LUND UNIVERSITY

SCHOOL OF ECONOMICS AND MANAGEMENT

Master's Programme in Innovation and Global Sustainable Development

Genuinely Saving Denmark:

Genuine Savings and Long-Term Well-Being in Denmark from 1870–2010

by

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Abstract:

Genuine Savings has entered the picture as a new metric for sustainable development. The theory developed by Martin L. Weitzman is that savings has a one to one correlation with future well-being (measured by the present value of the change in consumption). In this thesis, long-term time series data from Denmark ranges from 1870 to 2010 for the purpose of empirically testing the correlation between Genuine Savings and

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future well-being. Based on OLS regression model results, there is evidence of a positive correlation between Genuine Savings and future well-being in Denmark. However, there is no supported evidence from the models for the one to one connection originally theorized. These results contribute support for Genuine Savings as a metric for weak sustainability, but cannot substantiate the full theory of Weitzman.

Acknowledgements

I would first like to send a big thank you to my thesis supervisor, Cristián Ducoing. He has made all the difference in my thesis writing experience, not only assisting in the more technical aspects of the thesis, but also with motivating me to produce the work he knew I was capable of doing. Next, I would like to thank all of my peers in the Innovation and Global Sustainable Development programme. Specifically, I would like to thank Christopher la Cour-Andersen and Veith Tluczykont for giving me encouragement throughout the thesis process. Furthermore, I would like to thank Dr. Patrick Conway for igniting my interests in international economics. Finally, I would like to thank my friends and family from the United States who helped me get to the place I am at now.

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List of Abbreviations & Acronyms

1. CFC- Consumption of Fixed Capital

2. CO_2- Carbon Dioxide

3. DKK- Danish Kronor

4. FAO- Food and Agriculture Administration of the United Nations

5. FMOLS- Fully-Modified Ordinary Least Squares Regression Model

6. GDP- Gross Domestic Product

7. GNI- Gross National Income

8. GNS- Gross National Savings

9. GS- Genuine Savings

10. GStp- Genuine Savings augmented by TFP

11. K- Capital

12. L- Labor

13. NNS- Net National Savings

14. NNSF- Net National Savings Minus Resource Rents Plus Forestry

15. NNSFtp- Net National Savings Minus Resource Rents Plus Forestry augmented by TFP

16. NNSNR- Net National Savings Minus Resource Rents

17. NNSNRtp- Net National Savings Minus Resource Rents augmented by TFP

18. OECD- Organization for Economic Co-operation and Development

19. OLS- Ordinary Least Squares Regression Model

20. PVC- Net Present Value of the Change in Consumption

21. SE- Standard Error

22. TFP- Total Factor Productivity

23. USD- United States Dollar

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1 Introduction

Since the origin of Gross Domestic Product (GDP) in the 1930s developed by Simon Kuznets, GDP has been the leading metric for analyzing the state of a country's development (Costanza, Hart, Kubizewski and Talberth, 2014). Essentially GDP is formulated through the summation of all the final goods and services sold for currency in a country in a specific period of time (typically done quarterly and annually). In the same time period of this GDP dominance, many of the general factors considered for sustainable development (climate change and well-being) have taken the turn for the worst (Millar and Woolfenden, 1999). All of this takes place at the same time global GDP has steadily grown, from 2009 to 2019 global GDP has increased every year (World Bank, 2021). The issue is apparent through the misuse and overindulgence of GDP, even Simon Kuznets himself warned about using GDP as a metric for well-being rather than for economic production (Costanza et al., 2014). As sustainability has become a highly attractive concept in the preceding years, it is worth identifying a metric that is connected to future well-being, since GDP is unsuitable for this feat.

Genuine Savings (GS) is an alternative metric to GDP that has exceptional data collected in a shorter term compared to GDP, which is measured by the accumulation of change in a specific country's aggregate capital stocks. In simpler terms, GS is a metric calculated by the net change in all forms of capital stocks. The introduction of GS first came from the researchers Pearce and Atkinson (1993), but as a measure of "weak sustainability". Weak sustainability is the concept that natural capital can be substituted by physical and human capital, while strong sustainability states that natural capital can only be complemented not substituted. GS is a metric commonly implemented as an indicator to show the sustainability of a country's development (Lindmark, Nguyen and Stage, 2018 and Hamilton, 2000).

1.1 Previous Research

Most analysis on the relationship between GS and future well-being has been done in the short-term. Ferreira and Vincent (2005), the World Bank (2006) and Ferreira, Hamilton and Vincent (2008) implement data collected by the World Bank with a plethora of countries in the short term. This research yielded the result that there is a correlation between genuine savings and changes in future consumption. Although this relationship has been identified in the short-term, the relationship theorized by Weitzman (1976) that an investment in capital should yield a one to one measure of the discount rate of utility in the future is not found. However, Denmark, along with the other Nordic countries, have a long-standing cultivated time series data on the most important variables when concerning GS: physical, natural and human capital stocks. This presents the ability to complete a study of the relationship in the long-term, rather than only in the short-term.

Lindmark and Acar (2013) and (Lindmark, Nguyen and Stage (2018) analyze the correlations between GS and "long-term welfare" with data from Sweden from 1850-2000. However, in both studies by Lindmark and Acar (2013) and Lindmark, Nguyen and Stage (2018), no strong sustainability connection between GS and future well-being was confirmed.

The previous research done with the short-term World Bank data leaves many questions of the Weitzman (1976) theory. This mainly arises because the theory that developed is stated the one to one correlation is over an infinite time-horizon. So, the later research done by Blum, McLaughlin and Hanley (2019) and Greasley, Hanley, Kunnas, McLaughlin, Oxley and Warde (2014) are some of the first attempts at understanding the correlation between GS and future well-being in the long-term. In the Greasley et al. (2014) research, the country that is focused on is Great Britain from 1765 to 2000. Ultimately in these findings, the correlation between GS and future well-being is substantiated in the data, but only in terms of 'weak sustainability'. The Blum, McLaughlin and Hanley (2019) research implements data from Germany from 1850 to 2000. This research also identifies a correlation between GS and future well-being, but not the one to one connection theorized (Blum, McLaughlin and Hanley, 2019). After the Blum, McLaughlin and Hanley (2019) and Greasley et al. (2014) research, Hanley, Oxley, Greasley, McLaughlin and Blum (2016) performs a long-term GS study with three countries: The United Kingdom, the United States of America and Germany. At length, the Hanley et al. paper also find statistical support for GS as a weak sustainability indicator. Lindmark, Nguyen and Stage (2018) perform a similar research design to Greasley et al. (2014), however, they implement data from Sweden from 1850-2000. Their study identifies the use of Great Britain, as the country of study, as an anomaly due to peculiarities like: being the first country to industrialize and vast colonies held, providing varying amounts of capital. Lindmark, Nguyen and Stage (2018) focus on Sweden from 1850 to 2000 because of Sweden's availability of data in terms of a "comprehensive green national account," that allows the analysis to take place. Once again, this study also found a correlation in the weak sustainability model tests, but not in the stronger sustainability model tests. Lindmark, Nguyen and Stage (2018) produce three key reasons why only weak sustainability is supported rather than the stronger sustainability models: the measurement of capital stocks, the use of national accounts and consumption as a proxy and weak sustainability is a flawed concept. Although Denmark and Sweden have cultural similarities, the two countries have developed differently over the course of time and have differences in industry. This makes Denmark an interesting study when analyzing the hypothesized relationship between GS and long-term development and welfare that is based in theory.

1.1.1 Denmark's Background

Denmark during this selected time period has the potential to provide empirical evidence of the relationship between GS and future well-being due to its development in the late nineteenth century (Henriques and Sharp, 2015). According to Henriques and Sharp (2015), Denmark had relatively cheap access to coal in the late nineteenth century for a coal-poor country, due to this fact Denmark industrialized (mainly in the agriculture sector) rapidly. Although coal reserves were relatively scarce in Denmark, they continued to perform "coal surveys", with little success of finding suitable mining areas (Ranestad and Sharp, 2021). This phenomena is seen in the Danish National Account Project (2015), when considering the beginning of the rapid growth of livestock value that began in 1989. Economic growth based in the agriculture sector, has the potential to alter GS estimates from the beginning of the study period. However, the best example of a postponed industrial revolution in Denmark is the delayed spike in agriculture production until 1918, without consistent growth until 1940 (Danish National Account Project, 2015). Although, relatively speaking, Denmark was able to dodge the devastating effects of the First World War, by continuously exporting products to both sides (Henriksen, 2016). However, the trade surplus they ran during the war slumped in post-war Denmark, leading to poor monetary policy decisions that decreased Danish exports (Henriksen, 2006). Learning from this mistake, Denmark was able to swiftly recover from the economic issues that followed the Second World War (Henriksen, 2006). The relatively low impact from exogenous destruction caused by war in Denmark, compared to the United Kingdom could result in drastically different GS estimates. Denmark, like other modern welfare-states, began to rapidly increase their government expenditure on welfare (in areas like health care and education expenditure) in the mid 20th century (Pedersen, 1995). Welfare spending in Denmark is significant to GS as increasing health and education can contribute to increases in human capital formation (Kunnas, 2016). Along with this economic development, Denmark has been vigilant in maintaining natural capital with the national government beginning forest restoration since 1800 (Danish National Forest Programme, 2002). In addition to this reforestation of Denmark, there has been negligible mining for minerals and oil in Denmark. These unique features of Denmark's historical industrialization and change in GS accounts could lead to a significant correlation between GS and future well-being. Currently through both of the major studies (i.e. Greasley et al., 2014 and Lindmark, Nguyen and Stage, 2018) that examine this relationship, there is still low empirical support for the theory of a one to one relationship between GS and future well-being.

1.2 Research Question

Given the fact that Denmark does not have a long-term GS calculation, and the fact that Denmark has a differing history in terms of economic development, the research question aims to fill the current gap.

> Research Question: Is Genuine Savings an indicator of long-term welfare for Denmark in the period from 1870 to 2010?

1.3 Outline of the Thesis

The first phase after finishing the introduction is to outline the theoretical framework and approach implemented in this thesis. The next section will outline the data, calculations and variable definitions used. After the data is outlined, the econometric approach to displaying the correlation between GS and future well-being will be configurated. In section five, the empirical results of the research will be shown. Once the empirical results are laid out, the results will be discussed in both terms of hypotheses and holistically. Then the thesis will be concluded with aims, results, practical implications, limitations, and future research prospects.

2 Theory

Using the Pearce, Markandya and Barbier (1989) framework, when GS has negative values it denotes that the economy of the country is developing in an unsustainable manner. As cited by Atkinson and Hamilton (2006), no matter what definition of sustainability is given, if total wealth has a connection to well-being then it involves the production and conservation of wealth. Genuine Savings is also referred to as Adjusted Net Savings (ANS), Comprehensive Investment (CI) and Inclusive Investment (II) in varying literatures (Qasim, M., Oxley, L. and McLaughlin, E., 2020).

2.1 Theoretical Framework

Tested by Ferreira, Hamilton and Vincent (2008), GS will be equal to the present value of the change in consumption, as long as GS is measured correctly and the correct assumptions are made (Lindmark, Nguyen and Stage, 2018). The imperative assumption made by all GS estimates is that all forms of capital, physical, human and natural, are perfectly substitutable in an economic sense with the parameters that GS does not fall below zero and that the entirety of capital stock does not diminish. In other words, this is the *weak sustainability* assumption of GS. The major difference between weak and strong sustainability is that for weak sustainability it is only necessary that total savings do not diminish over time, while strong sustainability requires only natural capital savings to not decrease over time. The weak sustainability parameter defined above is known as Hartwick's Rule, which in more depth explains that the extracted natural resources must be reinvested to produce equal or more physical capital for sustainable development (Hamilton, 1995). Pearce, Markandya and Barbier (1989) develop four separate reasons why strong sustainability is preferred to weak sustainability in terms of increasing future well-being: weak sustainability is not adequately sustainable, the loss of natural capital can be irreversible, the loss of natural capital has unknown consequences and the loss of natural capital adversely effects poorer communities compared to the rich.

The general model of the theory, outlined in Hanley, Dupuy and McLaughlin (2015), states that the three forms of capital (natural, human and physical) need to be maintained/increased for an economy to grow and well-being to increase in the long term. The reason for this is the use of a basic economic structure that all production is defined by its application of capital, K, and Labor, L, and the exogenous technical progress. By this logic, if physical capital or natural capital, described by K, or human capital, described by L, decreases then there is less total inputs for production. However, the reason why all forms of capital can merely be maintained and still experience economic growth is the exogenous technological growth (i.e. larger quantities of production can be made with better technology). In this model, the reduction of physical capital is due to the consumption of fixed capital (i.e. the wearing down of machinery over time) (Hanley, Dupuy and McLaughlin, 2015). The reduction of natural capital is when natural capital is reduced for the production process (i.e. chopping down trees for paper production) (Hanley, Dupuy and McLaughlin, 2015). The reduction of human capital is due to death (i.e. accumulated human capital from work experience cannot be passed intergenerationally) (Hanley, Dupuy and McLaughlin, 2015).

This theoretical relationship between GS and future consumption has been put into use for empirical study by Ferreira, Hamilton and Vincent (2008) and Greasley et al. (2014). Another essential assumption that is made in the vast empirical literature is the adaptation of the changes in natural and human capital, created in United Nations (2014), so that the display the values, in an economic sense, in a form that can test the theories assumptions.

Neither of these key assumptions have been exempt from academic criticism since their creation. Several authors (Ekins, Simon, Deutsch, Folke and De Groot, 2003 | Pelenec and Ballet, 2015) have offered the idea of a *strong sustainability* model. A strong sustainability model defines natural capital as inherently different in its properties, mainly that when natural capital is destroyed to almost extinction there are negative effects at some critically low level. In this argument, natural capital is not a substitute for human and physical capital, rather it is an essential compliment. Additionally, regardless whether weak sustainability is correct or incorrect, the prices from the accounting would be altered by market and structural failures, which would in turn would skew any GS calculations even with the adaptation done to create the metric (Lindmark, Nguyen and Stage, 2018). What this means is that any GS estimates would not provide any useful information regarding if the economy is developing in a sustainable manner. Most of the empirical studies either examine special cases, such as Blum, McLaughlin and Hanley, (2019), or examine short-term GS research, like the World Bank (2006), which creates difficulty because the Genuine Savings theory is meant to be over an infinite time span. Since the prior long-term GS studies fell short of establishing this long-term connection between Genuine Savings and future consumption, it is of high regard in the academic world to continue the study of the long-term relationship between Genuine Savings and future well-being, which is attempted in this thesis.

2.2 Theoretical Approach

The theoretical framework implemented for this research would be drawn from the previous literature Lindmark, Nguyen and Stage (2018) and Hanley et al. (2016) which have been pieced together from Greasley et al. (2014) and Ferreira et al. (2008). This framework claims that if the GS and future well-being relationship is accurate, then GS per capita (G) at a specific time (t) can be displayed as:

$$G = \sum_{v=t+1}^{\infty} \frac{\left(\frac{C_{v+1}}{N_{v+1}} - \frac{C_v}{N_v}\right) + (\gamma_{v+1} - \gamma_v)\frac{W_v}{N_v}}{\prod_{j=t+1}^{v}(1+\varrho-\gamma_j)} \quad (1)$$

In this equation, consumption is denoted as C_t at the time t, population is denoted by N_t at time t, population growth is denoted by γ at time t, aggregate wealth is denoted as W_t and the discount rate is denoted by ϱ. Population growth is assumed to be constant, this is in order to simplify the equation and make it possible to formulate the hypothesis equation. This equation is formulated in the Greasley et al. (2014) in order to test the relationship between GS and future well-being:

$$PV\Delta C_t + PV\left(\Delta\gamma_t \frac{W_t}{N_t}\right) = \beta_0 + \beta_1 G_t + \varepsilon_t \quad (2)$$

In this equation, Net Present Value of the Change in Consumption at time t is written as $PV\Delta C_t$. The Net Present Value of the Change in Population Growth at time t is denoted as $PV\left(\Delta\gamma_t \frac{W_t}{N_t}\right)$, but equates to zero since population growth is held constant.

The theory estimates that over an infinite amount of time, $\boldsymbol{\beta}_0 = 0$ and $\boldsymbol{\beta}_1=1$ these coefficients should approach these numbers with an infinite amount of time. The meaning of $\boldsymbol{\beta}_0 = 0$ and $\boldsymbol{\beta}_1=1$, from the equation above is that the present value of consumption is directly correlated with Genuine Savings and no other variables. If this stands true, then this indicates that Genuine Savings is an appropriate measure for estimating future well-being or in economic terms sustainable development. These observed coefficients will be how the hypotheses will be formulated and answered through empirical testing.

The research question identified above the will be answered through a series of hypotheses that were employed in the Lindmark, Nguyen and Stage (2018) research:

H$_1$: $\boldsymbol{\beta}_0 = 0$ and $\boldsymbol{\beta}_1 = 1$

This hypothesis states that as time approaches infinity the values for both of the coefficients will approach these values, which is in line with the theory of genuine savings and future well-being. This hypothesis will be tested in order to determine if there is an empirical correlation between genuine savings and future well-being in a 'strong sustainability' sense.

H_2: $\boldsymbol{\beta}_0 \rightarrow 0$

This hypothesis examines how further savings measures over longer periods of time change the genuine savings. If the theory holds, the constant's coefficient should approach zero as time increases. If the constant's coefficient equates to zero, this means that the coefficient for GS is not being overstated.

