the purpose of enhanced interpretation. Although not presented, the logarithmic transformation substantially affected the regression estimates. Given the (raw) data structure, the change in sign, magnitude and significane was an unexpected outcome and likely to be attributed to an inferior fit of the data. Therefore, the estimates resulting from the logarithmic transformation are omitted from this thesis as they are not considered to be instructive.

Finally, international effects of the energy market might play a more pronounced role. Though Section 3 showed developments of imports and exports of fossil fuels, the energy market in the Netherlands has been evaluated (as if) in isolation. This might not accurately reflect the nature of the European energy market. International dynamics might, therefore, affect responses to national policies (such as RES) through alterations in the composition of the energy mix for import and export. To illustrate, RES might have promoted the production renewable energy production in the Netherlands but, at the same time, increased fossil fuel exploration and extraction elsewhere for the energy market in the Netherlands. This implies that the welfare gains identified might be location-specific. Although this is beyond the scope of this thesis, it serves as an interesting link for future research.

### 5.4 Recommendations

To conclude, several recommendations for data improvement and suggestions for future research are provided. As noted in Section 1, this thesis comprised a novel attempt to assess the associations and potential trade-offs in the Monitor and harness it for the purpose of policy evaluation. To allow for a better evaluation of both trade-offs and government policy, several recommendations concerning the data and characteristics of the Monitor are made. Firstly, the number of observations in the Monitor is limited. As it covers the years 1995 through 2019, this yields 25 observations at best. For the purpose of accurate and robust statistical inference, it is deemed expedient to feature quarterly or monthly time series. This would furthermore allow for the assessment of cyclical effects. Secondly, there are many missing observations for key indicators. This hinders a wide variety of statistical tests (such as PCA) that requires complete data matrices. Even though limitations for data collection exist, it is considered of significance to importune on this issue. Thirdly, the Monitor presents data on other Member States of the European Union for the most recent year. This serves the purpose of international comparison/ranking of Member States. By extending (and publishing) the data of other Member States alongside the Netherlands, the Monitor becomes a more desirous tool for (academic) research and policy evaluation alike, as it would allow for panel data estimation techniques even as extensions to different settings. Finally, the Monitor sports observations for the Netherlands as a whole, taking macroeconomic perspective. By breaking the indicators down by, for example, sector or region would similarly contribute to its power in (academic) research and policy evaluation. This might also accommodate the assessment of higher-order effects of individual indicators.

This thesis constitutes an exploration of the Monitor and, as such, provides many links for future research. The associations within the Monitor point towards trade-offs between various aspects of welfare. Notably, “economic progress” and “well-being” seem to be closely related whereas “externalities” and “subjective evaluations” feature a more inverse relationship. An inquiry into the quantitative and qualitative dimensions and implications of individual trade-offs might help in better understanding developments in welfare even as the scope for policy intervention. This also strongly relates to higher-order effects of developments in individual aspects of welfare. What is more, it might be of interest to more closely examine the (comovement of) flow and stock variables in the Monitor across dimensions of welfare. This could constitute a powerful deliberation on the dynamics between welfare in the present (containing mainly flow variables) and the future (containing mainly stock variables). Finally, to contribute to further data improvement and advance the study of welfare in a broad sense, utilizing the Monitor in a conceptually coherent way in order to better identify its limitations is crucial. Hence, the author calls upon the application and improvement of the framework constructed in this thesis to recognize areas in which progress needs to be made.

## Section 6. Conclusion

Thus far, evaluations of welfare in a broad sense feature marginally in the empirical literature. However, there is a rich potential for new types of statistical analyses that unify the debate on Beyond GDP with the evaluation of government policy. The main objective of this thesis is to assess the effect of renewable energy policy in the Netherlands on welfare in a broad sense. Thereto, the thesis is composed as a diptych. Firstly, by utilizing the Monitor on Well-being and Sustainable Development Goals, associations and potential trade-offs between a wide variety of aspects and dimensions of welfare in a broad sense are evaluated. Secondly, a major renewable energy subsidy scheme can be exploited to assess the effect of government policy on welfare in a broad sense in the Netherlands.

Using data from a variety of government institutions, Pearson product-moment and Spearman rank correlation coefficients implied strong positive and negative associations between several aspects and dimensions of welfare throughout the Monitor. Cluster analysis further elucidated these associations and identified five clusters of association. Here, relationships between economic development, well-being, subjective evaluations and externalities are detected. Most notably, economic progress appears to be strongly aligned with measures of subjective well-being. However, these are both inversely related with subjective evaluations (of employment, housing and social contacts) even as environmental aspects of welfare (in externalities) such as the emission of CO2, nitrogen and phosphorus. All in all, this indicates strong associations between various aspects of welfare and provides evidence for trade-offs between economic progress and well-being on the one hand and subjective evaluations and environmental quality on the other. To further analyse the data structure and reduce the high-dimensionality of the Monitor for subsequent analyses, principal component analysis is employed.

Exploiting a renewable energy subsidy scheme in the Netherlands, broader welfare effects of energy policy are investigated. After assessing stationarity and cointegration of the time series data and accounting for potential confounding factors and reverse causality, dynamic multivariate OLS regression even as instrumented regression techniques were employed. These provided evidence for a positive and significant effect of renewable energy subsidies on renewable energy production. To illustrate, a 1 percentage point increase in subsidy payments potentially results in an 0.334 percentage point increase in renewable energy production. Moreover, subsidy payments are found to significantly contribute to economic activity, induce to greenhouse gas abatement, stimulate employment and reduce labor costs in the energy sector. An evaluation of the principal components constructed from the Monitor indicated that renewable energy subsidies have long-term effects on renewable energy production, economic growth, imports (of raw materials and fossil fuels) and the accumulation of physical and knowledge capital. Moreover, nitrogen emissions and nitrogen deposition are reduced and fauna on land appears to increase through renewable energy subsidies.

In conclusion, taking into account the various regression estimates with their respective internal and external validities, there is evidence that renewable energy policy in the Netherlands significantly affected welfare in a broad sense. This means the hypotheses constructed can be confirmed. Although further inquiry is needed into several aspects related to bordering fields and disciplines, the findings are in line with intuition and (some) predictions by theory. This thesis hopefully sparks interest in the significance of research in the domain of Beyond GDP and leads to further contributions to this field.

**Acknowledgement**

This thesis is written as part of an internship at the Ministry of Economic Affairs and Climate Policy of the Netherlands. Any opinions and conclusions expressed in this thesis are those of the author only and do not necessarily represent the views of the Ministry of Economic Affairs and Climate Policy. All results have been reviewed to ensure that no confidential information is disclosed.

I would like to express my gratitude to my supervisors Bram van Dijk and Maaike Stoel for their assistance. Moreover, I am grateful for helpful conversations with a variety of colleagues from the Ministry, Statistics Netherlands, PBL Netherlands Environmental Assessment Agency and SCP Netherlands Institute for Social Research. Finally, I would like to thank my thesis supervisor at the Erasmus School of Economics Gloria Moroni for her support and patience throughout the writing process.

**Appendix**

Table A1 Multivariate OLS Regression (Lütkepohl) Bayesian Information Criteria.

| | (1) | (2) |
|---|---|---|
| Order of Lags | BIC | Lütkepohl BIC |
| Lag 0 | 31.67 | 25.71 |
| Lag 1 | 21.75* | 21.79* |
| Lag 2 | 27.99 | 22.03 |
| Lag 3 | 28.39 | 22.44 |
| Observations | 22 | 22 |

The asterisk indicates the lowest BIC value.