H_3: $\boldsymbol{\beta}_1 > 0$ and $\boldsymbol{\beta}_1 \rightarrow 1$

This hypothesis states that as time increases, the coefficient for GS is greater than zero and approaches one as the time-horizon implemented increases. This hypothesis was supported in both the Greasley et al. (2014) paper and the Lindmark, Nguyen, and Stage (2018) paper and is expected to also be supported with the different datasets.

H_4: $\boldsymbol{\beta}_1 > 1$

This hypothesis states that, the coefficient for GS is greater than one. Meaning that GS has a positive correlation with future well-being, but not the exact one to one relationship developed in the Weitzman (1976) theory. This hypothesis was also supported in both the Greasley et al. (2014) paper and the Lindmark, Nguyen and Stage (2018) paper.

3 Data

The data that is implemented throughout the rest of this research are formulated from Danish time-series data (1870-2010) that have been collected from multiple different national account databases and publications. The data will provide more in-depth detail on the individual variables, as well as descriptive statistics and data sources below. In order to have a clear starting position, a comparison between some of the most important statistics for calculating Genuine Savings will be shown directly after defining and explaining the variables.

3.1 Collected Variables

The first variable collected in order to do the long term GS calculation for Denmark is the total population collected from Kim Abildgren's compiled database (2017) (Shown in *Figure 3.1.1*).

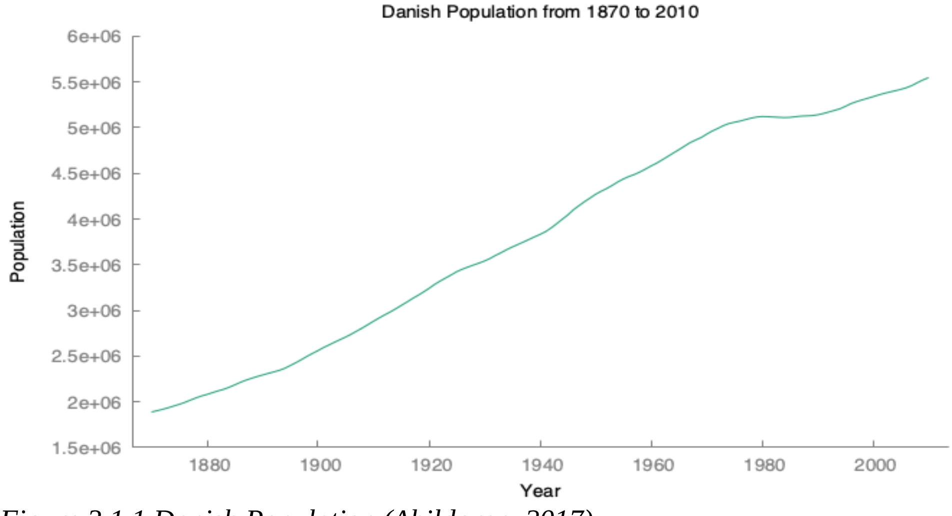

Figure 3.1.1 Danish Population (Abildgren, 2017)

The next statistic collected was Denmark's GDP in the local currency (DKK) also collected from Kim Abildgren's compiled database (2017) (Shown in *Figure 3.1.2*). The GDP metric was converted to Denmark's GDP in 2010 United States Dollars (USD) in order to have one common currency. The steps in order to convert GDP from current DKK to USD are to divide GDP in DKK by the corresponding DKK to USD exchange rate, then dividing the GDP in USD by the USD deflator with 2010 as the base year. The DKK to USD exchange rate was also collected from Kim Abildgren's compiled database (2017), while the USD deflator data was collected from the Inflation Calculator (2021).

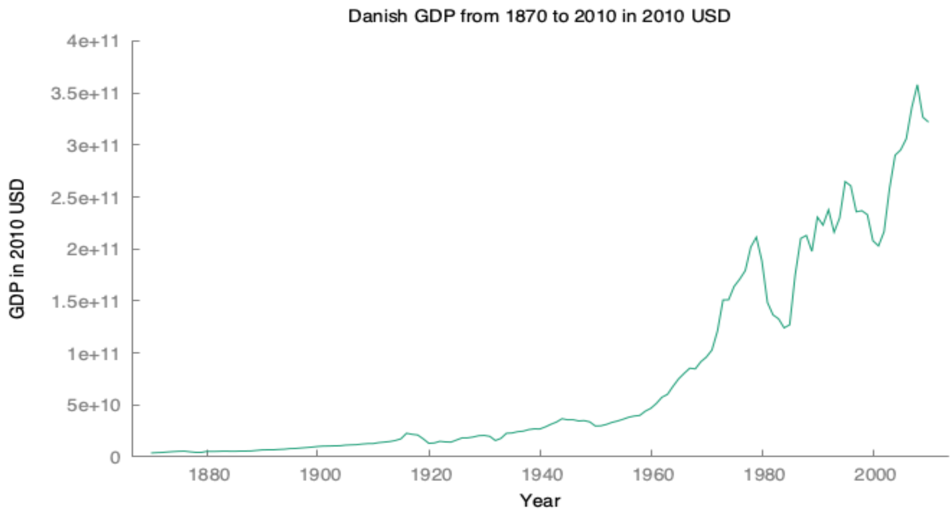

Figure 3.1.2 Danish GDP (Abildgren, 2017)

The next variable collected was the CO_2 emissions of Denmark in tonnes collected from Ritchie and Roser's (2020) CO_2 database (Shown in *Figure 3.1.3*). This metric needed to be converted into kilo-tonnes for use in calculating GS, so the data was multiplied by .001 in order to convert tonnes into kilo-tonnes.

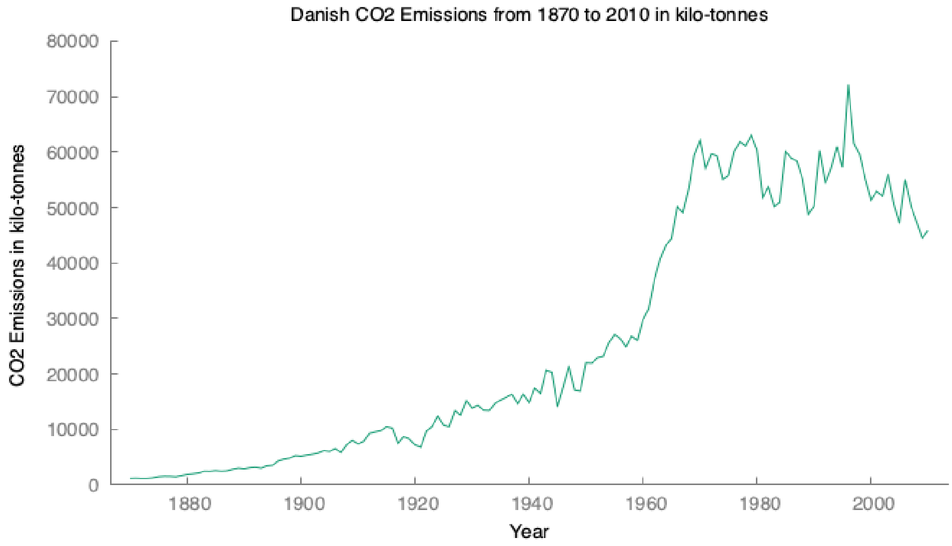

Figure 3.1.3 Danish CO_2 Emissions (Ritchie and Roser, 2020)

After collecting CO_2 emission data, the data for education expenditure was collected. This variable is calculated by totaling the education expenditure of the national government of Denmark. The data to calculate this metric came from two different sources: The World Bank and Kim Abildgren's (2017) compiled database. However, in Abildgren's database the data was for national government expenditure on education, health and social protection. So in order to isolate education from the other variables, calculation of the average percent of GDP education expenditure was calculated from the World Bank data and then applied to the Abildgren (2017) data (Shown in *Figure 3.1.4*).

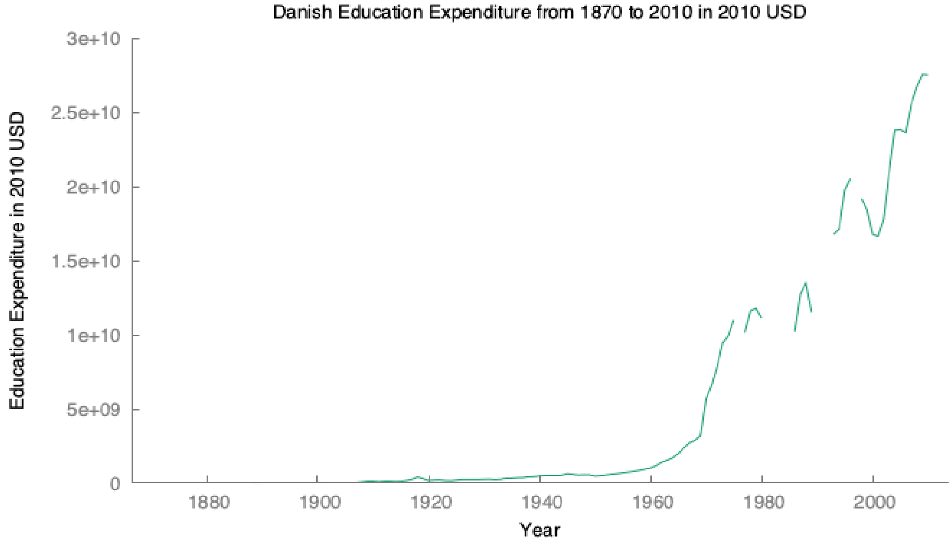

Figure 3.1.4 Danish Education Expenditure (Abildgren, 2017 | World Bank, 2020)

The next variable collected is the woodland area in hectares of Denmark, collected from the Danish *Skrovressourcer*[1] (2000). In order to be used to calculate GS, the woodland area change in hectares was calculated and multiplied by the forest volume in meters cubed (m^3). Then in order to calculate the resource rent of forestry, this metric was multiplied by timber price in USD/m^3 (Shown in *Figure 3.2.1*).

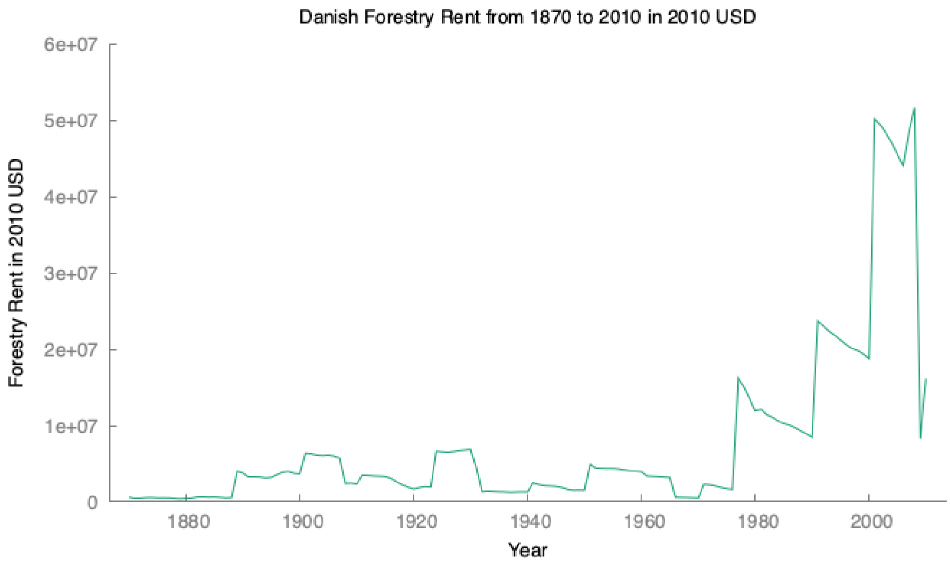

Figure 3.2.1 Danish Forestry Rent (Danish Skrovressourcer, 2000)

The next variable collected was Danish Fishery data from 1870 to 2010. From the years 1960 to 2010 the data was collected from the World Bank as metric tons of fish caught (World Bank, 2018). In order to get this data into the form needed for resource rents it was first converted to kilograms, then multiplied by the average fish price per kilogram. Then data was collected for 1894 to 1935 from the Danish National Trade Statistics (Danish National Trade Stat-book, 1935). This data was collected as revenue from the exportation of fish. The data for the years in-between 1935 to 1960 had to be interpolated by finding the average rate of

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[1] Skrovressourcer: Forest Resources

change per year and applying it to the data collected from 1935. The same technique was taken for finding the data for the years between 1894 to 1870. The next step taken in order to obtain the fishery resource rent is to subtract the costs of fishing (i.e. labor costs). The first step to obtain the costs was data collected on number of employees in the fishing industry from 2000 to 2013 collected from Nielsen, Waldo, Hoff, Nielsen, Asche, Blomquist, Bergesen, Viðarsson, Sigurðardóttir and Sveinþórsdóttir (2017). To complete this data for the entire time period, the rate of change in employment from Abildgren (2017) was applied. The same method was used for calculating fishing employees' wages by collecting wages from Nielsen et al. (2017) and interpolating the prior years' using the rate of change in wages from Abildgren (2017). With both series complete the last step was to subtract the costs of fishing from the revenues to obtain the Danish fishery resource rent from 1870 to 2010 (Shown in *Figure 3.2.2*).

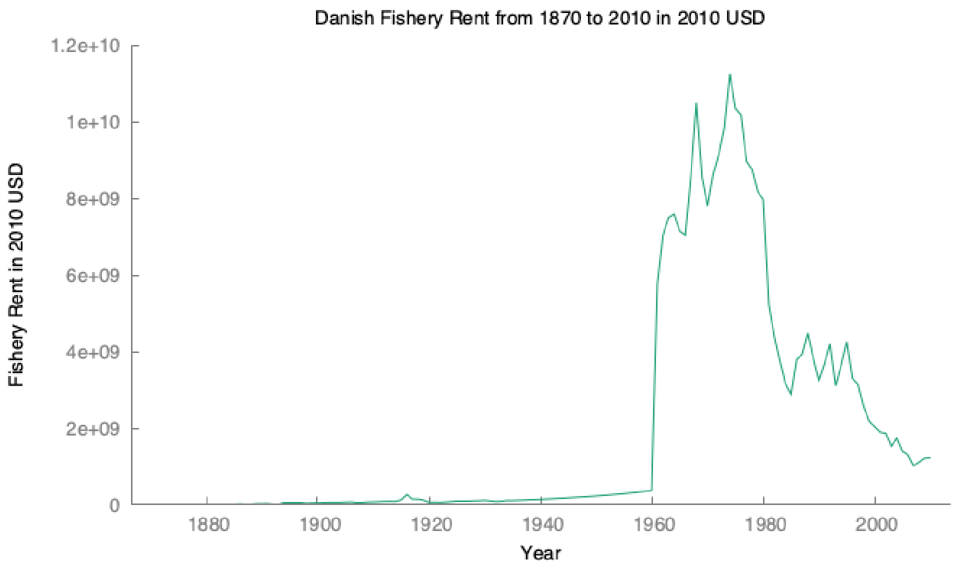

Figure 3.2.2 Danish Fishery Rent (World Bank, 2018 | Nielsen et al. 2017 | Danish National Trade Statistic, 1935 | Abildgren, 2017)

In a normal GS calculation, mineral and energy resource rents would need to be calculated. However, due to Denmark having little to no precious mineral mining and energy depletion this data was not needed in the calculations. The next variable collected is the wages earned in

Denmark from 1875 to 2010 from Kim Abildgren's (2017) compiled database. This data was converted to 2010 USD through the exchange rate and USD deflator (Shown in *Figure 3.2.3*).

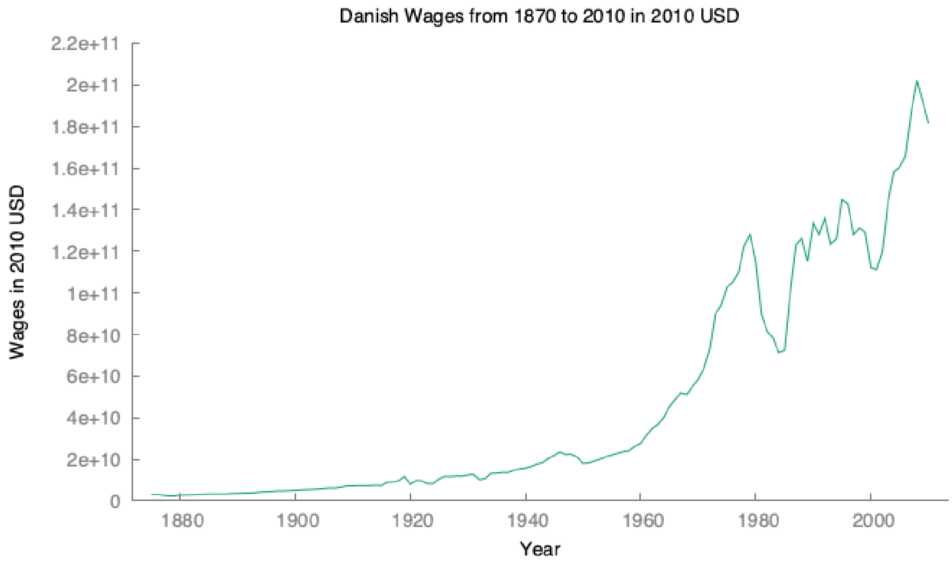

Figure 3.2.3 Danish Wages (Abildgren, 2017)

The next variable collected was the consumption of fixed capital (CFC) in DKK from Kim Abildgren's (2017) compiled database. Consumption of fixed capital is the depreciation of fixed capital. This variable needed to be converted into 2010 USD as well, so the same steps taken to convert GDP into 2010 USD were implemented (Shown in *Figure 3.3.1*).

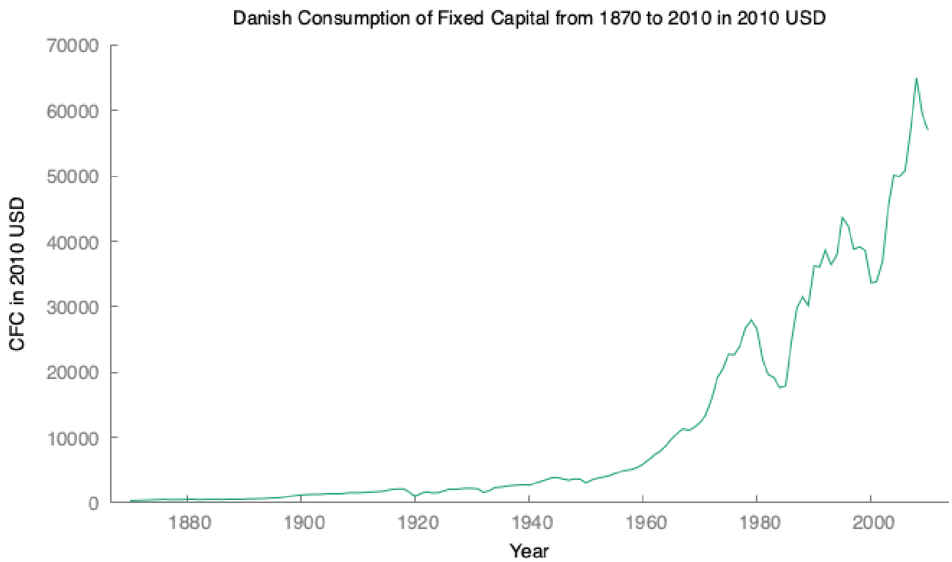

Figure 3.3.1 Danish Consumption of Fixed Capital (Abildgren, 2017)

The last variable collected is Gross National Savings (GNS) in DKK from Kim Abildgren's (2017) compiled database. Gross National Savings is the difference between gross national income and gross national consumption. The same steps for converting GDP and CFC to 2010 USD were taken for GNS (Shown in *Figure 3.3.2*).

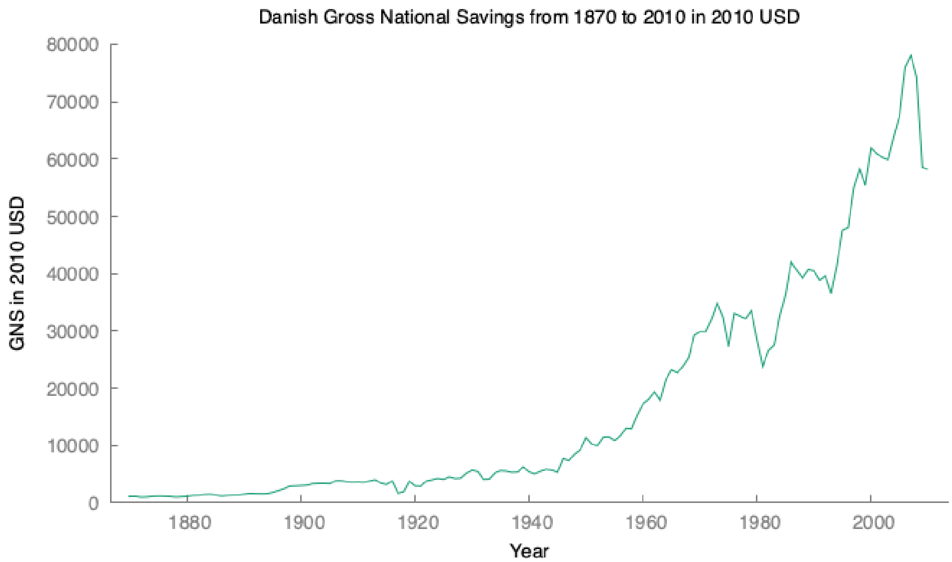

Figure 3.3.2 Danish Gross National Savings (Abildgren, 2017)

3.2 Calculated Variables

Five comprehensive measures of savings will be calculated using the aforementioned data, as well as the Net Present Value of the Change in Consumption . These saving metrics are formulated based on Bolt, Matete and Clemens (2002) manual for calculating Genuine Savings.

1. Net National Savings (NNS)
2. Net National Savings minus rents (NNSNR)
3. Net National Savings minus rents plus forestry (NNSF)
4. Genuine Savings (GS)
5. Total Factor Productivity (TFP) Growth Series for NNSNR, NNSF and GS measures

6. Net Present Value of Consumption at 20, 50 and 70 time-horizons and 3% and 4% discount rates

Net National Savings (NNS):

In compliance with the World Bank's manual for calculating Genuine Savings (Bolt, Matete and Clemens, 2002), Net National Savings is calculated by subtracting consumption of fixed capital (CFC) from gross national savings (GNS). Gross national savings are calculated by the difference between gross national income and consumption in addition to net current transfers (both public and private consumption). In this study, both GNS and CFC are found in Kim Abildgren's (2017) working compilation of Denmark's monetary and financial history. Shown in *Figure 3.4*.

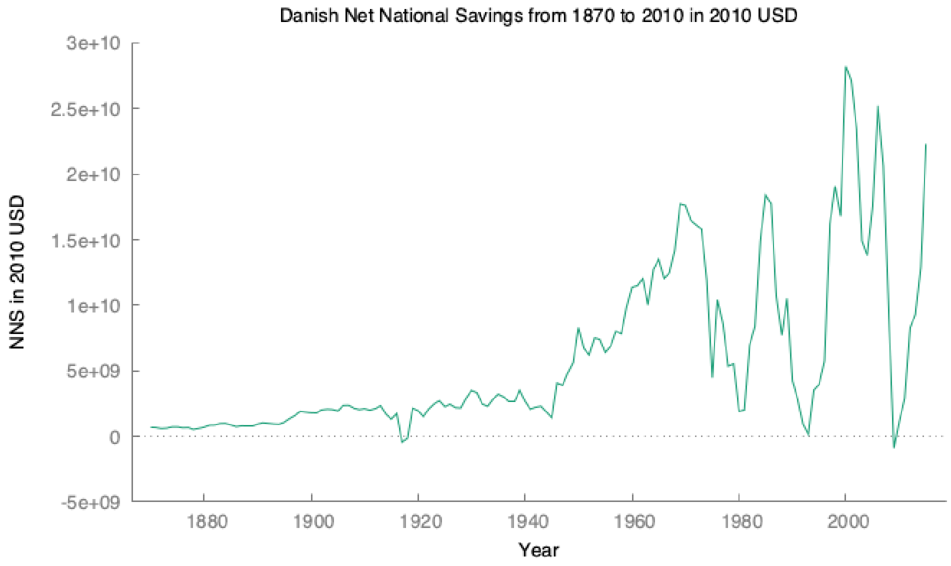

Figure 3.4 Danish Net National Savings

Net National Savings Minus Rents (NNSNR):

The NNSNR in this thesis is calculated by subtracting the resource rent (other than forestry) from the NNS. Due to Denmark having low amounts of mining, in both mineral and energy terms, these resource rents have been excluded. Instead, the main resource rent that will be subtracted is fishing depletion. This resource rent is calculated by subtracting the costs of fishing (i.e. wages) from the revenue (i.e. tonnes of fish and price of fish).

The time-series data collected for this variable comes from Danish National Trade records from 1894 to 1935 and World Bank data on captured fish from 1960 to 2010 with the gaps in the timeframes being interpolated. The labor market costs were collected from Nielsen et al. (2017) and combined with data from Abildgren (2017) data to create the entire series.

The Danish economy has greatly benefited from its high levels of fishing, in terms of GDP, by exporting vast amounts of fish. Danish fishing began its major rise in the 1960s due to 'technical innovation' (Verstergaard, 1990). Denmark's fishing hit a peak in 1980, having captured over 2 million metric tonnes of fish. These figures have been slowly decreasing since 1980, however, spiked again in 1999. Since 1980, fishing in Denmark has decreased by 58.9 percent. Shown in *Figure 3.5*.

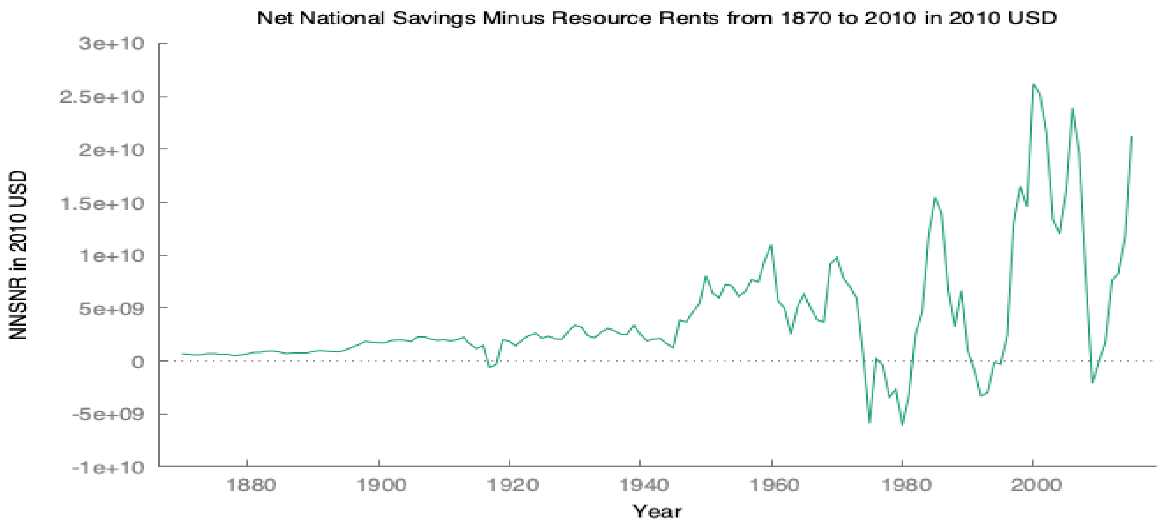

Figure 3.5 Danish Net National Savings Minus Resource Rents

Net National Savings Minus Rents Plus Forestry (NNSF):

In this portion of ultimately calculating GS, forestry rents are added to the NNSNR in cases of forest depletion to be considered. Unlike many countries, Denmark, as previously stated, began restoring it's forests in the early 1800s (Danish National Forest, 2002). While in most cases forest depletion would be subtracted from NNSNR, forest replenishment will actually be added as it is a positive value. The change in woodland coverage of Denmark was collected from the *Danish Skrovressourcer* (*Skrovressourcer*, 2000). This data combined with the FAO's (2000) Global Forest Resource Assessment provided the data to calculate the added resource "rent". Shown in Figure 3.6.

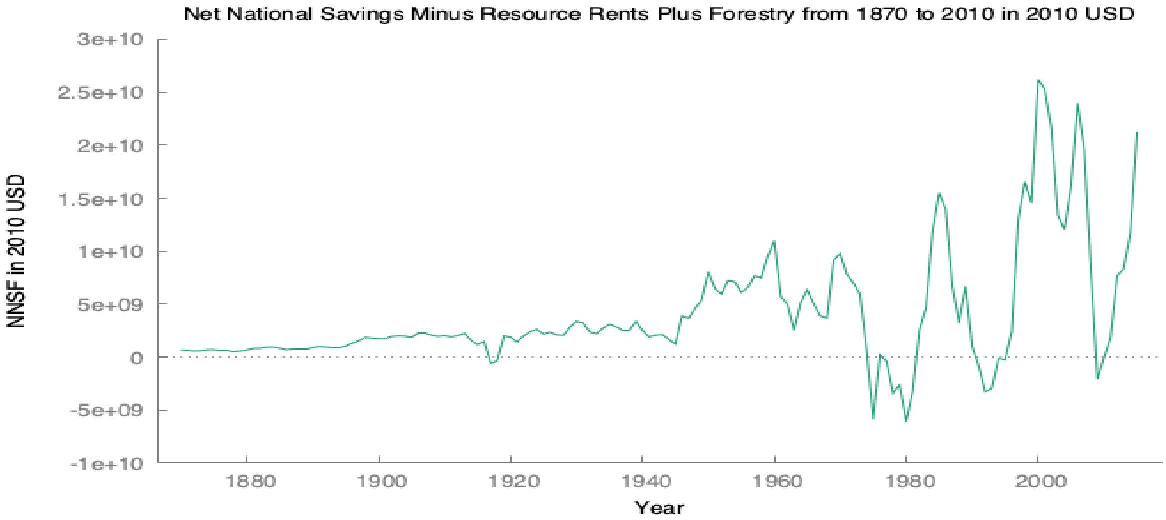

Figure 3.6 Danish Net National Savings Minus Resource Rents Plus Forestry

Genuine Savings (GS):

Genuine Savings is then possible to calculate by adding education expenditure to the total of NNSF calculated. The data for this calculation is collected from both the World Bank and Kim Abildgren's (2017) compiled database as previously stated. The data from Abildgren's (2017) database needed to be interpolated due to it being intertwined with other governmental expenditures, the process for this is mentioned previously. The use of government expenditure for the measure of human capital has precedence from the World Bank's calculation of GS. Although there is precedence for this procedure, the limitations on this methodology must be noted. Through research, mainly from Hanley et al. (2016), government expenditure does not adequately equal human capital development. However, government spending on education does seamlessly fit into the GS framework. Along with this, there has been no adequate alternative metric for calculating human capital formation to replace government expenditure. With this in mind, government expenditure will continue to be used in this research. Shown in *Figure 3. 7*.

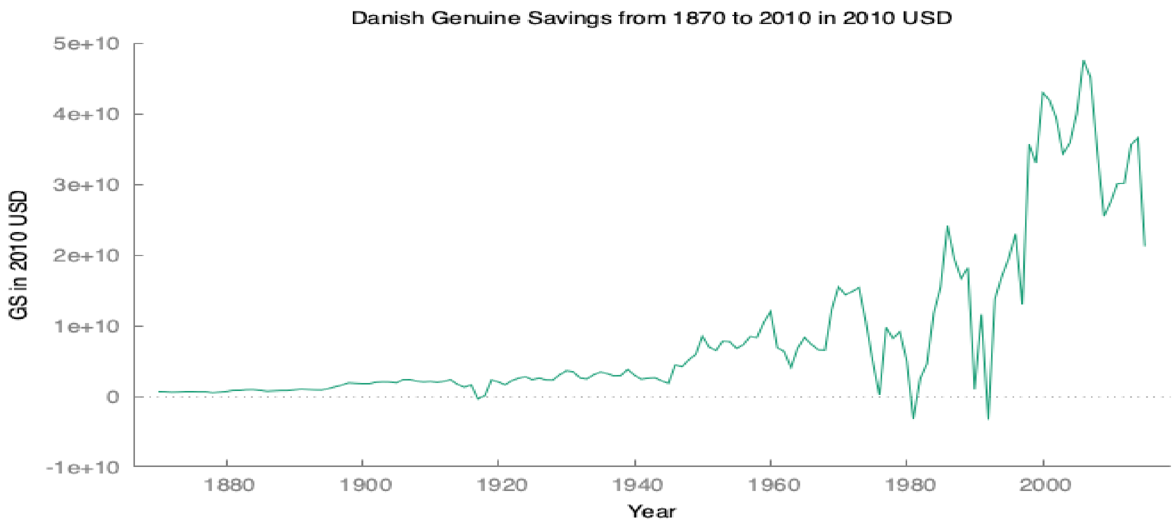

Figure 3.7 Danish Genuine Savings

TFP Growth Series for NNSNR, NNSF and GS measures: Written as NNSNRtp, NNSFtp and GStp:

Total Factor Productivity (TFP) is a way to measure the progress of technology as an exogenous growth overtime. The use of TFP in this manner is preceded by Weitzman (1997) when calculating GS and the prior measures leading to GS. For TFP to be a measure of technological progress the assumption that all advancement in technology is exogenous, which in turn raises the potential of increasing consumption as time moves forward (Pezzey, Hanley, Turner and Tinch, 2006 | Pezzey, 2004). The inclusion of TFP into NNSNR, NNSF, and GS (which are all comprehensive investment measures) is imperative for OECD countries as productivity has a significant responsibility in the growth of income (Ferreira and Vincent, 2005). Although TFP growth has a large influence on income growth, the limitation of TFP growth's addition to GS is necessary as there is less evidence of terms of trade favoring exportation of natural resources in a long term period. This limitation of TFP growth's amplification of GS is done by using trend growth in TFP. The formula to calculate the annual TFP index is shown here:

TFP = GDP / (Labor $^{\alpha}$ Capital $^{1-\alpha}$), The Labor variable is measured through hours worked, while the variable capital is measured through capital stock. Alpha is the labor share of GDP and one subtracted by alpha is the capital share of GDP.