Table A2 Augmented Dickey-Fuller Test for Stationarity on (1) renewable energy production and (2) RES.

| | (1) | (2) |
|---|---|---|
| | Z-statistic | Z-statistic |
| Test Statistic | 1.541 | -0.015 |
| 10 % Critical Value | -2.630 | -2.630 |
| 5 % Critical Value | -3.000 | -3.000 |
| 1 % Critical Value | -3.750 | -3.750 |
| Observations | 23 | 23 |

Table A3 Augmented Dickey-Fuller Test for Stationarity with Trend on (1) renewable energy production and (2) RES.

| | (1) | (2) |
|---|---|---|
| | Z-statistic | Z-statistic |
| Test Statistic | -1.094 | -2.959 |
| 10 % Critical Value | -3.240 | -3.240 |
| 5 % Critical Value | -3.600 | -3.600 |
| 1 % Critical Value | -4.380 | -4.380 |
| Observations | 23 | 23 |

Table A4 Augmented Dickey-Fuller Test for Stationarity on (1) renewable energy production and (2) RES after first differencing.

| | (1) | (2) |
|---|---|---|
| | Z-statistic | Z-statistic |
| Test Statistic | -4.130 | -4.104 |
| 10 % Critical Value | -2.630 | -2.630 |
| 5 % Critical Value | -3.000 | -3.000 |
| 1 % Critical Value | -3.750 | -3.750 |
| Observations | 23 | 23 |

Table A5 Engle-Granger Augmented Dickey-Fuller Test for Cointegration between renewable energy production and RES.

| | Z-statistic |
|---|---|
| Test Statistic | -1.965 |
| 10 % Critical Value | -3.226 |
| 5 % Critical Value | -3.603 |
| 1 % Critical Value | -4.392 |
| Observations | 25 |

Critical value follow from MacKinnon (1990, 2010).

Table A6 Engle-Granger Augmented Dickey-Fuller Test for Cointegration between renewable energy production and RES after first differencing.

| | Z-statistic |
|---|---|
| Test Statistic | -2.731 |
| 10 % Critical Value | -3.234 |
| 5 % Critical Value | -3.615 |
| 1 % Critical Value | -4.415 |
| Observations | 24 |

Critical value follow from MacKinnon (1990, 2010).

Table A7 Granger Causality Wald Test for renewable energy production and RES.

| Equation | Excluded | F-statistic | DF | P-value |
|---|---|---|---|---|
| Renewable Energy Production | RES | 12,401 | 3 | 0,003 |
| RES | Renewable Energy Production | 0,1746 | 3 | 0,175 |
| Observations | 20 | | | |

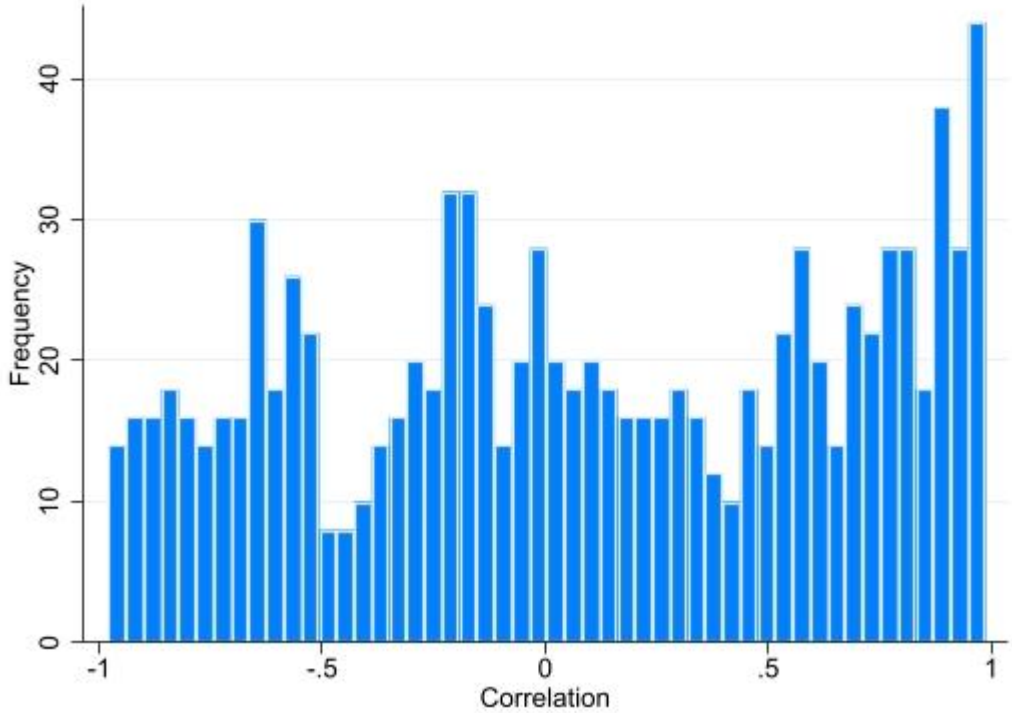


Figure A5.1 The distribution of Pearson product-moment correlation coefficients in the dimension “here and now”.

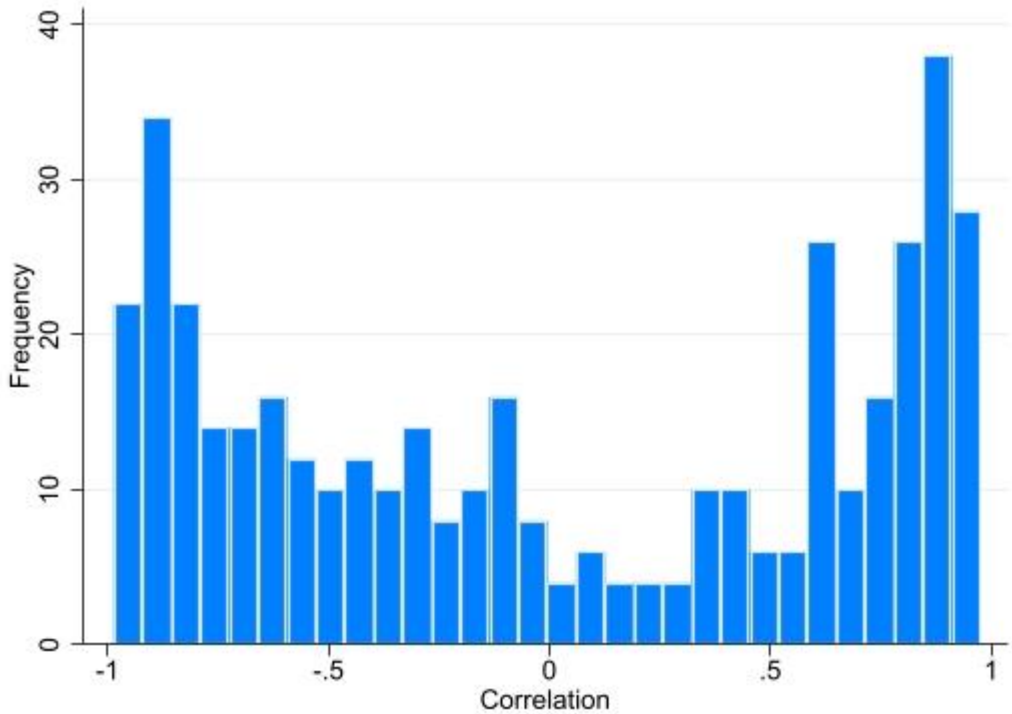


Figure A5.2 The distribution of Pearson product-moment correlation coefficients in the dimension “later”.

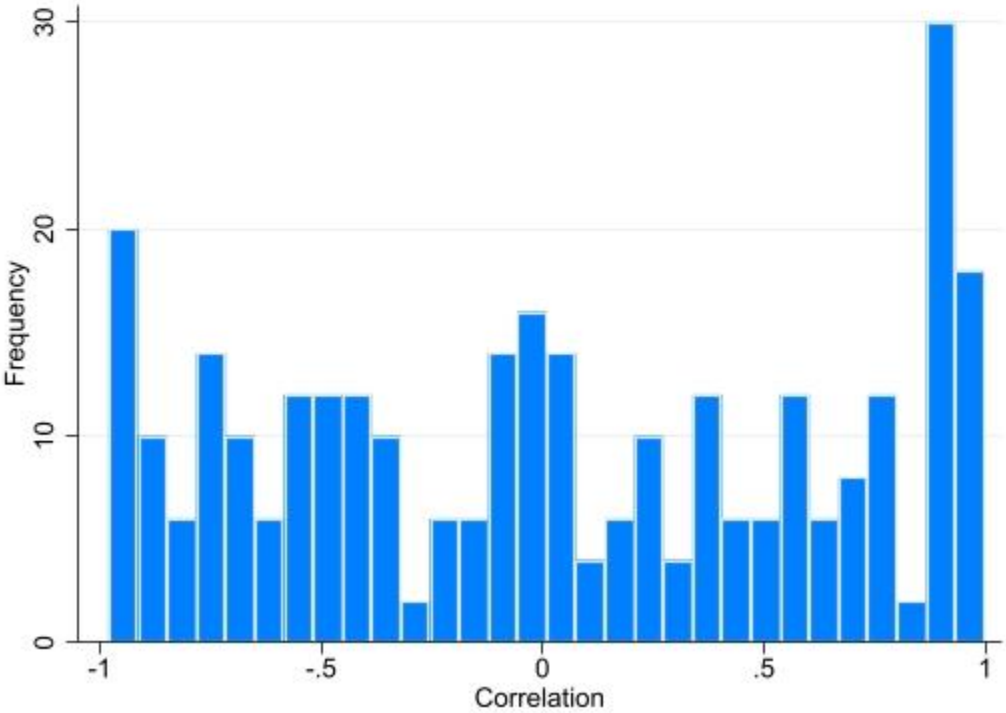


Figure A5.3 The distribution of Pearson product-moment correlation coefficients in the dimension “elsewhere”.