As stated prior, TFP, in terms of trend growth, is the metric implemented to uphold the value of progression in exogenous technology. This method is also implemented in Arrow, Dasgupta, Goulder, Mumford and Oleson (2012), to display that technical progress has positive effects on income levels. Moreover, this means that TFP must be included in the measure of Genuine Savings as it serves a influential contribution to the change in wealth. The method implemented in this thesis to calculate TFP growth's contribution to changes in wealth follows both Pezzey et al. (2006) and Qasim, Oxley and McLaughlin (2018). The discount rate will also resemble the Lindmark, Nguyen and Stage (2018) research with one discount rate implemented, 3%, when calculating TFP. Shown in *Figure 3.8*. The Difference between GS and GStp are shown in *Figure 3.9*.

Figure 3.8 Danish TFP Series

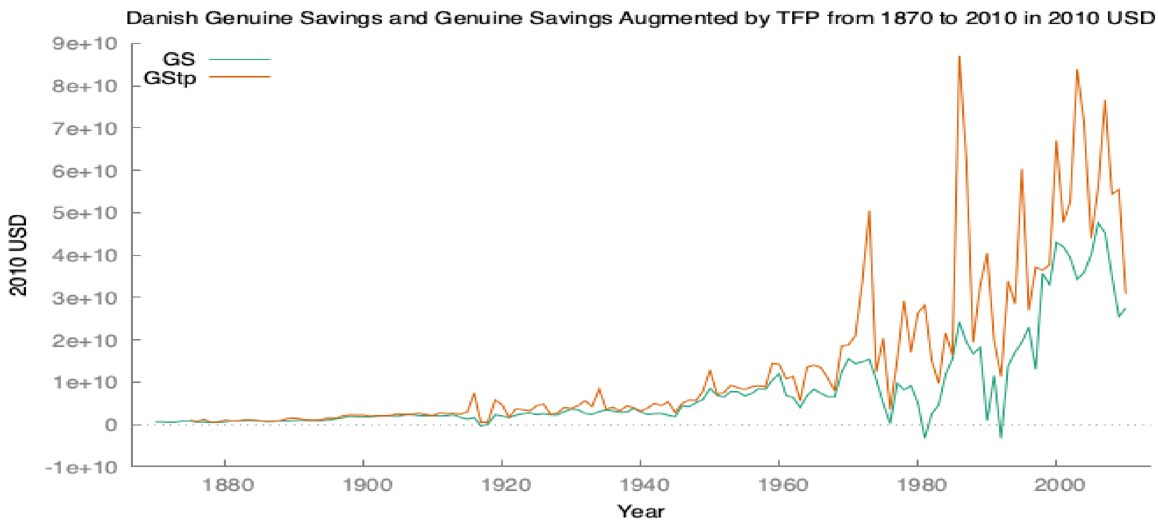

Figure 3.9 Danish GS and GStp

Present Value of Consumption at 20, 50 and 70 time-horizons and 3% and 4% discount rates:

Net Present Value of the Change in Consumption, or PVC, is the calculated variable that will be used to calculate future well-being. This use of PVC is implemented in both Greasley et al. (2014) and Lindmark, Nguyen and Stage (2018). PVC is calculated by the summation of dividing the change in wage by one plus the discount rate raised to the power of how many years away the change in wage is. The formula:

$$PVC = \sum \frac{\Delta w_t}{(1+i)^t} + \frac{\Delta w_{t+1}}{(1+i)^{t+1}} \dots \frac{\Delta w_{t+n}}{(1+i)^{t+n}} \tag{3}$$

This formula will be calculated over three different time horizons 20, 50 and 70 years, as implemented in Greasley et al. (2014) and Lindmark, Nguyen and Stage (2018). Along with three different time horizons, there will be two different discount rates implemented three and four percent as done in Lindmark, Nguyen and Stage (2018). The calculated PVC at the three and four percent discount rates is shown in *Figure 3.10 and Figure 3.11*.

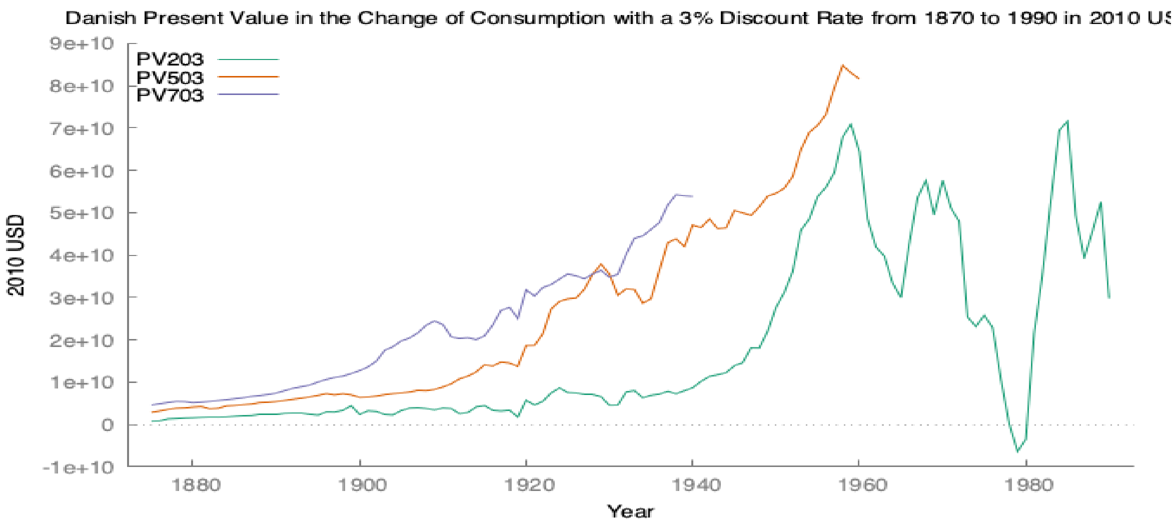

Figure 3.10 Danish PVC 3% Discount Rate

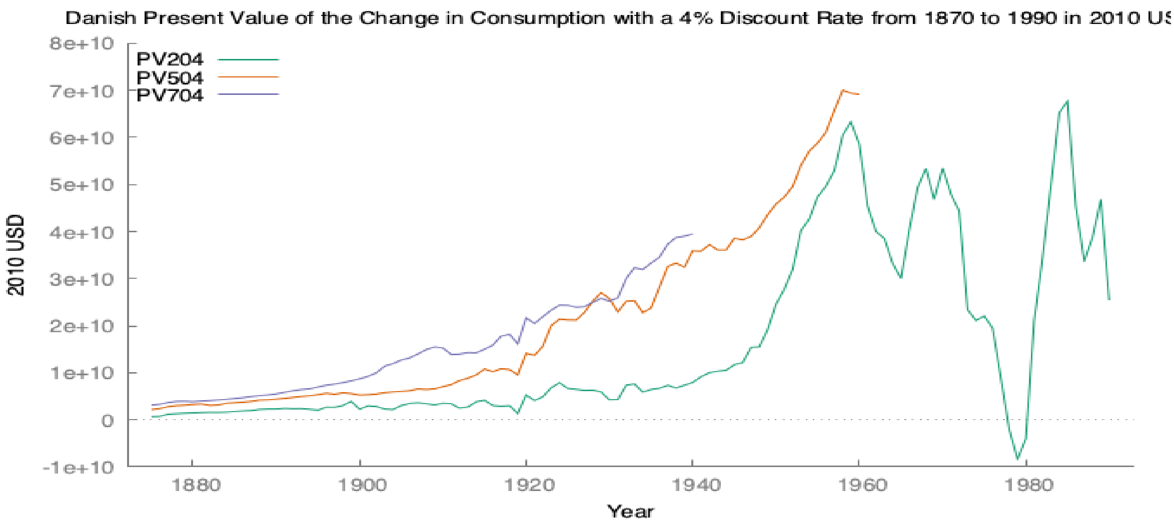

Figure 3.11 Danish PVC 4% Discount Rate

Note that in both time series (*Figures 3.10 and 3.11*) of PVC the 20 year time-horizon is the longest. This is due to the fact that for each calculation the change in consumption is needed for the following 20, 50 and 70 years respectively. With limited data, the 20 year time-horizon will be the longest as there are the most data points available.

4 Econometric Approach

The econometric approach implemented in this thesis will deviate from both the Hanley et al. (2016) and Lindmark, Nguyen and Stage (2018) papers. The Hanley et al. (2016) paper implements a Fully-Modified Ordinary Least Square, or FMOLS, model because in this paper they are calculating the effect of GS on future well-being for multiple countries. Since the data from Hanley et al. (2016) resembles closely to panel data, a regular FMOLS model is suitable. Since this thesis only implements Danish GS and PVC data, a FMOLS model type is not recommended. The Lindmark, Nguyen and Stage (2018) paper implements more complex cointegrated Fully-Modified Ordinary Least Squares model, or cointegrated FMOLS model, that requires a more extensive dataset. The reasoning for a cointegrated FMOLS is to determine how two cointegrated series correlate. In the case of the Lindmark, Nguyen and Stage (2018) research they implement Swedish GS and Swedish PVC, which are a cointegrating series. This cointegrated FMOLS model type needs a thoroughly extensive dataset, which is not possible to create in the time parameters set for this thesis. This thesis will implement multiple Ordinary Least Squares models, or OLS models, to show the relationship between Genuine Savings and future well-being.

4.1 Econometric Model

The econometric models applied in this thesis will be to test the four hypothesis stated previously:

H$_1$: $\boldsymbol{\beta}_0 = 0$ and $\boldsymbol{\beta}_1 = 1$

H$_2$: $\boldsymbol{\beta}_0 \rightarrow 0$

H$_3$: $\boldsymbol{\beta}_1 > 0$ and $\boldsymbol{\beta}_1 \rightarrow 1$

H$_4$: $\boldsymbol{\beta}_1 > 1$

In order to test these hypotheses, 12 OLS regressions will be ran by changing the dependent PVC variable by the three different time-horizons and implementing the two different discount rates. Along with testing six different PVC variables, two different GS variables will be implemented, one regular GS and one that has been augmented by TFP. The models created will all be variations of this model:

$$PV\Delta C_t = \beta_0 + \beta_1 G_t + \varepsilon_t \tag{4}$$

The purpose of the OLS regression is to identify influential variables on the dependent variable (Meloun and Militky, 2001). In order for an OLS model to produce statistically meaningful results, there are several parameters that need to be met (Hayes & Cai, 2007). The first of these parameters is homoskedasticity, which means the variance of the residuals in the model are constant (Hayes and Cai, 2007). The second parameter that must be met for an OLS model "normal distribution", or Gaussian distribution, of both the dependent and independent variables (Hayes and Cai, 2007). What normal distribution means is that the distribution of the variable is symmetric around the mean (Hayes and Cai, 2007). The last parameter that need to be met for an OLS model to be statistically meaningful is the absence of multicollinearity between independent variables (Hayes and Cai, 2007). Multicollinearity between independent variables means that one variable strongly correlates with another. In this regression multicollinearity will not be an issue, as there is only one independent variable in the models. The other two parameters will be analyzed in a robustness check following each model.

All the variables implemented, both dependent and independent, are not normally distributed without a logarithmic transformation applied. The figures for the distribution of each variable is found in Appendix A (*Figures 1-8*). The 12 OLS models created will use the untransformed data, due to the loss of observations that happens with transforming the variables. However, the OLS models will also be done with the transformed variables with the outputs shown in Appendix C. Along with abnormal distributions, all models originally suffered from heteroskedasticity, in order to make the variance in residuals constant, robust standard errors are implemented. A robustness check will show the difference in regression when all three criteria for an OLS regression are in place.

By creating an OLS model with only one independent variable, along with the constant, the model will display the correlation between GS and PVC only. Weitzman (1976) predicts there to be a one to one relationship between GS and PVC, with the constant variable equating to zero. In order to test this theory, no other variables have a necessary presence in the OLS model. The first hypothesis is the strongest of the four, and has not been statistically proven in any of the long-term analyses of GS and PVC. The second hypothesis will be tested by analyzing how the constant variable changes with the longer time-horizons being implemented. The third hypothesis will be tested by measuring the $\boldsymbol{\beta}_1$ from the regression table and it's statistical significance, as well as analyzing how it moves over the longer time-horizons. The fourth hypothesis is the weakest of the four and will be tested by identifying if the $\boldsymbol{\beta}_1$ value is greater than one and statistically significant.

5 Empirical Results

5.1 OLS Regression Results

The OLS regression results, for clarity, will be displayed in a formatted table structure. The columns in the tables below are described by what dependent and independent variables are being tested, the coefficients for both the constant and GS (or GStp), the hypothesis results, the range in years of the data and the number of observations in each OLS regression model. The rows in the tables describe which specific dependent and independent variable is used in each specific model. The original result output from the statistical software (STATA) applied is displayed in Appendix B.

The first six OLS regressions ran are with the PVC using a three percent discount rate over all time-horizons, tested by both GS and GStp. Robust standard errors are also implemented in the model in order to make the variance in the residuals constant, or homoscedastic. Shown in *Table 5.1*.

Table 5.1 OLS Results Testing PVC at a 3% Discount Rate Robust SE

Dependent	Independent	$\boldsymbol{\beta}_0$	$\boldsymbol{\beta}_1$	$\boldsymbol{\beta}_0 = 0$ and $\boldsymbol{\beta}_1 = 1$	$\boldsymbol{\beta}_1 > 1$	Sample	Obs.
PVC20	GS	3.42**	3.19***	4.90**	31.46***	1870-2010	116
		(0.03)	(0.00)	(0.03)	(0.00)		
PVC50		1.99	8.52***	1.21	176.21***	1870-2010	86
		(0.28)	(0.00)	(0.27)	(0.00)		
PVC70		-1.11	12.82***	0.10	45.79***	1870-2010	66
		(0.76)	(0.00)	(0.76)	(0.00)		

PVC20	GStp	1.09***	0.81***	36.18***	1.09	1875-2010	116
		(0.00)	(0.00)	(0.00)	(0.29)		
PVC50		1.45	6.50***	0.63	93.00***	1875-2010	86
		(0.43)	(0.00)	(0.43)	(0.00)		
PVC70		5.65**	6.41***	4.58**	21.27***	1875-2010	66
		(0.04)	(0.00)	(0.03)	(0.00)		

Dependent = the present value of future changes in real wages measured over three time-horizons 20, 50 and 70. For columns three and four, the null hypotheses are H$_0$*:* β_0 *=0 and H*$_0$*:* β_1 *= 0, respectively. These are tested with the p-values in the parentheses at the 1, 5, and 10% levels, denoted by ***, **, * respectively. For column five for null hypothesis is H*$_0$*:* β_0 *= 0 and* β_1 *= 1, tested jointly with a Wald test. For column six the null hypothesis is H*$_0$*:* β_1 *> 1, tested with a t-test.*

The following six OLS regressions are ran with the PVC using a four percent discount rate over all time-horizons, tested by both GS and GStp. Robust standard errors are also implemented in the model in order to make the variance in the residuals constant, or homoscedastic. Shown in *Table 5.2*.

Table 5.2 OLS Results Testing PVC at a 4% Discount Rate Robust SE

Dependent	Independent	β_0	β_1	β_0 = 0 and β_1 = 1	β_1 > 1	Sample	Obs.
PVC20	GS	3.07**	2.91***	4.60**	27.26***	1870-2010	116
		(0.03)	(0.00)	(0.03)	(0.00)		
PVC50		3.78	7.15***	0.08	198.87***	1870-2010	86
		(0.78)	(0.00)	(0.78)	(0.00)		
PVC70		-1.24	9.2***	0.26	45.71***	1870-2010	66
		(0.61)	(0.00)	(0.61)	(0.00)		
PVC20	GStp	9.90***	0.72***	36.20***	2.52	1875-2010	116
		(0.00)	(0.00)	(0.00)	(0.11)		
PVC50		4.55	5.43***	0.00	94.09***	1875-2010	86
		(0.97)	(0.00)	(0.97)	(0.00)		
PVC70		3.71**	4.57***	4.02**	17.74***	1875-2010	66

		(0.05)	(0.00)	(0.04)	(0.00)		

*Dependent = the present value of future changes in real wages measured over three time-horizons 20, 50 and 70. For columns three and four, the null hypotheses are H_0: β_0 =0 and H_0: β_1 = 0, respectively. These are tested with the p-values in the parentheses at the 1, 5, and 10% levels, denoted by ***, **, * respectively. For column five for null hypothesis is H_0: β_0 = 0 and β_1 = 1, tested jointly with a Wald test. For column six the null hypothesis is H_0: β_1 > 1, tested with a t-test.*

5.2 Robustness Check

Stated in Creswell (2014), a robustness check needs to be done on qualitative research, such as this thesis, to determine the validity of the models. As mentioned in the econometric approach, since the original variables have a non-normal distribution, the OLS regression models do not meet the specifications outlined by Hayes and Cai (2007). This issue needs to be addressed by implementing a logarithmic transformations of the variables. The following OLS regression models will utilize both logarithmic transformations of the data, as well as robust standard errors to satisfy all three of Hayes and Cai's (2007) criterium for an OLS regression. The OLS regression models' results will be displayed in two ways: the first is the same table method implemented above for the original models, and the second is the output directly from the statistical software used in Appendix C.

The following six OLS regressions are ran with the PVC using a three percent discount rate over all time-horizons, tested by both GS and GStp. Robust standard errors are also implemented in the model in order to make the variance in the residuals constant, or homoscedastic. Along with robust standard errors, a logarithmic transformation of all variables has been used in order to make the distribution normal. Shown in *Table 5.3*.