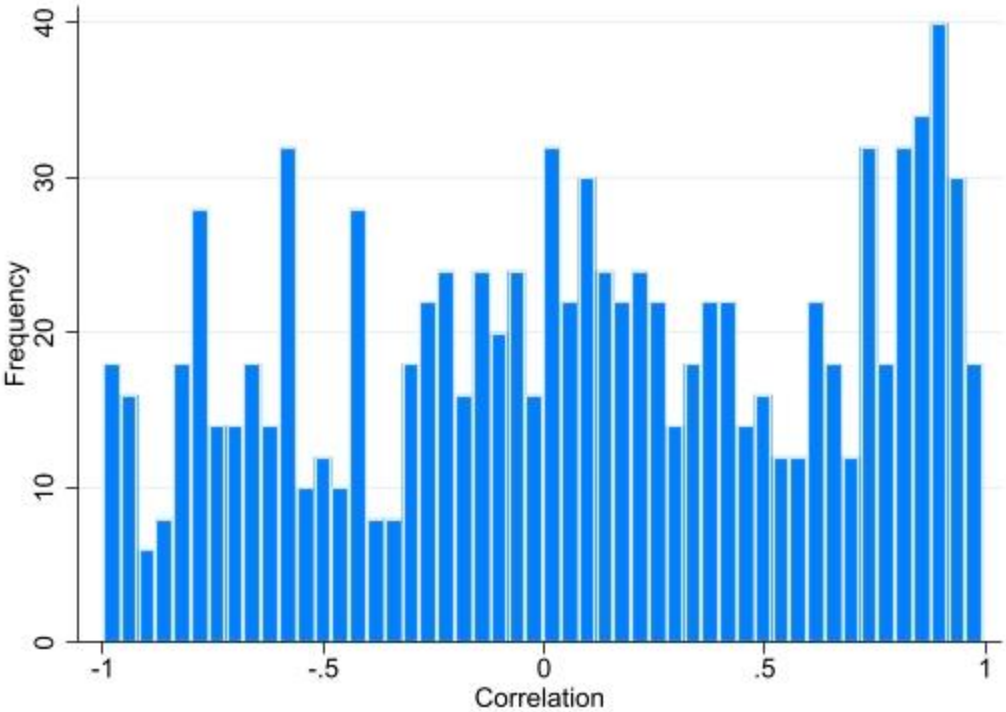


Figure A6.1 The distribution of Spearman rank correlation coefficients in the dimension “here and now”.

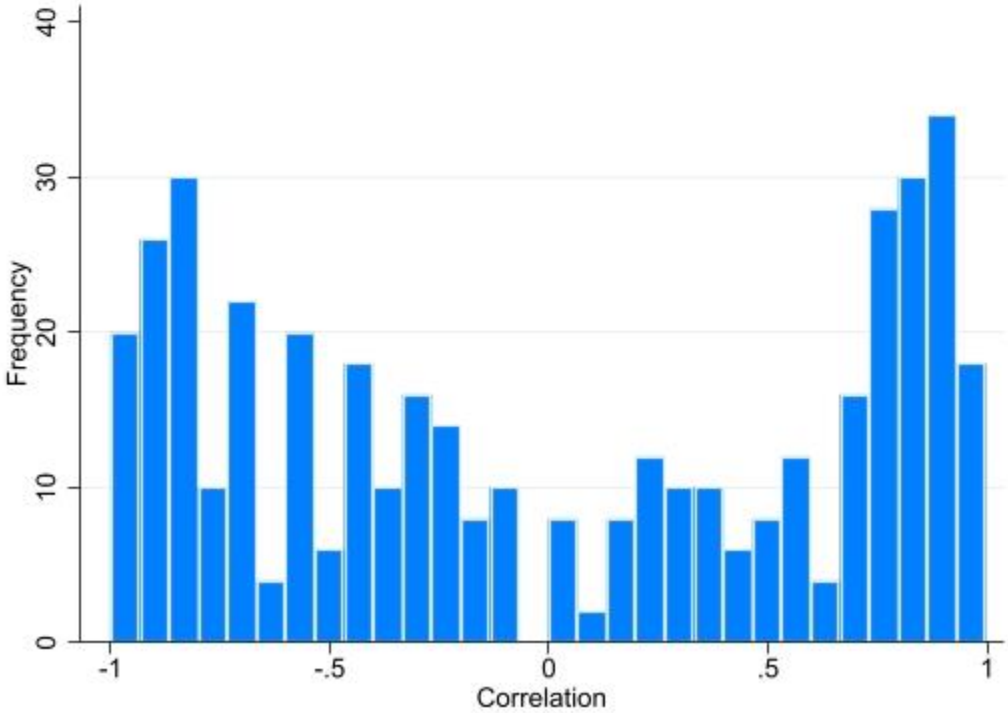


Figure A6.2 The distribution of Spearman rank correlation coefficients in the dimension "later".

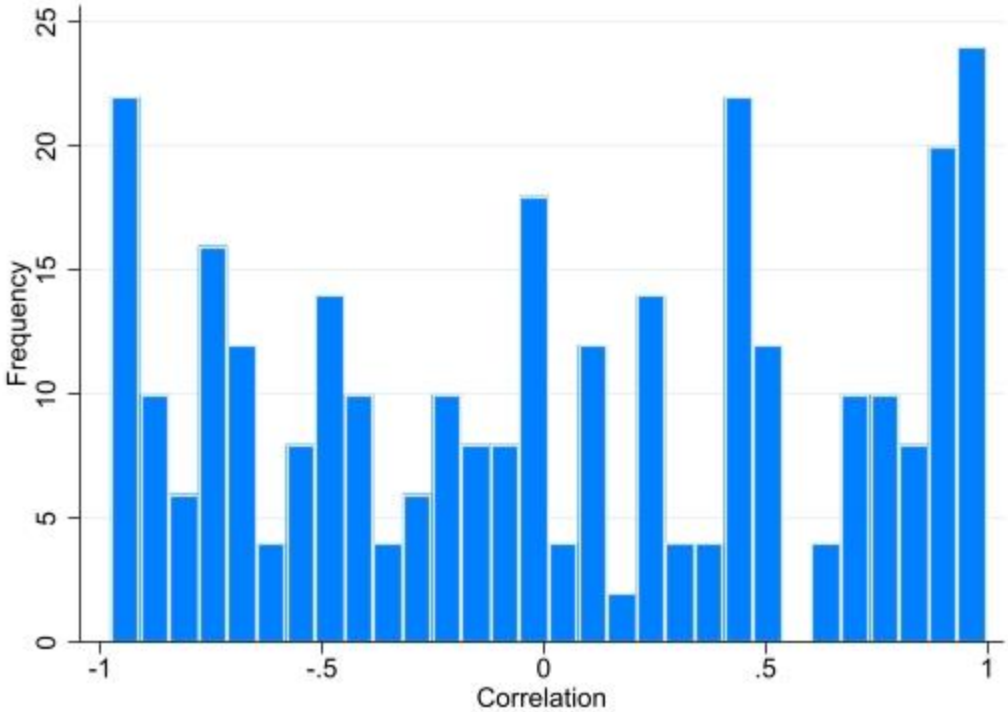


Figure A6.3 The distribution of Spearman rank correlation coefficients in the dimension "elsewhere".

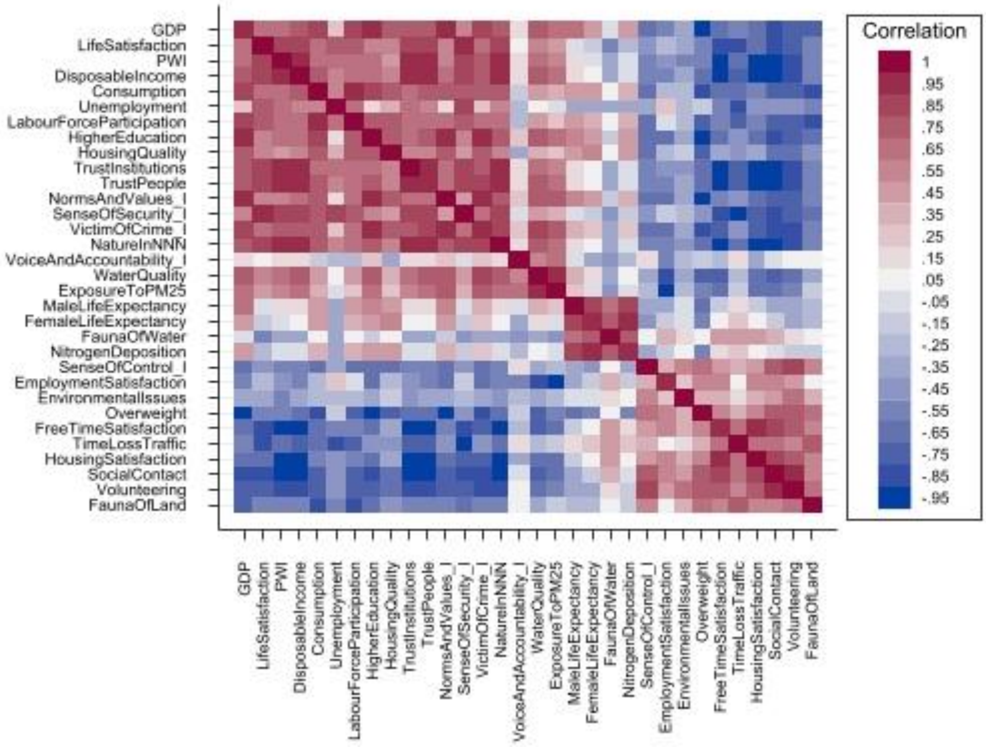


Figure A7.1.1 Heatmap of the Pearson product-moment correlation coefficients in the dimension “here and now”.

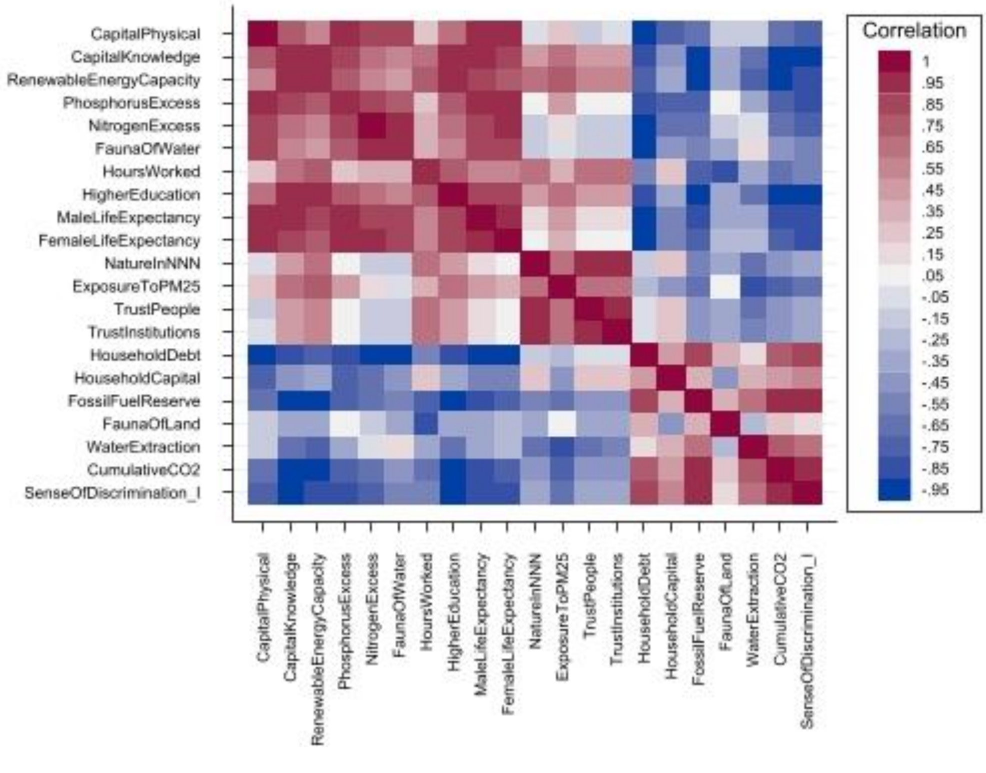


Figure A7.2.1 Heatmap of the Pearson product-moment correlation coefficients in the dimension “later”.

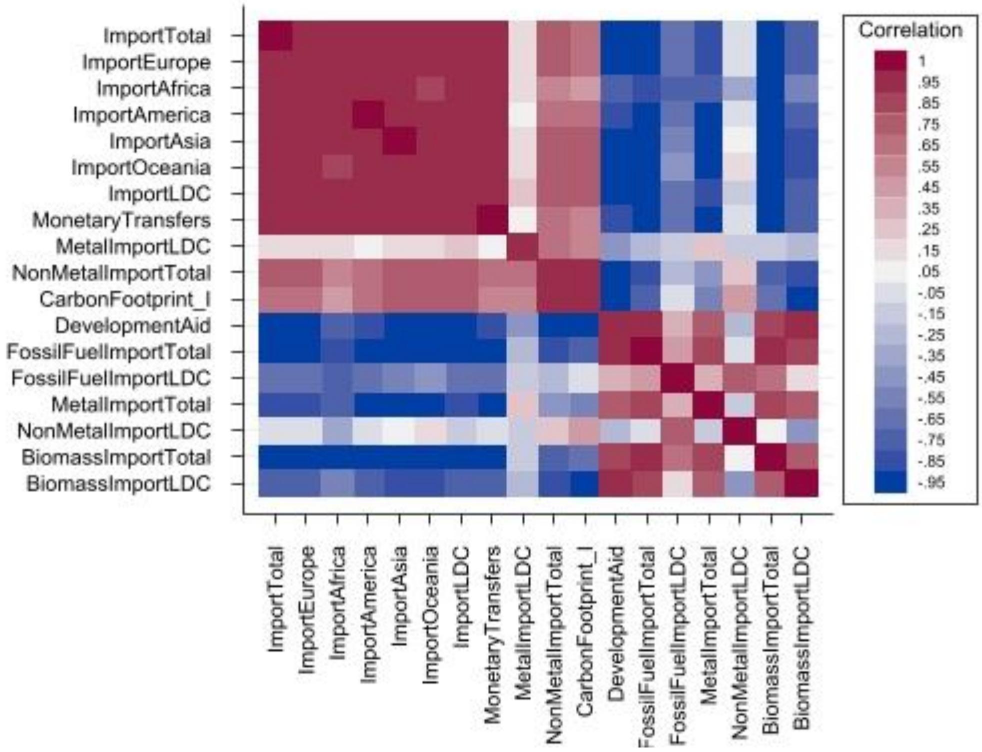


Figure A7.3.1 Heatmap of the Pearson product-moment correlation coefficients in the dimension “elsewhere”.