Table 5.3 OLS Results Testing PVC at 3% Discount rate with Normal Dist. and Robust SE

Dependent	Independent	β_0	β_1	β_0 = 0 and β_1 = 1	β_1 > 1	Sample	Obs.

lgPVC20	lgGS	1.62	0.98***	0.36	0.04	1870-2010	111
		(0.55)	(0.00)	(0.55)	(0.85)		
lgPVC50		1.25	1.04***	0.11	0.05	1870-2010	85
		(0.74)	(0.00)	(0.74)	(0.83)		
lgPVC70		4.58	0.89***	0.27	0.10	1870-2010	65
		(0.51)	(0.01)	(0.60)	(0.75)		
lgPVC20	lgGStp	2.88	0.90***	0.82	1.07	1875-2010	113
		(0.17)	(0.00)	(0.37)	(0.30)		
lgPVC50		-0.23	1.09***	0.02	1.55	1875-2010	86
		(0.88)	(0.00)	0.89	0.21		
lgPVC70		3.46	0.94***	0.96	0.30	1875-2010	66
		(0.17)	(0.00)	(0.33)	(0.58)		

*Dependent = the present value of future changes in real wages measured over three time-horizons 20, 50 and 70. For columns three and four, the null hypotheses are H_0: β_0 =0 and H_0: β_1 = 0, respectively. These are tested with the p-values in the parentheses at the 1, 5, and 10% levels, denoted by ***, **, * respectively. For column five for null hypothesis is H_0: β_0 = 0 and β_1 = 1, tested jointly with a Wald test. For column six the null hypothesis is H_0: β_1 > 1, tested with a t-test.*

The following six OLS regressions are run with the PVC using a four percent discount rate over all time-horizons, tested by both GS and GStp. Robust standard errors are also implemented in the model in order to make the variance in the residuals constant, or homoscedastic. Along with robust standard errors, a logarithmic transformation of all variables has been used in order to make the distribution normal. Shown in *Table 5.4*.

Table 5.4 OLS Results Testing PVC at 4% Discount rate with Normal Dist. and Robust SE

Dependent	Independent	β_0	β_1	β_0 = 0 and β_1 = 1	β_1 > 1	Sample	Obs.
lgPVC20	lgGS	0.33	1.03***	0.02	0.08	1870-2010	111
		(0.89)	(0.00)	(0.89)	(0.78)		
lgPVC50		0.65	1.05***	0.03	0.10		85

		(0.86)	(0.00)	(0.86)	(0.76)	1870-2010	
lgPVC70		4.46	0.89***	0.27	0.14	1870-2010	65
		(0.51)	(0.01)	(0.60)	(0.71)		
lgPVC20	lgGStp	0.92	0.99***	0.46	0.05	1875-2010	113
		(0.49)	(0.00)	(0.49)	(0.83)		
lgPVC50		-0.68	1.10***	0.18	1.93	1875-2010	86
		(0.67)	(0.00)	(0.67)	(0.16)		
lgPVC70		3.37	0.92***	0.94	0.45	1875-2010	66
		(0.17)	(0.00)	(0.33)	(0.50)		

*Dependent = the present value of future changes in real wages measured over three time-horizons 20, 50 and 70. For columns three and four, the null hypotheses are H_0: $\beta_0 = 0$ and H_0: $\beta_1 = 0$, respectively. These are tested with the p-values in the parentheses at the 1, 5, and 10% levels, denoted by ***, **, * respectively. For column five for null hypothesis is H_0: $\beta_0 = 0$ and $\beta_1 = 1$, tested jointly with a Wald test. For column six the null hypothesis is H_0: $\beta_1 > 1$, tested with a t-test.*

6 Hypothesis Results and Discussion

This section will discuss the results in the context of the hypotheses and then discuss the results in the overall context. Beginning with the hypothesis results to understand what the specifically the models found with regard to how Present Value of the Change in Consumption correlates with Genuine Savings. Once the hypothesis results are presented, the overall discussion of the results are presented to put the findings in a holistic context.

6.1 Hypothesis Results

6.1.1 Hypothesis 1: $\boldsymbol{\beta}_0 = 0$ and $\boldsymbol{\beta}_1 = 1$

The first and strongest hypothesis that the constant is equal to zero and the coefficient for GS is equal to one is only found statistically significant in half of the twelve untransformed OLS regressions, and none of the twelve logarithmic transformed OLS regressions. In regards to the Weitzman (1976) theory, the expected outcome of the OLS regressions is for the first null hypothesis to be more likely to be not rejected with longer time-horizons. However, only twice in the original twelve OLS regressions does the longest time-horizon (70 years) display a significant result. Both of these significant results occur when testing PVC with GStp (one with a 3% discount rate and the other with a 4% discount rate). The other four occurrences of statistically significant results for the first hypothesis appear with 20 year time-horizons. These occur across both discount rates and both GS and GStp. As mentioned prior, none of the logarithmically transformed OLS regressions found statistically significant coefficients for the joint hypothesis, thus the null hypothesis in these OLS regression models are rejected. A potential reason for these results in the transformed data is the loss of observations when either PVC, GS or GStp is negative. The loss of these key data points has the potential to break the joint hypotheses in these models. Although the hypothesized results of this test are rejected, the research by Greasley et al. (2014), Lindmark, Nguyen and Stage (2018) and Blum, McLaughlin and Hanley (2019) also recorded the same results.

6.1.2 Hypothesis 2: $\boldsymbol{\beta}_0 \rightarrow 0$

The second hypothesis states that as the tested PVC's time-horizon increases, the coefficient of the constant should approach zero. In the first six OLS regressions (regressing PVC with a 3% discount rate over all time-horizons by GS and GStp), when normal GS is the independent variable, as the time-horizon increases, the coefficient for the constant does approach zero. However, when GStp is the independent variable the coefficient for the constant increases, grows farther from zero. In the second six OLS regressions (regressing PVC with a 4% discount rate over all time-horizons by GS and GStp), when the independent variable is normal GS, the coefficient for the constant does not linearly approach zero, but the longest time-horizon (70 years) is the closest to zero. While GStp is the independent variable, in the second six OLS regressions, the coefficient for the constant does appear to approach zero as the time-horizon increases. It is important to note that only half of the coefficients for the constant in the original twelve OLS regression models are statistically significantly not equal to zero. This means that in half of the OLS regression models cannot significantly determine that the coefficient for the constant is not equal to zero. With this information in mind, half of the OLS regression models show that the coefficient for the constant is statistically no different from zero. This result means only half of the null hypotheses can be rejected. In all twelve of the logarithmically transformed OLS regression models there is no statistical evidence that the coefficient for the constant is different than zero, thus the null hypothesis cannot be rejected. These results from the OLS regression models may be due to the low number of observations available for the models.

6.1.3 Hypothesis 3: $\boldsymbol{\beta}_1 > 0$ and $\boldsymbol{\beta}_1 \rightarrow 1$

The third hypothesis states that the coefficient for GS and GStp is greater than zero and approaches one as the time-horizon increases. In the original 12 OLS regressions, none of the coefficients for GS and GStp approach one as the time-horizon of PVC increases for either discount rate. This means the null hypothesis is rejected in the original twelve OLS regression models. However, in the logarithmically transformed OLS regressions, the coefficient for GS and GStp is stationary around one, without much variation between models. In all of the original OLS regression models there is significant statistic evidence that the coefficient for GS and GStp is greater than zero. Along with this, all of the transformed OLS regression models show statistical significance of the coefficient for GS and GStp to be greater than zero. This means the null hypothesis cannot be rejected in the case of the transformed OLS regression models.

6.1.4 Hypothesis 4: $\boldsymbol{\beta}_1 > 1$

The fourth hypothesis states that the coefficient for GS and GStp is greater than one. In all but two of the original OLS regression models, there is significant statistic evidence that the coefficient for GS and GStp is greater than one. Both of the cases that the coefficient for GS and GStp were not statistically significantly greater than one were both when GStp was the independent variable and PVC with a 20 year time-horizon (both 3% and 4%) was the dependent variable. Despite that fact, none of the transformed OLS regression models show statistical significance of the coefficient for GS and GStp to be greater than one. This result is potentially influenced by the fact that the coefficient for GS and GStp, in the transformed models, is so near to zero that without more observations it is unlikely to have statistically significant results. The null hypothesis is rejected in all of the transformed OLS regression models, but in only two of the original OLS regression models.

6.2 Discussion

6.2.1 Hypothesis Discussion

It is clear, through the inability to statistically reject the fourth null hypothesis, that there is a statistically significant positive correlation between Present Value of the Change in Consumption and Genuine Savings. The fact that the coefficient for GS and GStp remains significantly greater than zero across all OLS regression models holds weight, even though there are limited observations available. Despite the fact that all the original 12 OLS regression models reject the third hypothesis, the coefficients for GS and GStp are still greater than zero, they just do not approach one through the time-horizons utilized. Along with this, the second hypothesis cannot be rejected in most cases, meaning the constant's coefficient is not truly correlating with PVC. Although there is evidence PVC and GS have a correlation unaltered by the constant, only half of the first null hypothesis could not be rejected in the original 12 OLS regression models. This means there is a lack of evidence from this study to support the hypothesis. With this result, the one to one connection theorized by Weitzman (1976) is rejected.

6.2.2 Holistic Discussion

The implications of this is that the theory developed by Weitzman (1976) is not shown from this research of Danish GS and PVC. However, the results from this study cannot be used as an argument against the original theory. This is because Weitzman's (1976) theory states that the one to one connection between PVC and GS is over an infinite time-horizon, rather than a finite one. By extending the time-horizon between OLS regression models the study attempts to display how longer time-horizons effect the correlation between the two variables. However, there is an exuberant difference between a 70 year time-horizon and an infinite time-horizon. The same issues from the Greasley et al. (2014), the Lindmark, Nguyen and Stage (2018) and Blum, McLaughlin and Hanley (2019) research is likely a factor in this research on Denmark as well. That is the exogenous development factors, such as war, have varying impacts on development and future well-being. These impacts contained in a limited dataset can have unquantifiable consequences on both variables, as noted by Blum, McLaughlin and Hanley (2019) in the German study, the effects of the World Wars were only marginally accounted for by TFP growth. The reason a longer dataset diminishes these fluctuations is because with more data points, outliers caused by exogenous development factors hold a lower percentage of overall data points. The results from can, however, be utilized in support of a correlation between Genuine Savings and future well-being. Even if the exact relationship is unable to be discerned from this research, there is evidence displayed for a positive relationship to further bolster the theory of Weitzman (1976).

7 Conclusion

The final section intends to reiterate the research aims and results of the research conducted. Along with this, the conclusion will also discuss the practical implications, future research and limitations of the research, ultimately, tying together the entire thesis.

7.1 Research Aims

The aim of this research is to identify the one to one connection between Genuine Savings and future well-being that Weitzman (1976) theorizes. The extensive prior research done on the topic of GS and future well-being has not conclusively validated this relationship. The World Bank (2006), Greasley et al. (2016), Hanley et al. (2016), and Lindmark, Nguyen and Stage (2018) research papers have all aimed to determine this relationship, using data from a plethora of countries. None of this prior research has utilized Genuine Saving data from Denmark over a long term time period. Denmark has a peculiar development history, with little mining for precious metals or fossil fuels, reforestation since the early 19th century and more recent commitments to environmentally-friendly advancement (Henriques and Sharp, 2015 | Danish National Forest Programme, 2002 | Lund, 2007). These peculiarities make Denmark a suitable case for analysis when attempting to identify the GS and future well-being. The initial step to testing the relationship between GS and future well-being was to collect all the necessary data, in order to calculate GS. Data for population, Gross Domestic Product, education expenditure, CO_2 emissions, forestry resource rent, fishery resource rent, wages, Gross National Savings and consumption of fixed capital was collected in order to calculate five comprehensive savings measures and Net Present Value in the Change of Consumption. The savings measures are: Net National Savings, Net National Savings Minus Resource Rents, Net National Savings Minus Resource Rents Plus Forestry, Genuine Savings and Genuine Savings Augmented by TFP. Once these measures were calculated, the econometric model used to test the hypotheses was introduced. The models implemented to test the hypotheses are OLS regress models with different variations of PVC as the dependent variable, with GS and GStp applied as the independent variables. In total 24 OLS regression models were created, with 12 models serving as a robustness check.

7.2 Research Results

The results of the original 12 OLS regression models all displayed the clear result that both the coefficients for GS and GStp have a positive correlation with PVC. This positive correlation was also statistically significant in all of the logarithmically transformed OLS regression models. This means that when the Genuine Savings of Denmark increased that the PVC (the measure used to quantify future well-being) also increased. This result is consistent with the prior long-term studies done with other countries' data (Greasley et al., 2014 | Lindmark, Nguyen and Stage, 2018 | Blum, McLaughlin and Hanley, 2019). Along with this, the coefficient for the constant, for the majority of all 24 OLS regression models, was not statistically different from zero. The coefficient for the constant, when there is only one independent variable, absorbs the correlations of all non-present independent variables. What this means is that in the majority of the OLS regression models the coefficients for all other potential variables was not statistically significant. Although these hypothesis tests were consistent with the Weitzman (1976) theory, the hypothesis that the coefficient for GS and GStp would approach one over longer time-horizons was rejected by all 12 of the original OLS regression models. Instead of the expected outcome, There was no clear approach of the coefficient towards one, rather the coefficient continued to increase as the time-horizon increased. Along with this, in the majority of the OLS regression models there was no support that both the coefficient for the constant was equal to zero and the coefficient for GS and GStp was equal to one. As this is the strongest hypothesis tested, there have been no current research that has achieved this one to one connection between GS and PVC.

7.3 Practical Implications

Research regarding Genuine Savings as a suitable development metric is imperative for solidifying an alternative development metric to Gross Domestic Product. As discussed in the introduction, GDP is a poor indicator in terms of measuring development that is sustainable. With the purpose of replacing GDP, researching GS to substantiate the Weitzman (1976) theory to determine its validity can have major ramifications. If GS is observed to hold the theorized relationship with future well-being, the consequences could assist in the shift of the global development path from impending environmental crisis to an environmentally sustainable one. A major potential repercussion of GS becoming the leading development metric is the decrease in exploitation of natural capital like deforestation, uncontrolled CO_2 emission, unrestrained fishing and excessive mining.

Specifically, in the case of Denmark, since the positive correlation between GS and future well-being has been substantiated, the implications of this research are considerable. It is clear from the data collected, Denmark has reduced their CO_2 emissions and fishing. With the true understanding that reducing these resource rents coincide with a higher GS, which in turn has some positive correlation with future well-being, should bolster the efforts to continue reducing their exploitation of natural capital. Along with this, the research from this study should also support the continuation of Denmark’s reforestation initiatives that has been in place since the 19th century. This research could particularly have an impact on the passage of a higher carbon tax in Denmark that is currently being considered. The main argument against the proposed carbon tax is that the industries involved would suffer and in turn decrease the well-being of the Danish population (Jacobsen, 2020). This research shows that by increasing GS, by decreasing CO_2 emissions, would have a positive correlation with future well-being, rather than a negative one. If current research on the topic progresses, these are the types of impacts GS could have.

7.4 Limitations

All long-term GS research suffers from similar limitations, most of these limiting factors are due to a lack of data. The main limitation of the overall GS theoretical framework is the use of education expenditure as a metric for human capital formation. In multiple different studies (see e.g. Kokkinen, 2011 and Kunnas, 2016), there are findings that the investment in human capital formation (i.e. education expenditure) accounts for less than the actual human capital formed. This is to say that by using education expenditure as the metric for human capital, human capital is being under-valued in the estimates calculated for the study. Although this is a limitation, all of the GS estimates from the World Bank (2006), Greasley et al. (2014) and Lindmark, Nguyen and Stage (2018) implement education expenditure as the metric. This is due to not only a lack of better alternatives, but also by using education expenditure there is the possibility to link the investment accumulation with stocks (Lindmark, Nguyen and Stage, 2018). The specific data limitations in this research are found in the collected variables for fishery resource rents and education expenditure. Starting with fishery resource rents, there was no complete dataset for revenue from fishing from 1870 to 2010. Instead, fishing revenue data from 1870 to 1893 and 1936 to 1959 had to be interpolated between found datasets. The limiting factor here is a sizeable increase from the collected data ending in 1935 and the collected data beginning in 1960. This caused interpolation of the between years more difficult, with the decision to use the newer dataset as the root for estimating the gapped years. With this information, it is possible that the fishing revenue from 1936 to 1959 is over-estimated, ultimately decreasing the GS calculations for those years. Along with this, the fishing labor market data for Denmark from 1870 to 2010 could not be found. So the data for costs of the fishing industry had to be estimated through the entire time period. As this is the case, the overall fishery resource rent could be over or under-estimated through the entirety of the GS calculation. The education expenditure data limitation is that two separate datasets were implemented one from the World Bank (2021) that covers 1960 to 2010 and one from Abildgren (2017) that covers 1870 to 1959, but the data from the Abildgren (2017) dataset combined government expenditure on education, health and social protection. As a result of having to untangle education from the other expenditures, the calculation for governmental education expenditure might be over or under-estimated, resulting in over or under-estimates in GS from 1870 to 1959. The last major limitation of this study is the type of OLS regression model implemented. The Hanley et al. (2016) paper implements a FMOLS model to regress PVC and GS. However, this procedure was incompatible with the research in this thesis because FMOLS models are appropriate for panel datasets when testing multiple countries. The Lindmark, Nguyen and Stage (2018) utilizes a cointegrated FMOLS model to regress PVC and GS, which is better suited for a single country time-series analysis. However, the dataset implemented in the Lindmark, Nguyen and Stage is more comprehensive than this study's dataset. As a result, an unmodified OLS regression model was implemented in this thesis. The limitation of using an unmodified OLS regression model is that of time-series cointegration causing parameter estimate inefficiencies and invalid significance test (Hanley et al., 2016).