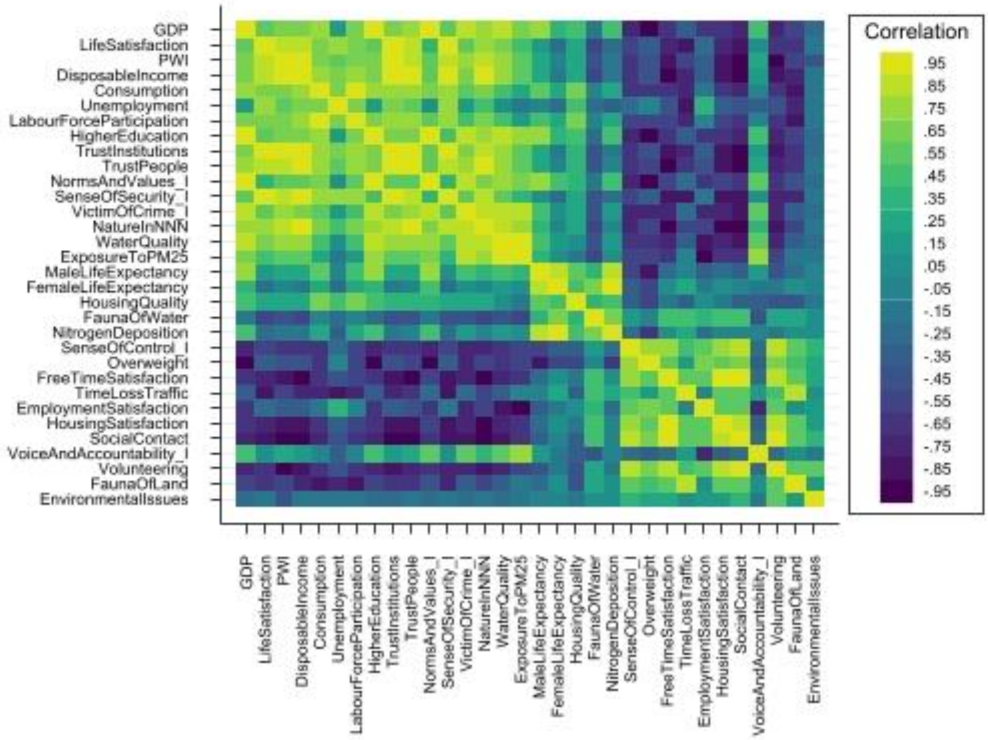


Figure A8.1.1 Heatmap of the Spearman rank correlation coefficients in the dimension “here and now”.

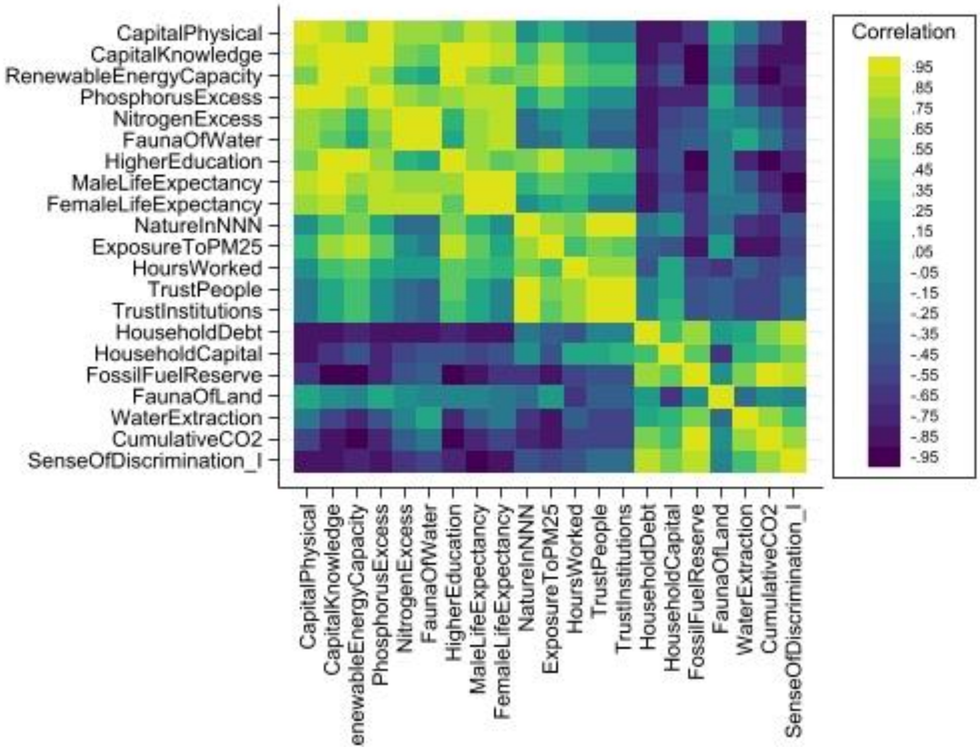


Figure A8.2.1 Heatmap of the Spearman rank correlation coefficients in the dimension "later".

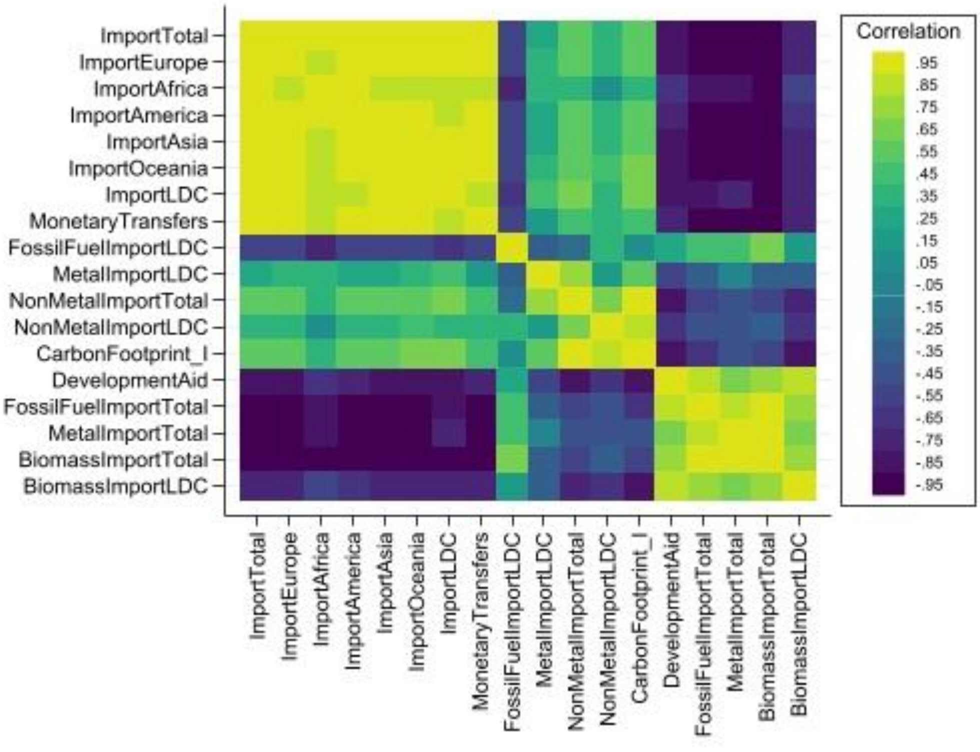


Figure A8.3.1 Heatmap of the Spearman rank correlation coefficients in the dimension "elsewhere".

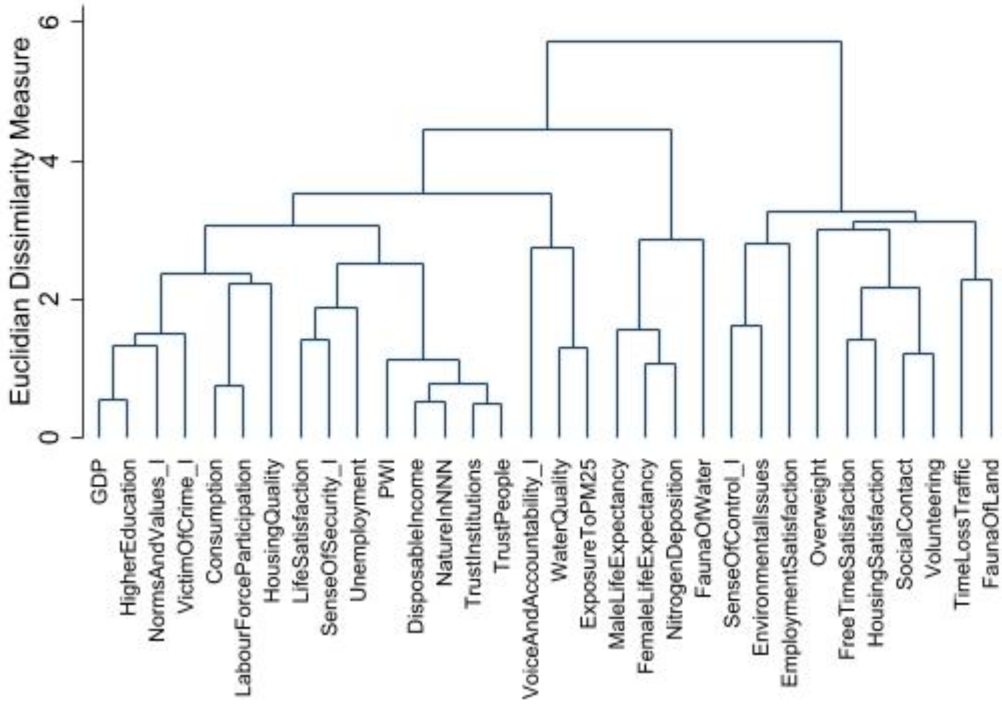


Figure A7.1.2 Dendrogram of Pearson product-moment correlation coefficients in the dimension “here and now”.