7.5 Future Research

The proceeding research that should follow this study is continuous long-term calculations and testing of PVC and GS for every country that has capable data to produce the estimates. The further research and understanding of how PVC and GS correlate will provide more insight on the overall calculation of GS and its practical implications. In the specific case of further research on Danish Genuine Savings, more expansive compiled datasets need to be created. Constructing a more comprehensive Danish database will improve the validity of the calculated variables used in the models. As the constructed dataset improves in quality, the next step in future research to be taken is applying the new Danish dataset to a more appropriate cointegrated FMOLS to test the same four hypotheses deployed in this study. The continuation of Danish GS research have the potential to establish the theorized correlation between GS and future well-being.

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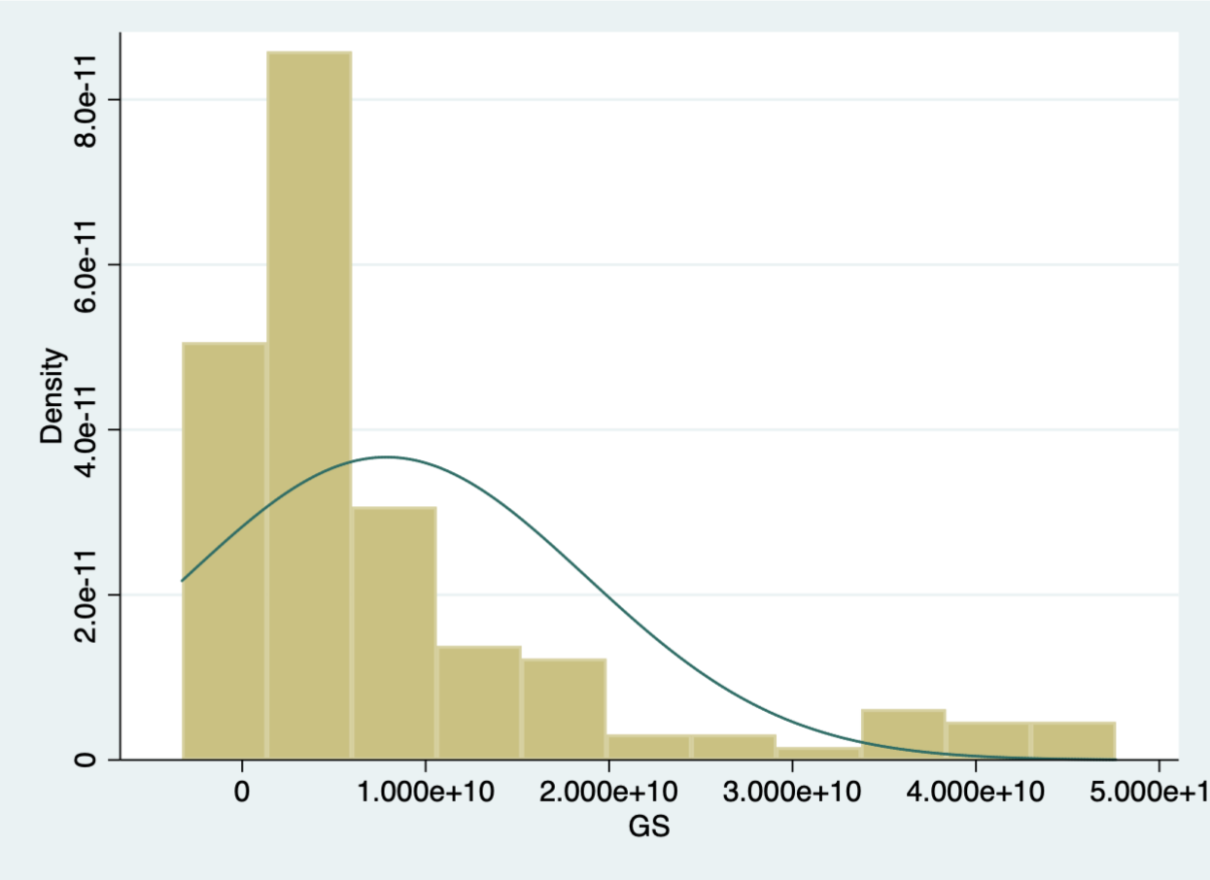
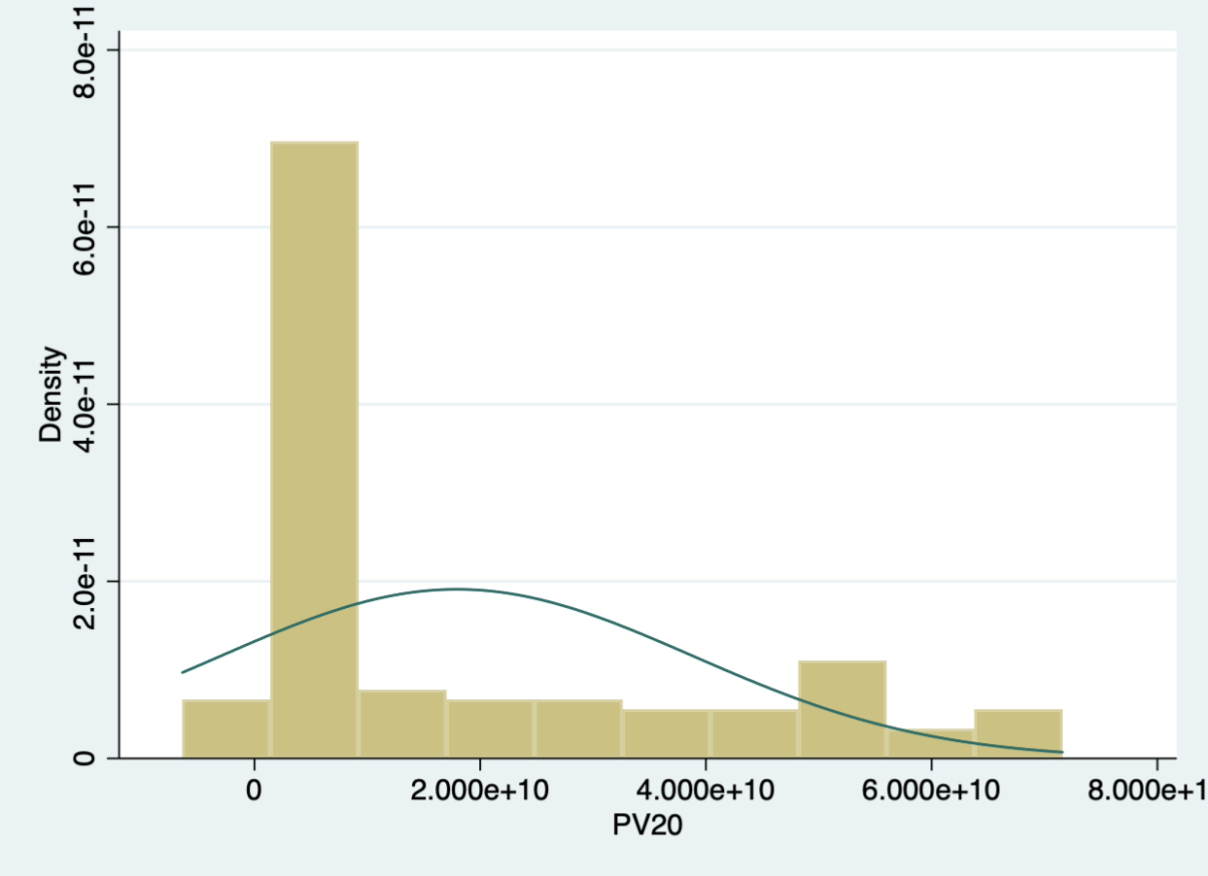
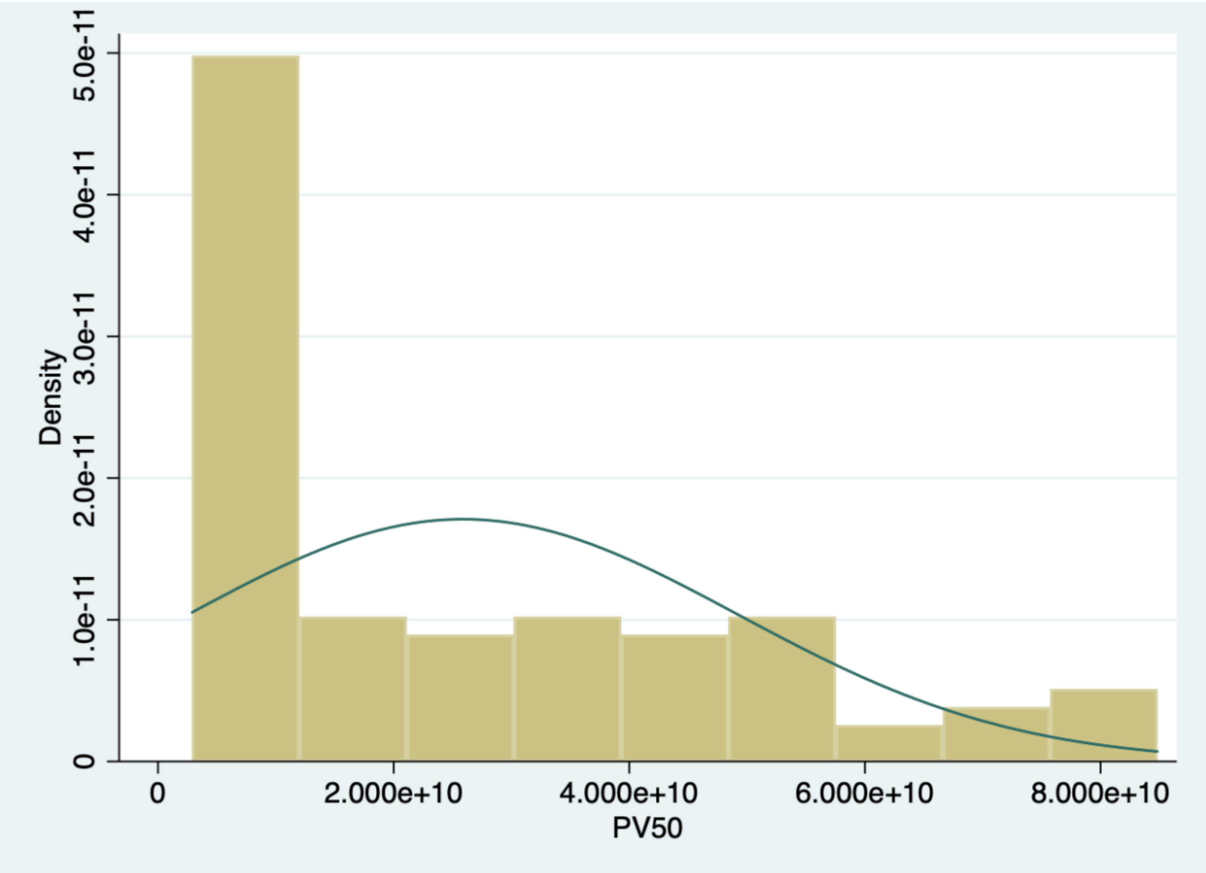
Appendix A



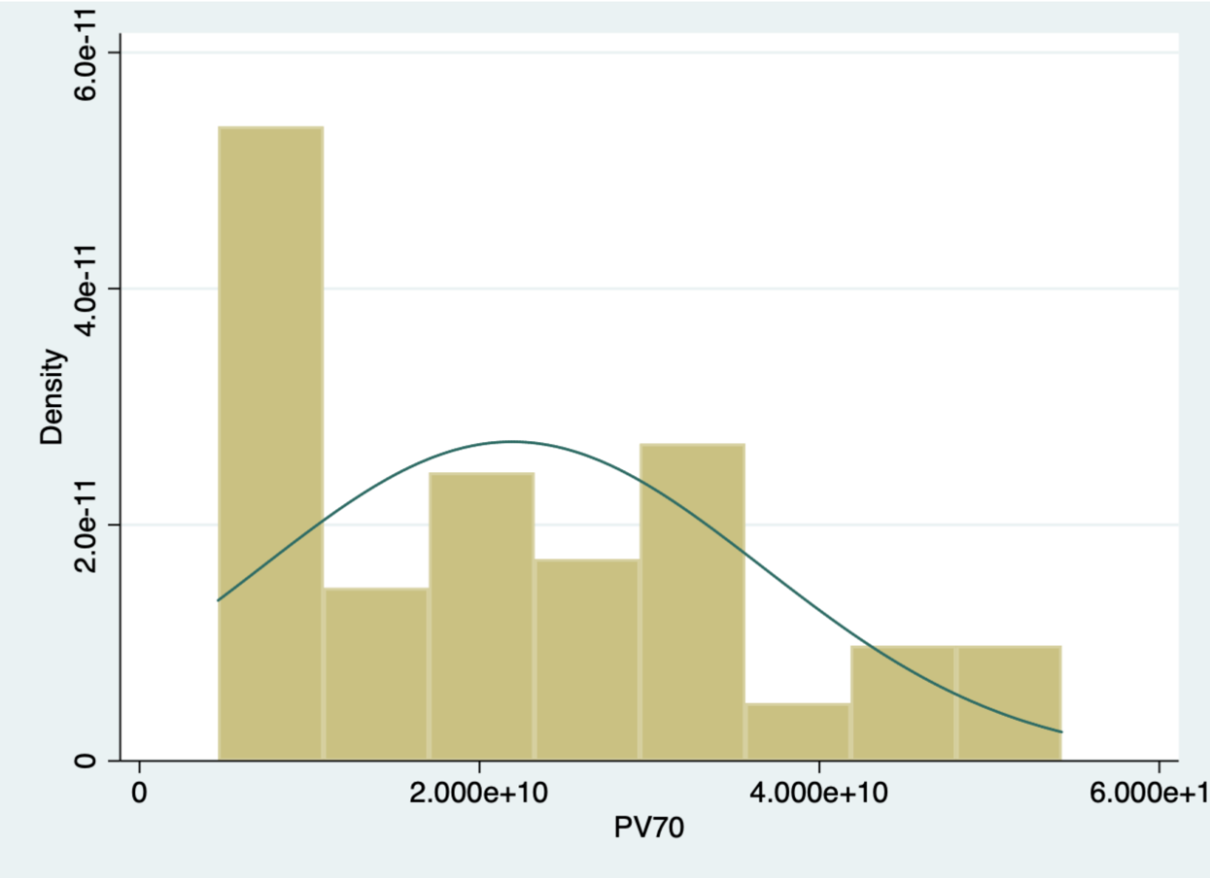
Appendix A Figure 1. Distribution of GS non-TFP augmented



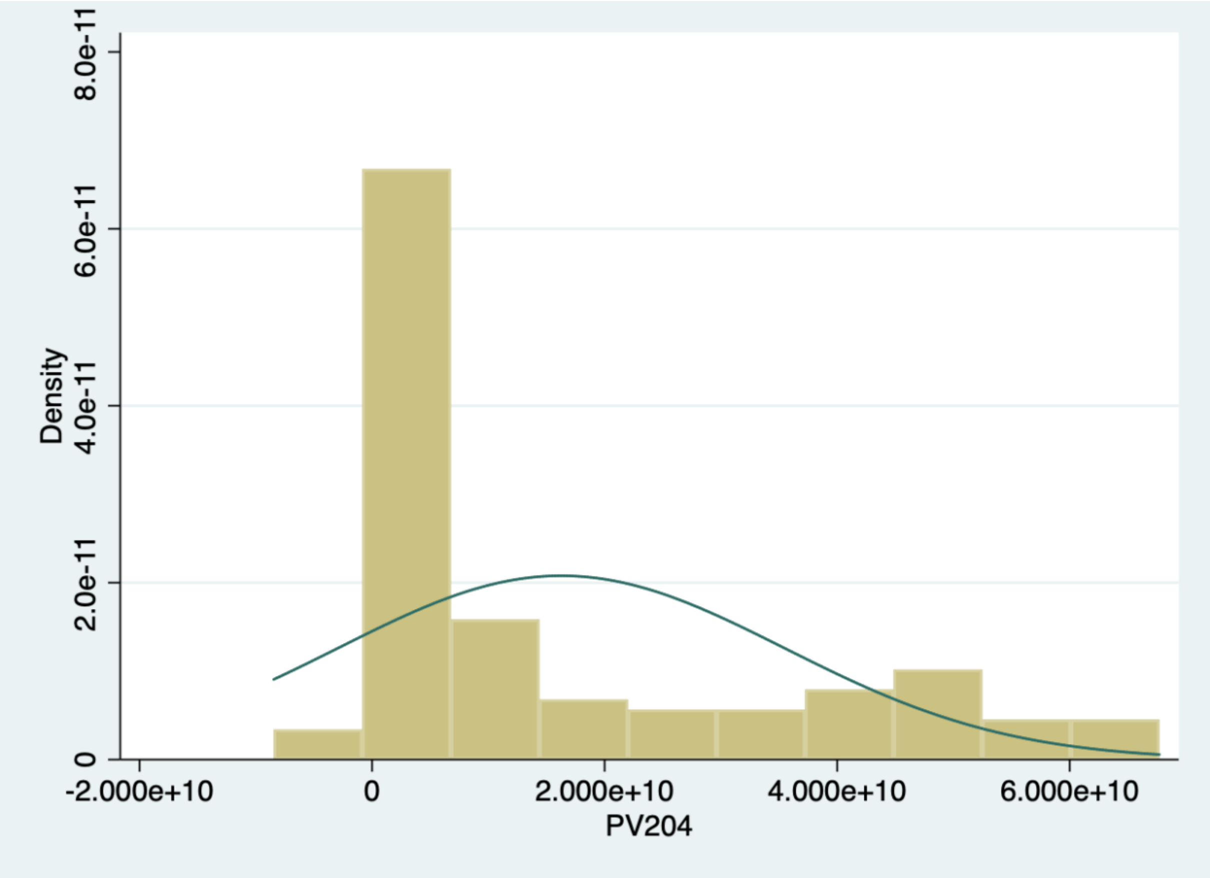
Appendix A Figure 2. Distribution of PVC20 at 3% discount rate



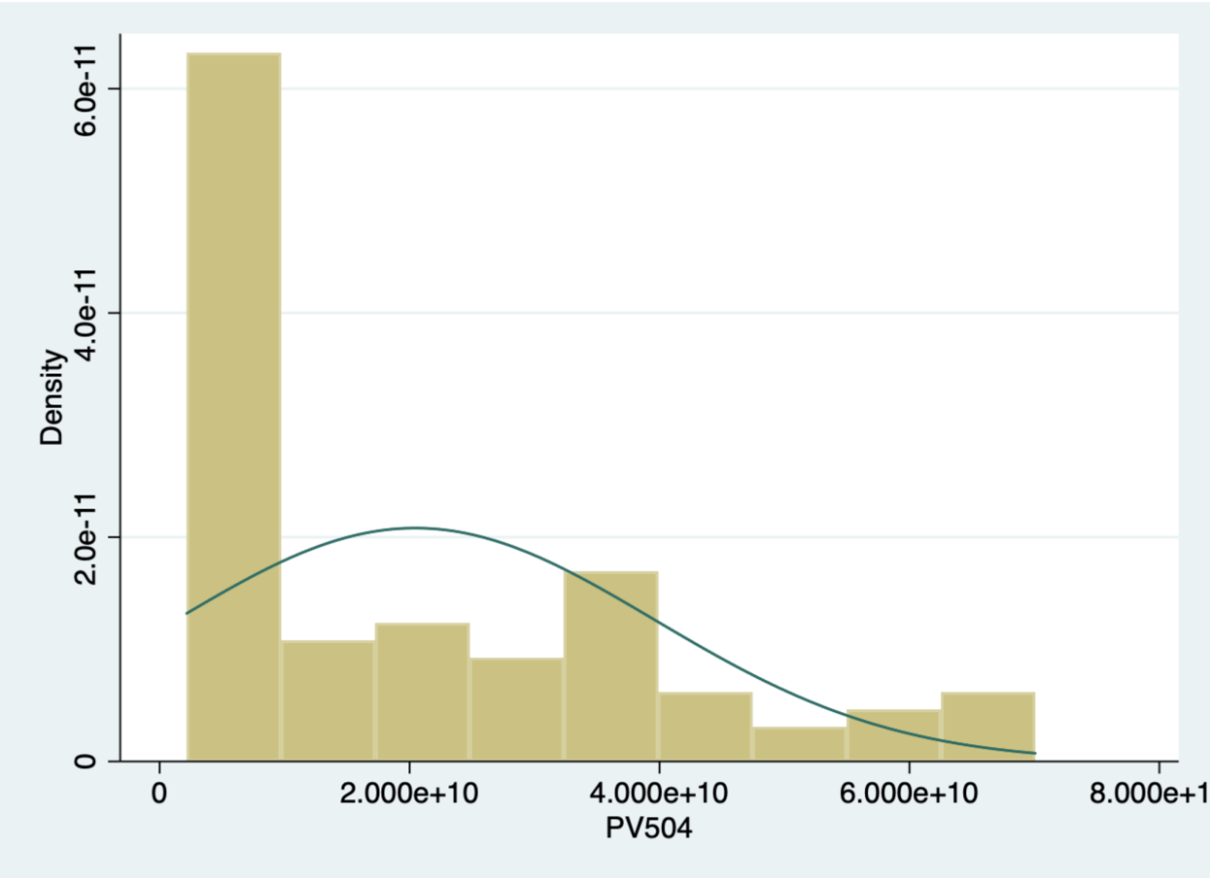
Appendix A Figure 3. Distribution of PVC50 at 3% discount rate



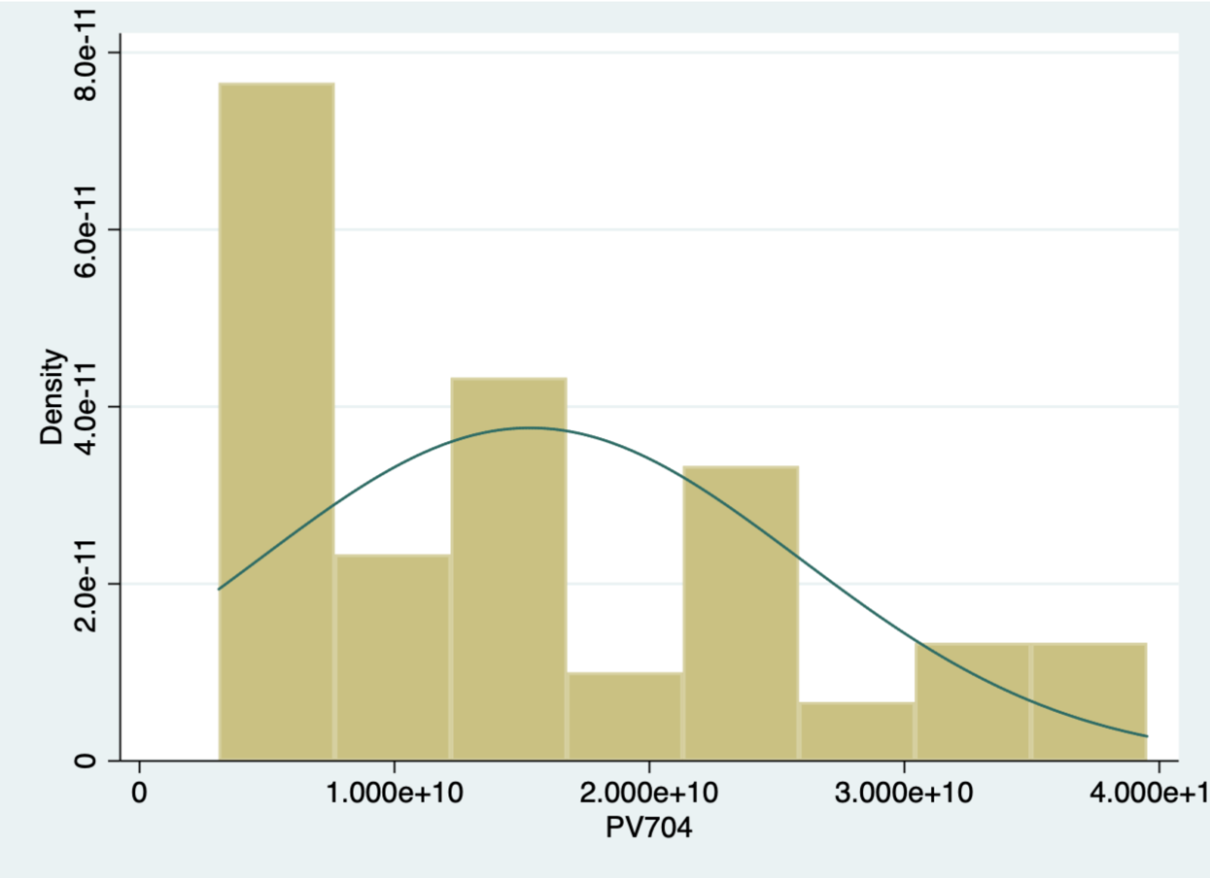
Appendix A Figure 4. Distribution of PVC70 at 3% discount rate



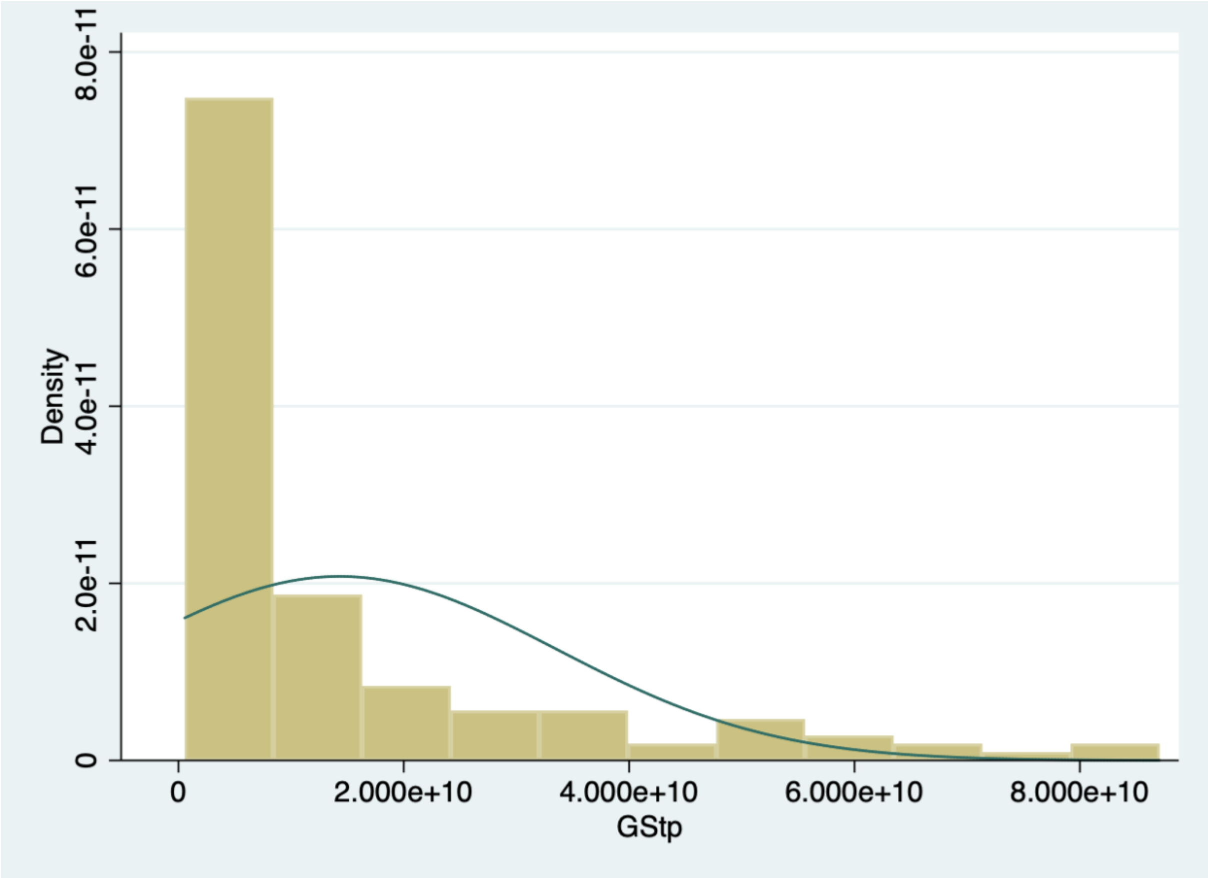
Appendix A Figure 5. Distribution of PVC20 at 4% discount rate



Appendix A Figure 6. Distribution of PVC50 at 4% discount rate



Appendix A Figure 7. Distribution of PVC70 at 4% discount rate



Appendix A Figure 8. Distribution of GS augmented by TFP

Appendix B

Appendix B Table 1. OLS Regression Model PVC 20 Year Time-Horizon at 3% Discount Rate with GS

Linear regression

PV203	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
GS	3.2	.392	8.16	0	2.423	3.977	***
Constant	3.420e+09	1.545e+09	2.21	.029	3.583e+08	6.481e+09	**

Mean dependent var	17928173452.537	SD dependent var	20887204986.765
R-squared	0.536	Number of obs	116.000
F-test	66.567	Prob > F	0.000
Akaike crit. (AIC)	5756.044	Bayesian crit. (BIC)	5761.551

**** p<.01, ** p<.05, * p<.1*

Test Constant = 0 & GS = 1

(1) _b[_cons] = 0 & _b[GS]
(2) _b[_cons] = 1
Constraint (1) dropped
chi2(1) = 4.90
Prob > chi2 = 0.0269

Test GS > 1

(1) _b[GS] = 1
chi2(1) = 31.46
Prob > chi2 = 0.0000

Appendix B Table 2. OLS Regression Model PVC 50 Year Time-Horizon at 3% Discount Rate with GS

Linear regression

PV503	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
GS	8.519	.566	15.04	0	7.393	9.645	***
Constant	1.994e+09	1.815e+09	1.10	.275	-1.616e+09	5.603e+09	

Mean dependent var	25883562131.453	SD dependent var	23336241497.643
R-squared	0.787	Number of obs	86.000
F-test	226.201	Prob > F	0.000
Akaike crit. (AIC)	4220.203	Bayesian crit. (BIC)	4225.112

**** p<.01, ** p<.05, * p<.1*

Test Constant = 0 & GS = 1

(1) _b[_cons] = 0 & _b[GS]
(2) _b[_cons] = 1
Constraint (1) dropped
chi2(1) = 1.21
Prob > chi2 = 0.2721

Test GS > 1

(1) _b[GS] = 1
chi2(1) = 176.21
Prob > chi2 = 0.0000

Appendix B Table 3. OLS Regression Model PVC 70 Year Time-Horizon at 3% Discount Rate with GS

Linear regression

PV703	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
GS	12.819	1.747	7.34	0	9.329	16.308	***
Constant	-1.113e+09	3.578e+09	-0.31	.757	-8.261e+09	6.035e+09	

Mean dependent var	21922393619.136	SD dependent var	14757779517.685
R-squared	0.661	Number of obs	66.000
F-test	53.866	Prob > F	0.000
Akaike crit. (AIC)	3209.596	Bayesian crit. (BIC)	3213.975

*** p<.01, ** p<.05, * p<.1*

Test Constant = 0 & GS = 1

(1) _b[_cons] = 0 & _b[GS]
(2) _b[_cons] = 1
Constraint (2) dropped
chi2(1) = 0.10
Prob > chi2 = 0.7557

Test GS > 1

(1) _b[GS] = 1
chi2(1) = 45.79
Prob > chi2 = 0.0000

Appendix B Table 4. OLS Regression Model PVC 20 Year Time-Horizon at 3% Discount Rate with GStp

Linear regression

PV203	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
GStp	.805	.187	4.31	0	.435	1.175	***
Constant	1.091e+10	1.814e+09	6.02	0	7.316e+09	1.450e+10	***

Mean dependent var	17928173452.537	SD dependent var	20887204986.765
R-squared	0.234	Number of obs	116.000
F-test	18.583	Prob > F	0.000
Akaike crit. (AIC)	5814.092	Bayesian crit. (BIC)	5819.599

*** p<.01, ** p<.05, * p<.1*

Test Constant = 0 & GStp = 1

(1) _b[_cons] = 0 & _b[GStp]
(2) _b[_cons] = 1
Constraint (2) dropped
chi2(1) = 36.18
Prob > chi2 = 0.0000

Test GStp > 1

(1) _b[GStp] = 1
chi2(1) = 1.09
Prob > chi2 = 0.2959

Appendix B Table 5. OLS Regression Model PVC 50 Year Time-Horizon at 3% Discount Rate with GStp

Linear regression

PV503	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
GStp	6.502	.571	11.40	0	5.368	7.637	***
Constant	1.450e+09	1.831e+09	0.79	.43	-2.190e+09	5.091e+09	

Mean dependent var	25883562131.453	SD dependent var	23336241497.643

R-squared	0.731	Number of obs	86.000
F-test	129.880	Prob > F	0.000
Akaike crit. (AIC)	4240.451	Bayesian crit. (BIC)	4245.359

**** p<.01, ** p<.05, * p<.1*

Test Constant = 0 & GStp = 1
(1) _b[_cons] = 0 & _b[GStp]
(2) _b[_cons] = 1
Constraint (1) dropped
chi2(1) = 0.63
Prob > chi2 = 0.4282

Test GStp > 1
(1) _b[GStp] = 1
chi2(1) = 93.00
Prob > chi2 = 0.0000

Appendix B Table 6. OLS Regression Model PVC 70 Year Time-Horizon at 3% Discount Rate with GStp

Linear regression

PV703	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
GStp	6.41	1.173	5.46	0	4.067	8.754	***
Constant	5.652e+09	2.641e+09	2.14	.036	3.758e+08	1.093e+10	**

Mean dependent var	21922393619.136	SD dependent var	14757779517.685
R-squared	0.513	Number of obs	66.000
F-test	29.865	Prob > F	0.000
Akaike crit. (AIC)	3233.613	Bayesian crit. (BIC)	3237.993

**** p<.01, ** p<.05, * p<.1*

Test Constant = 0 & GStp = 1
(1) _b[_cons] = 0 & _b[GStp]
(2) _b[_cons] = 1
Constraint (2) dropped
chi2(1) = 4.58
Prob > chi2 = 0.0324