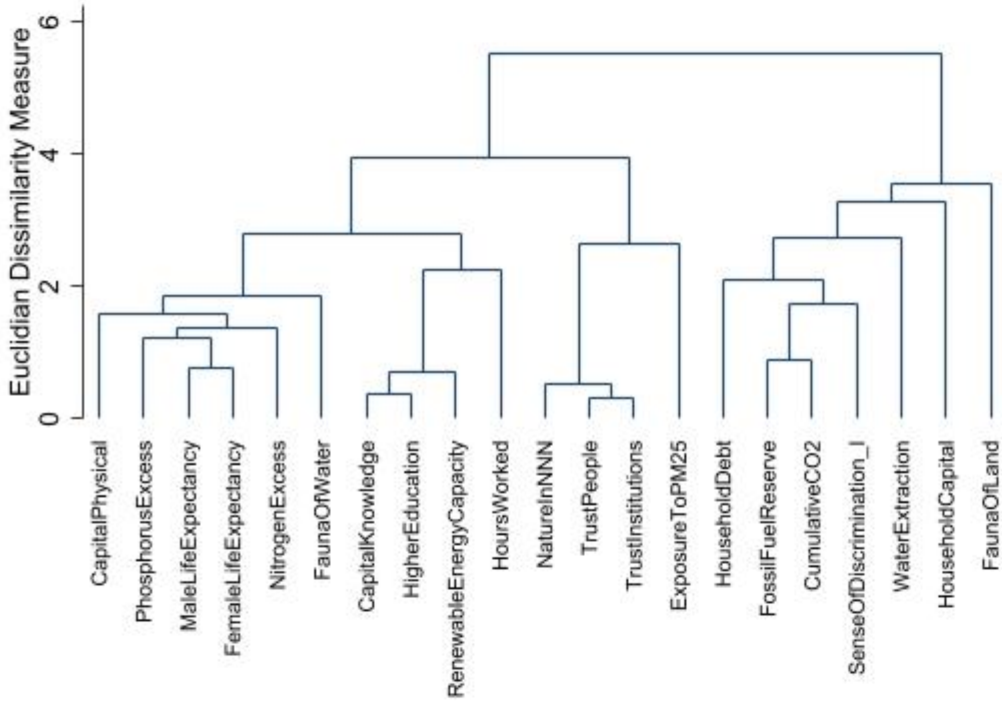


Figure A7.2.2 Dendrogram of Pearson product-moment correlation coefficients in the dimension “later”.

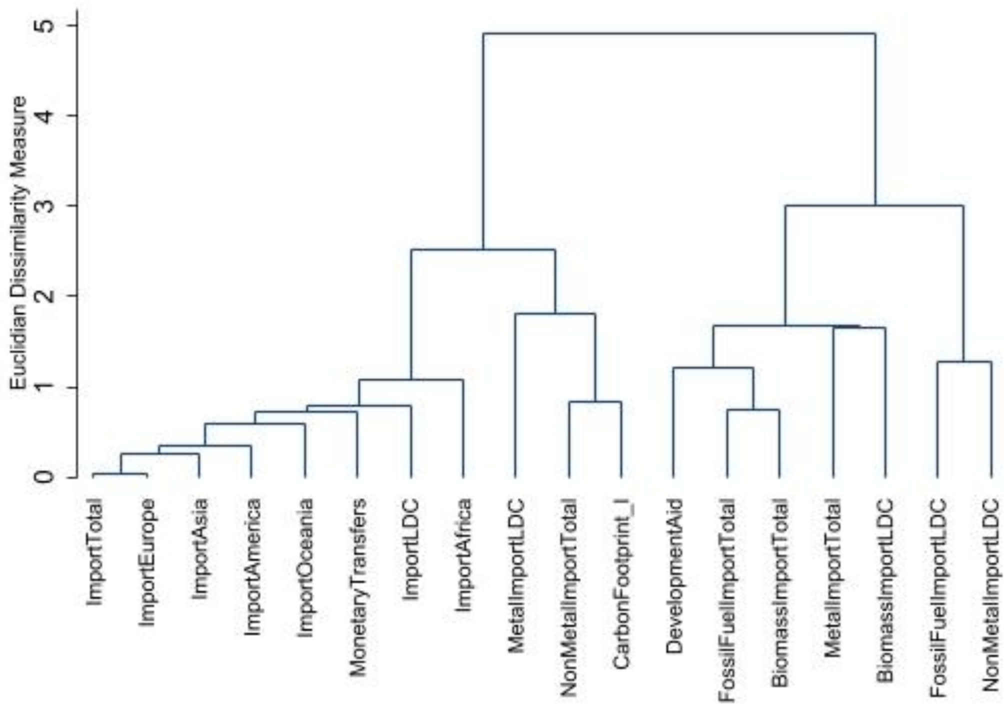


Figure A7.3.2 Dendrogram of Pearson product-moment correlation coefficients in the dimension “elsewhere”.

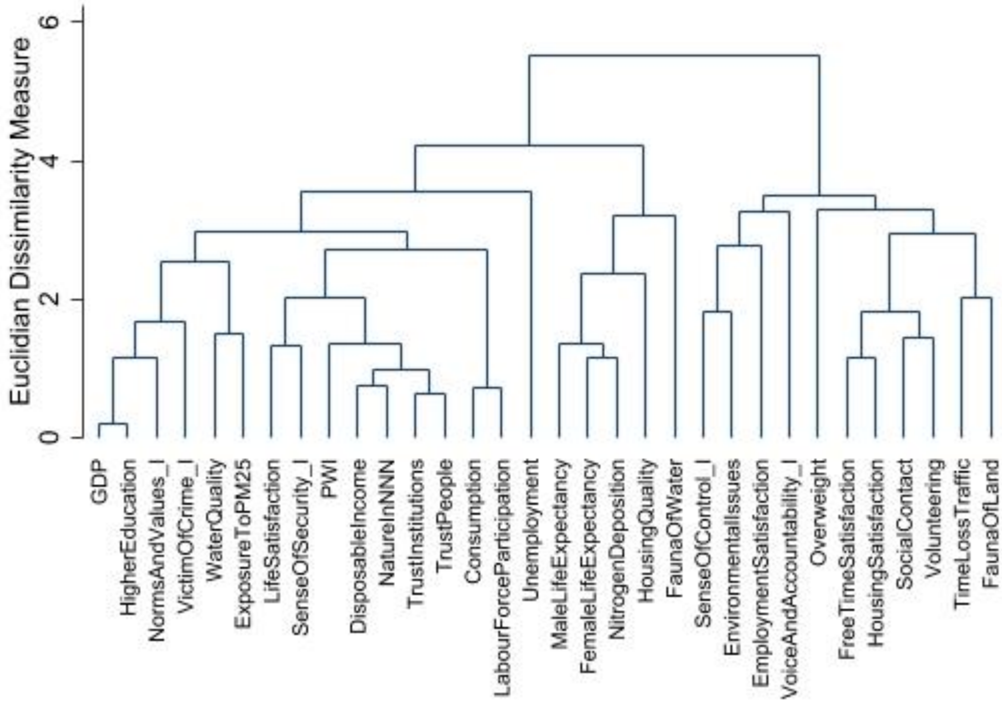


Figure A8.1.2 Dendrogram of Spearman rank correlation coefficients in the dimension “here and now”.