Test GStp > 1
(1) _b[GStp] = 1
chi2(1) = 21.27
Prob > chi2 = 0.0000

Appendix B Table 7. OLS Regression Model PVC 20 Year Time-Horizon at 4% Discount Rate with GS

Linear regression

PV204	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
GS	2.91	.366	7.95	0	2.185	3.635	***
Constant	3.072e+09	1.432e+09	2.14	.034	2.347e+08	5.910e+09	**

Mean dependent var	16266634108.962	SD dependent var	19193670803.207
R-squared	0.525	Number of obs	116.000
F-test	63.277	Prob > F	0.000
Akaike crit. (AIC)	5739.149	Bayesian crit. (BIC)	5744.656

**** p<.01, ** p<.05, * p<.1*

Test Constant = 0 & GS = 1
(1) _b[_cons] = 0 & _b[GS]
(2) _b[_cons] = 1
Constraint (1) dropped
chi2(1) = 4.60
Prob > chi2 = 0.0320

Test GS > 1
(1) _b[GS] = 1
chi2(1) = 27.26
Prob > chi2 = 0.0000

Appendix B Table 8. OLS Regression Model PVC 50 Year Time-Horizon at 4% Discount Rate with GS

Linear regression

PV504	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
GS	7.158	.437	16.39	0	6.29	8.027	***
Constant	3.778e+08	1.369e+09	0.28	.783	-2.344e+09	3.100e+09	

Mean dependent var	20451664971.360	SD dependent var	19167638761.505
R-squared	0.824	Number of obs	86.000
F-test	268.700	Prob > F	0.000
Akaike crit. (AIC)	4170.114	Bayesian crit. (BIC)	4175.022

*** *p<.01, ** p<.05, * p<.1*

Test Constant = 0 & GS = 1
(1) _b[_cons] = 0 & _b[GS]
(2) _b[_cons] = 1
Constraint (1) dropped
chi2(1) = 0.08
Prob > chi2 = 0.7825

Test GS > 1
(1) _b[GS] = 1
chi2(1) = 198.87
Prob > chi2 = 0.0000

Appendix B Table 9. OLS Regression Model PVC 70 Year Time-Horizon at 4% Discount Rate with GS

Linear regression

PV704	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
GS	9.209	1.214	7.58	0	6.783	11.635	***
Constant	-1.235e+09	2.438e+09	-0.51	.614	-6.106e+09	3.635e+09	

Mean dependent var	15313967002.015	SD dependent var	10607792902.594
R-squared	0.661	Number of obs	66.000
F-test	57.520	Prob > F	0.000
Akaike crit. (AIC)	3166.144	Bayesian crit. (BIC)	3170.524

*** *p<.01, ** p<.05, * p<.1*

Test Constant = 0 & GS = 1
(1) _b[_cons] = 0 & _b[GS]
(2) _b[_cons] = 1
Constraint (2) dropped

chi2(1) = 0.26
Prob > chi2 = 0.6123

Test GS > 1
(1) _b[GS] = 1
chi2(1) = 45.71
Prob > chi2 = 0.0000

Appendix B Table 10. OLS Regression Model PVC 20 Year Time-Horizon at 4% Discount Rate with GStp

Linear regression

PV204	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
GStp	.73	.17	4.28	0	.392	1.067	***
Constant	9.903e+09	1.646e+09	6.02	0	6.643e+09	1.316e+10	***

Mean dependent var	16266634108.962	SD dependent var	19193670803.207
R-squared	0.228	Number of obs	116.000
F-test	18.322	Prob > F	0.000
Akaike crit. (AIC)	5795.420	Bayesian crit. (BIC)	5800.927

**** p<.01, ** p<.05, * p<.1*

Test Constant = 0 & GStp = 1
(1) _b[_cons] = 0 & _b[GStp]
(2) _b[_cons] = 1
Constraint (2) dropped
chi2(1) = 36.20
Prob > chi2 = 0.0000

Test GStp > 1
(1) _b[GStp] = 1
chi2(1) = 2.52
Prob > chi2 = 0.1127

Appendix B Table 11. OLS Regression Model PVC 50 Year Time-Horizon at 4% Discount Rate with GStp

Linear regression

PV504	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
GStp	5.43	.457	11.89	0	4.522	6.339	***
Constant	45531110	1.382e+09	0.03	.974	-2.703e+09	2.794e+09	

Mean dependent var	20451664971.360	SD dependent var	19167638761.505
R-squared	0.755	Number of obs	86.000
F-test	141.363	Prob > F	0.000
Akaike crit. (AIC)	4198.304	Bayesian crit. (BIC)	4203.212

**** p<.01, ** p<.05, * p<.1*

Test Constant = 0 & GStp = 1
(1) _b[_cons] = 0 & _b[GStp]
(2) _b[_cons] = 1
Constraint (2) dropped
chi2(1) = 0.00
Prob > chi2 = 0.9737

Test GStp > 1
(1) _b[GStp] = 1

chi2(1) = 94.09
Prob > chi2 = 0.0000

Appendix B Table 12. OLS Regression Model PVC 70 Year Time-Horizon at 4% Discount Rate with GStp

Linear regression

PV704	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
GStp	4.572	.848	5.39	0	2.878	6.267	***
Constant	3.709e+09	1.849e+09	2.01	.049	15273891	7.404e+09	**

Mean dependent var	15313967002.015	SD dependent var	10607792902.594
R-squared	0.505	Number of obs	66.000
F-test	29.061	Prob > F	0.000
Akaike crit. (AIC)	3191.088	Bayesian crit. (BIC)	3195.467

**** p<.01, ** p<.05, * p<.1*

Test Constant = 0 & GStp = 1
(1) _b[_cons] = 0 & _b[GStp]
(2) _b[_cons] = 1
Constraint (2) dropped
chi2(1) = 4.02
Prob > chi2 = 0.0449

Test GStp > 1
(1) _b[GStp] = 1
chi2(1) = 17.74
Prob > chi2 = 0.0000

Appendix C

Appendix C Table 1. OLS Regression Model with PVC 20 Year Time-Horizon at 3% Discount Rate and GS Logarithmic Transformation

Linear regression

lgPV203	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lgGS	.976	.124	7.85	0	.73	1.222	***
Constant	1.62	2.718	0.60	.552	-3.766	7.006	

Mean dependent var	22.871	SD dependent var	1.334
R-squared	0.557	Number of obs	112.000
F-test	61.664	Prob > F	0.000
Akaike crit. (AIC)	294.308	Bayesian crit. (BIC)	299.745

**** p<.01, ** p<.05, * p<.1*

Test Constant = 0 & lgGS = 1
(1) _b[_cons] = 0 & _b[lgGS]
(2) _b[_cons] = 1
Constraint (2) dropped
chi2(1) = 0.36
Prob > chi2 = 0.5512

Test GS > 1
(1) _b[lgGS] = 1
chi2(1) = 0.04
Prob > chi2 = 0.8477

Appendix C Table 2. OLS Regression Model with PVC 50 Year Time-Horizon at 3% Discount Rate and GS Logarithmic Transformation

Linear regression

lgPV503	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lgGS	1.037	.173	5.99	0	.693	1.382	***
Constant	1.245	3.753	0.33	.741	-6.22	8.709	

Mean dependent var	23.505	SD dependent var	1.034
R-squared	0.670	Number of obs	85.000
F-test	35.884	Prob > F	0.000
Akaike crit. (AIC)	155.576	Bayesian crit. (BIC)	160.461

*** *p<.01, ** p<.05, * p<.1*

Test Constant = 0 & lgGS = 1
(1) _b[_cons] = 0 & _b[lgGS]
(2) _b[_cons] = 1
Constraint (2) dropped
chi2(1) = 0.11
Prob > chi2 = 0.7401

Test lgGS > 1
(1) _b[lgGS] = 1
chi2(1) = 0.05
Prob > chi2 = 0.8291

Appendix C Table 3. OLS Regression Model with PVC 70 Year Time-Horizon at 3% Discount Rate and GS Logarithmic Transformation

Linear regression

lgPV703	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lgGS	.896	.323	2.78	.007	.251	1.54	***
Constant	4.58	6.875	0.67	.508	-9.159	18.319	

Mean dependent var	23.540	SD dependent var	0.775
R-squared	0.552	Number of obs	65.000
F-test	7.709	Prob > F	0.007
Akaike crit. (AIC)	102.126	Bayesian crit. (BIC)	106.475

*** *p<.01, ** p<.05, * p<.1*

Test Constant = 0 & lgGS = 1
(1) _b[_cons] = 0 & _b[lgGS]
(2) _b[_cons] = 1

Constraint (1) dropped
chi2(1) = 0.27
Prob > chi2 = 0.6026

Test lgGS > 1
(1) _b[lgGS] = 1
chi2(1) = 0.10
Prob > chi2 = 0.7466

Appendix C Table 4. OLS Regression Model with PVC 20 Year Time-Horizon at 3% Discount Rate and GStp Logarithmic Transformation

Linear regression

lgPV203	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lgGStp	.9	.096	9.36	0	.71	1.091	***
Constant	2.882	2.076	1.39	.168	-1.232	6.996	

Mean dependent var	22.870	SD dependent var	1.328
R-squared	0.586	Number of obs	114.000
F-test	87.684	Prob > F	0.000
Akaike crit. (AIC)	290.807	Bayesian crit. (BIC)	296.280

**** p<.01, ** p<.05, * p<.1*

Test Constant = 0 & lgGStp = 1
(1) _b[_cons] = 0 & _b[lgGStp]
(2) _b[_cons] = 1
Constraint (1) dropped
chi2(1) = 0.82
Prob > chi2 = 0.3648

Test lgGStp > 1
(1) _b[lgGStp] = 1
chi2(1) = 1.07
Prob > chi2 = 0.3003

Appendix C Table 5. OLS Regression Model with PVC 50 Year Time-Horizon at 3% Discount Rate and GStp Logarithmic Transformation

Linear regression

lgPV503	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lgGStp	1.092	.074	14.83	0	.945	1.238	***
Constant	-.228	1.614	-0.14	.888	-3.437	2.982	

Mean dependent var	23.504	SD dependent var	1.028
R-squared	0.744	Number of obs	86.000
F-test	219.881	Prob > F	0.000
Akaike crit. (AIC)	134.608	Bayesian crit. (BIC)	139.516

**** p<.01, ** p<.05, * p<.1*

Test Constant = 0 & lgGStp = 1
(1) _b[_cons] = 0 & _b[lgGStp]
(2) _b[_cons] = 1
Constraint (2) dropped
chi2(1) = 0.02
Prob > chi2 = 0.8877

Test lgGStp > 1

(1) _b[lgGStp] = 1
chi2(1) = 1.55
Prob > chi2 = 0.2126

Appendix C Table 6. OLS Regression Model with PVC 70 Year Time-Horizon at 3% Discount Rate and GStp Logarithmic Transformation

Linear regression

lgPV703	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lgGStp	.937	.116	8.07	0	.705	1.168	***
Constant	3.459	2.512	1.38	.173	-1.56	8.478	

Mean dependent var	23.548	SD dependent var	0.772
R-squared	0.653	Number of obs	66.000
F-test	65.150	Prob > F	0.000
Akaike crit. (AIC)	86.202	Bayesian crit. (BIC)	90.582

**** p<.01, ** p<.05, * p<.1*

Test Constant = 0 & lgGStp = 1
(1) _b[_cons] = 0 & _b[lgGStp]
(2) _b[_cons] = 1
Constraint (1) dropped
chi2(1) = 0.96
Prob > chi2 = 0.3277

Test lgGS > 1
(1) _b[lgGStp] = 1
chi2(1) = 0.30
Prob > chi2 = 0.5849

Appendix C Table 7. OLS Regression Model with PVC 20 Year Time-Horizon at 4% Discount Rate and GS Logarithmic Transformation

Linear regression

lgPV204	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lgGS	1.033	.117	8.80	0	.8	1.265	***
Constant	.331	2.588	0.13	.898	-4.798	5.46	

Mean dependent var	22.807	SD dependent var	1.281
R-squared	0.676	Number of obs	111.000
F-test	77.501	Prob > F	0.000
Akaike crit. (AIC)	248.030	Bayesian crit. (BIC)	253.449

**** p<.01, ** p<.05, * p<.1*

Test Constant = 0 & lgGS = 1
(1) _b[_cons] = 0 & _b[lgGS]
(2) _b[_cons] = 1
Constraint (2) dropped
chi2(1) = 0.02
Prob > chi2 = 0.8982

Test lgGS > 1
(1) _b[lgGS] = 1
chi2(1) = 0.08
Prob > chi2 = 0.7795

Appendix C Table 8. OLS Regression Model with PVC 50 Year Time-Horizon at 4% Discount

Rate and GS Logarithmic Transformation

Linear regression

lgPV504	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lgGS	1.054	.172	6.12	0	.711	1.396	***
Constant	.651	3.733	0.17	.862	-6.774	8.076	

Mean dependent var	23.260	SD dependent var	1.035
R-squared	0.689	Number of obs	85.000
F-test	37.404	Prob > F	0.000
Akaike crit. (AIC)	150.652	Bayesian crit. (BIC)	155.537

**** p<.01, ** p<.05, * p<.1*

Test Constant = 0 & lgGS = 1
(1) _b[_cons] = 0 & _b[lgGS]
(2) _b[_cons] = 1
Constraint (2) dropped
chi2(1) = 0.03
Prob > chi2 = 0.8615

Test lgGS > 1
(1) _b[lgGS] = 1
chi2(1) = 0.10
Prob > chi2 = 0.7558

Appendix C Table 9. OLS Regression Model with PVC 70 Year Time-Horizon at 4% Discount Rate and GS Logarithmic Transformation

Linear regression

lgPV704	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lgGS	.885	.313	2.83	.006	.259	1.51	***
Constant	4.46	6.671	0.67	.506	-8.87	17.79	

Mean dependent var	23.182	SD dependent var	0.766
R-squared	0.552	Number of obs	65.000
F-test	7.982	Prob > F	0.006
Akaike crit. (AIC)	100.569	Bayesian crit. (BIC)	104.917

**** p<.01, ** p<.05, * p<.1*

Test Constant = 0 & lgGS = 1
(1) _b[_cons] = 0 & _b[lgGS]
(2) _b[_cons] = 1
Constraint (1) dropped
chi2(1) = 0.27
Prob > chi2 = 0.6040

Test lgGS > 1
(1) _b[lgGS] = 1
chi2(1) = 0.14
Prob > chi2 = 0.7122

Appendix C Table 10. OLS Regression Model with PVC 20 Year Time-Horizon at 4% Discount Rate and GStp Logarithmic Transformation

Linear regression

lgPV204	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lgGStp	.987	.062	15.89	0	.864	1.11	***

Constant	.92	1.35	0.68	.497	-1.756	3.595	

Mean dependent var	22.807	SD dependent var	1.276
R-squared	0.749	Number of obs	113.000
F-test	252.631	Prob > F	0.000
Akaike crit. (AIC)	222.599	Bayesian crit. (BIC)	228.054

**** p<.01, ** p<.05, * p<.1*

Test Constant = 0 & lgGStp = 1
(1) _b[_cons] = 0 & _b[lgGStp]
(2) _b[_cons] = 1
Constraint (2) dropped
chi2(1) = 0.46
Prob > chi2 = 0.4958

Test lgGStp > 1
(1) _b[lgGStp] = 1
chi2(1) = 0.05
Prob > chi2 = 0.8301

Appendix C Table 11. OLS Regression Model with PVC 50 Year Time-Horizon at 4% Discount Rate and GStp Logarithmic Transformation

Linear regression

lgPV504	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lgGStp	1.101	.073	15.09	0	.956	1.247	***
Constant	-.684	1.598	-0.43	.67	-3.861	2.494	

Mean dependent var	23.258	SD dependent var	1.029
R-squared	0.755	Number of obs	86.000
F-test	227.630	Prob > F	0.000
Akaike crit. (AIC)	131.015	Bayesian crit. (BIC)	135.924

**** p<.01, ** p<.05, * p<.1*

Test Constant = 0 & lgGStp = 1
(1) _b[_cons] = 0 & _b[lgGStp]
(2) _b[_cons] = 1
Constraint (2) dropped
chi2(1) = 0.18
Prob > chi2 = 0.6687

Test lgGStp > 1
(1) _b[lgGStp] = 1
chi2(1) = 1.93
Prob > chi2 = 0.1648

Appendix C Table 12. OLS Regression Model with PVC 70 Year Time-Horizon at 4% Discount Rate and GStp Logarithmic Transformation

Linear regression

lgPV704	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lgGStp	.924	.113	8.17	0	.698	1.15	***
Constant	3.368	2.446	1.38	.173	-1.518	8.254	

Mean dependent var	23.189	SD dependent var	0.762
R-squared	0.652	Number of obs	66.000
F-test	66.719	Prob > F	0.000

Akaike crit. (AIC)	84.608	Bayesian crit. (BIC)	88.987

**** p<.01, ** p<.05, * p<.1*

Test Constant = 0 & lgGStp = 1

(1) _b[_cons] = 0 & _b[lgGStp]
(2) _b[_cons] = 1
Constraint (1) dropped
chi2(1) = 0.94
Prob > chi2 = 0.3330

Test lgGStp > 1

(1) _b[lgGStp] = 1

chi2(1) = 0.45

Prob > chi2 = 0.5025