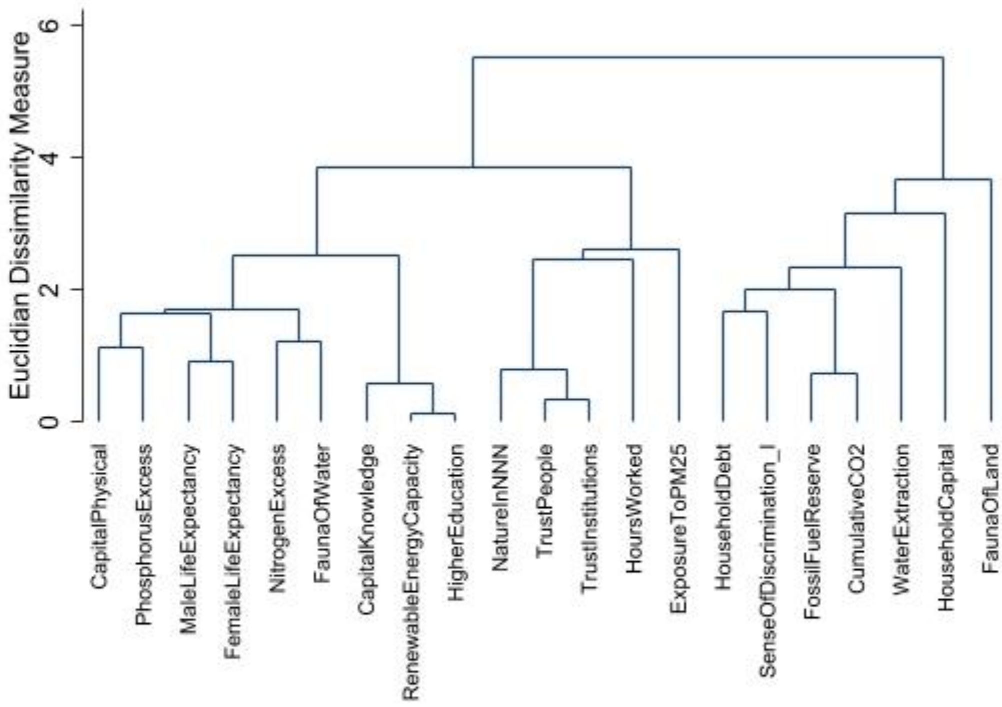


Figure A8.2.2 Dendrogram of Spearman rank correlation coefficients in the dimension “later”.

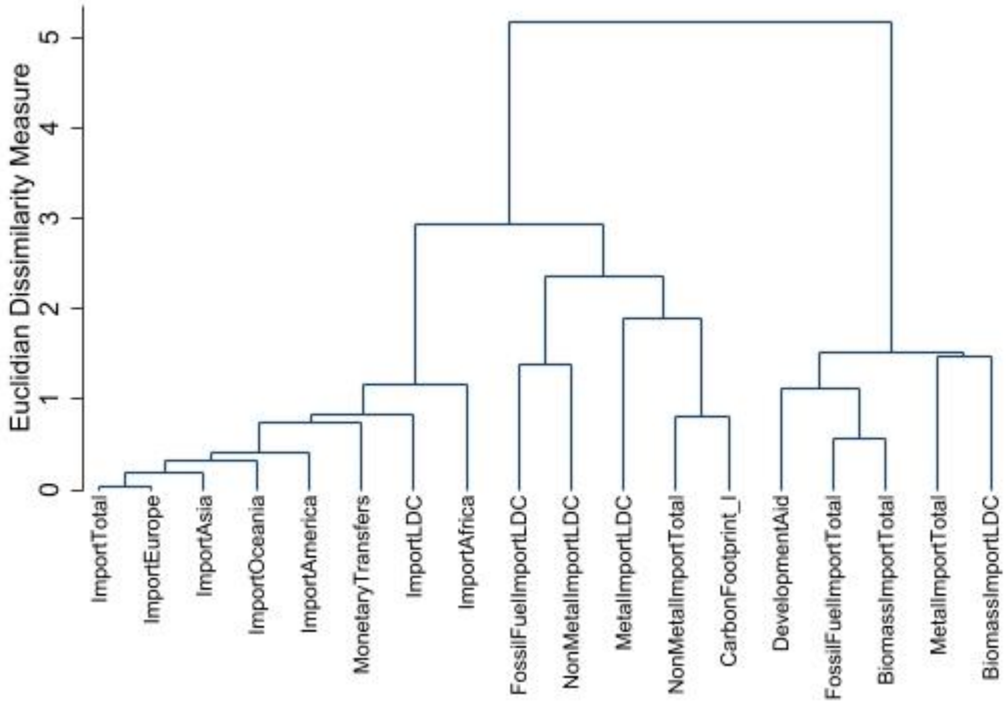


Figure A8.3.2 Dendrogram of Spearman rank correlation coefficients in the dimension “elsewhere”.

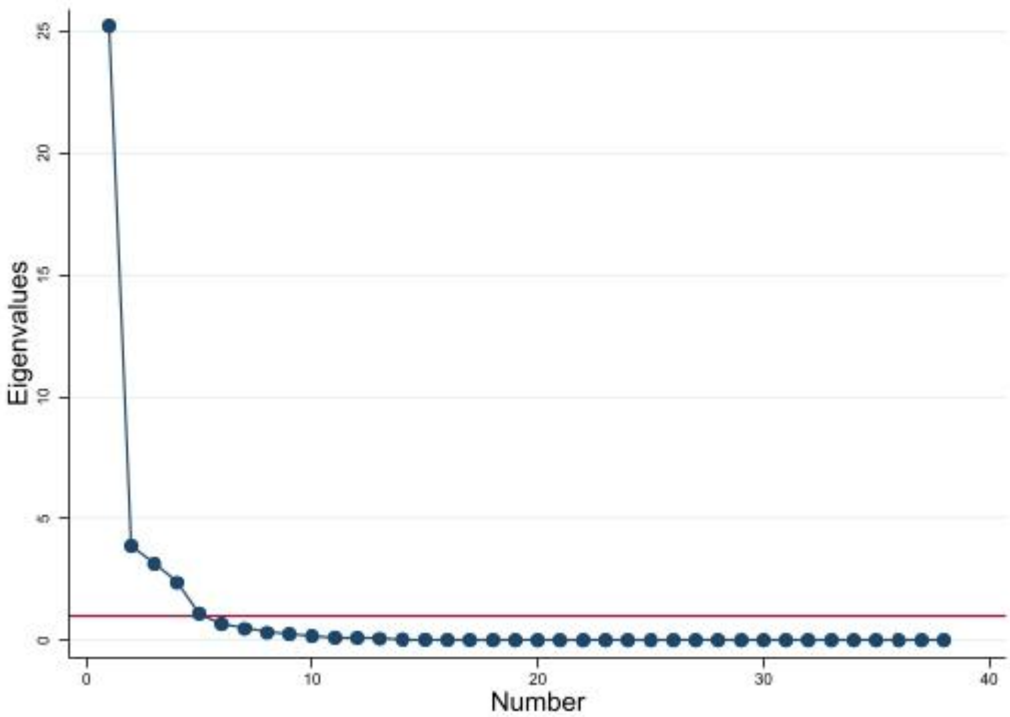


Figure A9 Scree Plot of PCA with the horizontal line indicating the Kaiser Criterion.

## References

Afifi, A. A., S. May, and V. A. Clark. 2012. Practical Multivariate Analysis. 5th ed. Boca Raton, FL: CRC Press.

Aguirre, M., & Ibikunle, G. (2014). Determinants of renewable energy growth: A global sample analysis. *Energy Policy*, *69*, 374-384.

Aitken, A. (2019). Measuring Welfare Beyond GDP. *National Institute Economic Review*, 249(1), 3-16.

Algemene Rekenkamer (2015). Stimulering van Duurzame Energieproductie (SDE+): Haalbaarheid en betaalbaarheid van beleidsdoelen, The Hague: 2015.

Al-Mulali, U., Fereidouni, H. G., Lee, J. Y., & Sab, C. N. B. C. (2013). Examining the bi-directional long run relationship between renewable energy consumption and GDP growth. *Renewable and sustainable energy reviews*, *22*, 209-222.

Boarini, R., Å. Johansson & M. d'Ercole (2006), Alternative Measures of Well-Being, *OECD Social*, *Employment and Migration Working Papers, No. 33*, Paris: OECD.

Böhringer, C., Keller, A., & Van der Werf, E. (2013). Are green hopes too rosy? Employment and welfare impacts of renewable energy promotion. *Energy Economics*, *36*, 277-285.

Bonett, D. G., & Wright, T. A. (2000). Sample size requirements for estimating Pearson, Kendall and Spearman correlations. Psychometrika, 65(1), 23-28.

Brock, W. A., and Taylor, M. S. (2010). The green Solow model. *Journal of Economic Growth*, 15(2), 127-153.

Carley, S. (2009). State renewable energy electricity policies: An empirical evaluation of effectiveness. *Energy policy*, 37(8), 3071-3081.

Statistics Netherlands (2018) Monitor Brede Welvaart 2018. Centraal Bureau voor de Statistiek, Den Haag/Heerlen/Bonaire.

Statistics Netherlands (2019) Monitor Brede Welvaart en Sustainable Development Goals 2019. Centraal Bureau voor de Statistiek, Den Haag/Heerlen/Bonaire.

Statistics Netherlands (2020) Monitor Brede Welvaart en Sustainable Development Goals 2020. Centraal Bureau voor de Statistiek, Den Haag/Heerlen/Bonaire.

Dickey, D. A. and Fuller, W.A. (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit Root, *Journal of the American Statistical Association*, 74 (366), 427-431.

Dolan, P., Peasgood, T., & White, M. (2008). Do we really know what makes us happy? A review of the economic literature on the factors associated with subjective well-being. *Journal of economic psychology*, *29* (1), 94-122.

Easterlin, R. A. (1974). Does economic growth improve the human lot? Some empirical evidence. In *Nations and households in economic growth* (p. 89-125). Academic Press.

Ehrlich, P. R. (1968). The population bomb. *New York: Sierra Club/Ballantine*.

Engle, R. F. and Granger, C. W. J. (1987). Cointegration and Error Correction: Representation, Estimation and Testing, *Econometrica*, 55 (2), 251-276.

Fang, Y. (2011). Economic welfare impacts from renewable energy consumption: the China experience. *Renewable and Sustainable Energy Reviews, 15*(9), 5120-5128.

Frondel, M., Ritter, N., Schmidt, C. M., & Vance, C. (2010). Economic impacts from the promotion of renewable energy technologies: The German experience. *Energy Policy*, 38(8), 4048-4056.

Gallardo-Albarrán, D. (2019). Missed opportunities? Human welfare in Western Europe and the United States, 1913–1950. *Explorations in Economic History*, 72, 57-73.

Grossman, G. M. and Krueger, A. B. (1991). Environmental impacts of a North American free trade agreement (No. W3914). National Bureau of Economic Research.

Granger, C. W. J. (1969). Investigating Causal Relations by Econometric Models and Cross-Spectral Methods. *Econometrica*, 37 (3), 424-438.

Haas, R., Resch, G., Panzer, C., Busch, S., Ragwitz, M., & Held, A. (2011). Efficiency and effectiveness of promotion systems for electricity generation from renewable energy sources–Lessons from EU countries. *Energy, 36*(4), 2186-2193.

Hill, J., Nelson E., Tilman, D., Polasky, S. and Tiffany, D. (2006) Environmental, economic, and energic costs and benefits of biodiesel and ethanol biofuels, Proceedings of the National Academy of Sciences, 103, (30).

Jones, C. I., & Klenow, P. J. (2016). Beyond GDP? Welfare across countries and time. *American Economic Review, 106* (9), 2426-57.

Kalkuhl, M., Edenhofer, O., & Lessmann, K. (2013). Renewable energy subsidies: Second-best policy or fatal aberration for mitigation?. *Resource and Energy Economics, 35*(3), 217-234.

Keyuraphan, S., Thanarak, P., Ketjoy, N., & Rakwichian, W. (2012). Subsidy schemes of renewable energy policy for electricity generation in Thailand. *Procedia Engineering*, *32,* 440-448.

Kilinc-Ata, N. (2016). The evaluation of renewable energy policies across EU countries and US states: An econometric approach. *Energy for Sustainable Development*, *31*, 83-90.

Kuznets, S. (1934). National Income 1929-1932. A report to the U.S. Senate, 73rd Congress, 2nd Session. Washington, DC. US Government Printing Office.

Liu, W., Zhang, X., & Feng, S. (2019). Does renewable energy policy work? Evidence from a panel data analysis. *Renewable energy*, *135*, 635-642.

MacKinnon, J. G. (1990). Critical Values for Cointeoration Tests. *University of California, San Diego, Department of Economics, Discussion Paper No 90-4.*

MacKinnon, J. G. (2010). Critical values for cointegration tests. *Queen's Economics Department Working Paper*.

Malkiel, B. G. (1989). Efficient market hypothesis. *Finance*, 127-134.

Marques, A. C., & Fuinhas, J. A. (2012). Are public policies towards renewables successful? Evidence from European countries. *Renewable Energy*, *44*, 109-118.

Martínez-Alier, J., Pascual, U., Vivien, F.-D., and Zaccai, E. (2010). Sustainable Degrowth: Mapping the Context, Criticisms and Future Prospects of an Emergent Paradigm. *Ecological Economics*, *69*, 1741–1747.

Menegaki, A. N. (2011). Growth and renewable energy in Europe: a random effect model with evidence for neutrality hypothesis. *Energy economics*, *33*(2), 257-263.

Murray, B. C., Cropper, M. L., de la Chesnaye, F. C., & Reilly, J. M. (2014). How effective are US renewable energy subsidies in cutting greenhouse gases?. *American Economic Review*, *104*(5), 569-74.

Nicolini, M., & Tavoni, M. (2017). Are renewable energy subsidies effective? Evidence from Europe. Renewable and Sustainable Energy Reviews, 74, 412-423.

Ostrom, E. (2012) Nested externalities and polycentric institutions: must we wait for global solutions to climate change before taking actions at other scales?, *Economic Theory*, 49, 353-369.

Papież, M., Śmiech, S., & Frodyma, K. (2018). Determinants of renewable energy development in the EU countries. A 20-year perspective. *Renewable and Sustainable Energy Reviews*, *91*, 918-934.

Patton, M.Q. (2002). Qualitative research and evaluation methods. *Thousand Oakes: Sage Publications.*

Raworth, K. (2017). Doughnut Economics: Seven Ways to Think Like a 21st-Centruy Economist. *London: Penguin Random House*.

Sen, A., (1999). Development as Freedom. Knopf, *New York: Oxord University Press*, New York.

Sinn, H.W. (2008) Public Policies against Global Warming: a supply-side approach, *International Tax and Public Finance*, 15, 360-394

Stern, N.H. (2007) The Economics of Climate Change: The Stern Review, Cambridge University Press, Cambridge.

Stiglitz, J. E., Sen, A., & Fitoussi, J. P. (2009). Report by the commission on the measurement of economic performance and social progress. Paris: OECD.

Stock, J. H. and Watson, M. W. (2015). *Introduction to Econometrics. Third Edition.* Harlow, United Kingdom. Pearson Education.

The Economist (2017), Can the world thrive on 100% renewable energy?, *The Economist,* Retrieved on July 30th, 2020, from https://www.economist.com/finance-and-economics/2017/07/13/can-the-world-thrive-on-100-renewable-energy.

The Economist (2018), Clean power is shaking up the global geopolitics of energy, *The Economist,* Retrieved on July 30th, 2020, from https://www.economist.com/special-report/2018/03/15/clean-power-is-shaking-up-the-global-geopolitics-of-energy.

The Economist (2020), The world's energy system must be transformed completely, *The Economist,* Retrieved on July 30th, 2020, from https://www.economist.com/schools-brief/2020/05/23/the-worlds-energy-system-must-be-transformed-completely.

Tugcu, C. T., Ozturk, I., & Aslan, A. (2012). Renewable and non-renewable energy consumption and economic growth relationship revisited: evidence from G7 countries. *Energy economics*, *34*(6), 1942-1950.

UNECE, Eurostat, OECD (2014). Conference of European Statisticians Recommendations on Measuring Sustainable Development. *New York/Genève: United Nations.*

Van de Ven, P. (2019). Measuring economic well-being and sustainability: a practical agenda for the present and the future. *EURONA Eurostat Review on National Accounts and Macroeconomic Indicators 1/2019*, 7-42.

Van den Bergh, J. C. (2009). The GDP paradox. *Journal of Economic Psychology*, *30* (2), 117-135.

Van den Bergh, J. C. J. M. (2017). A Third Option for Climate Policy within Potential Limits to Growth. *Nature Climate Change 7*, 107–112.

Van der Ree, J., Honig, E., Uijt de Haag, P. A. M., Kelfkens, G., and Van de Ven, M. F. (2019). Klimaatakkoord: effecten op veiligheid, gezondheid en natuur. Rijksinstituut voor Volksgezondheid en Milieu, Bilthoven.

WCED (1987). *Our Common Future*. World Commission on Environment and development, Oxford.

Wooldridge, J. M. (1995). Score diagnostics for linear models estimated by two stage least squares. In *Advances in Econometrics and Quantitative Economics*, 66-87. Oxford: Blackwell.

Zwijnenburg, J., Bournot, S., & Giovannelli, F. (2017). Expert Group on Disparities in a National Accounts Framework.