The Impact of Corporate Tax Policy Changes on U.S. Greenhouse Gas Emissions

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This paper assesses how changes in corporate tax policy impact U.S. greenhouse gas (GHG) emissions. Using data from the EPA, I evaluate how tax legislation that decreases the industry cost of capital, such as the Tax Cuts and Jobs Act (TCJA) of 2017, affects sector-level emissions. While a few industries experienced a statistically significant growth in emissions following the TCJA, overall GHG generation did not increase significantly. This is partially explained by the technique and composition effects, which complicate the positive relationship between growth and emissions typically described by the scale effect. However, the observed stability in overall GHG generation is also explained by sector characteristics and external factors that create differences in how industry emissions respond to changes in the cost of capital. Nevertheless, the findings suggest that corporate tax policy does have an impact on emissions through the cost of capital, which is an area for future research.

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I. Introduction

This paper assesses how changes in corporate tax policy impact U.S. greenhouse gas (GHG) emissions. This is a relevant topic given the growing discussions on climate change and its predicted consequences to our environment.

Since the industrial revolution, humans have rapidly altered natural carbon cycles by adding more CO2 to the atmosphere than other organisms can sequester. On May 9th, 2013, atmospheric CO2 levels reached 400 parts per million (ppm), marking the beginning of a new geological epoch — the Anthropocene, a time characterized by humanity's impact on the natural world. The 400ppm milestone served as a stark reminder that the world was not on a track to limit GHG emissions and consequent climate impacts.

Since reaching this environmental turning point and others in the past decade, the scientific community has increasingly collaborated with policy makers to develop legislation that mitigates the imminent impact of climate change. Economists are prominent contributors to this discourse, given that greenhouse gas emissions are considered to be one of the largest unpriced externalities in many countries. In the U.S. alone, current emissions are valued at around 266 billion dollars per year[1], making this a top issue. The magnitude of this externality has raised questions regarding legislation that could be used to decrease the rate of emissions, such as tax policy. The implementation of a Pigouvian tax or a cap and trade system have largely been considered as the best mechanisms to mitigate climate change through legislation (Mankiw 2013; Metcalf 2021), especially given the reported success of initiatives implemented in major economies like the European Union and Canada. Nevertheless, given the political barriers to implement such measures in the U.S., it is important to consider alternative policy tools. This research paper attempts to add to the literature on this topic.

To do so, it is necessary to better comprehend the mechanism by which taxation affects emissions — the price of goods and inputs (Nordhaus et al. 2013). When it comes to corporate taxes, the most impacted input price is the cost of capital. Therefore, this paper focuses on understanding how changes in corporate taxation affect emissions through the cost of capital. I do this by analyzing how sectoral GHG emissions are impacted by changes in the average industry cost of capital, controlling for sector characteristics and external factors. The time period analyzed (2012-2019) is pertinent due to the implementation of the Tax Cuts and Jobs Act (TCJA) in 2017, which allows me to leverage the resulting variation in the cost of capital to study this question.

The paper begins by briefly outlining some of the tax policy changes imposed by the TCJA that impacted the cost of capital for corporations, followed by a summary of related literature. I then describe the data used and the empirical approach taken to estimate changes in GHG emissions. Lastly, I present my results and discuss their implications for tax policy.

My results suggest that changes in corporate taxation impact sectoral emissions through their effect on the cost of capital. This impact is difficult to estimate at the industry level, largely because variations in emissions depend on firm-specific characteristics, such as capital composition. Given that

[1] At the social cost of carbon set by the Biden administration ($51/ton), the 5,215.6 million metric tons (mmt) of carbon dioxide equivalents emitted in the U.S. in 2020 are valued at approximately 266 billions of dollars.

firm-level data is not publicly available, this paper is limited to looking at the phenomenon at a sector level. Despite these challenges, there is compelling evidence of the impact of taxation on emissions through the cost of capital.

II. The Tax Cuts and Jobs Act

The Tax Cuts and Jobs Act was signed into law on December 22nd of 2017 with a majority of its modifications implemented on January 1, 2018. While many of the established policies had immense consequences on the United States economy, this paper focuses on the ones that impacted the cost of capital for corporations. The most relevant changes to corporate tax policy implemented by the TCJA, as it pertains to this analysis, are the following:

- It indefinitely changed the top corporate income tax rate from 35 percent to 21 percent, which contributed to a decrease in the cost of capital. However, there has been a lot of debate about increasing the corporate income tax rate again. In fact, the Biden presidency has discussed its intentions to raise the tax rate to 28 percent (Tax Foundation 2021).
- It allowed 100 percent corporate expensing on new investments in assets with less than 20-year depreciable life, up until 2022. Starting in 2023, the expensing will be reduced by 20 percentage points per year. This policy lowered the cost of capital of assets with a relatively short depreciable life, such as equipment.
- It limited corporate interest deductions to 30 percent of the "adjusted taxable income" of the business.
- It repealed the Corporate Alternative Minimum Tax.

III. Literature Review

The environmental consequences of different types of tax regulation have been extensively studied by economists, especially in the past few decades. Nevertheless, the specific impact of corporate tax policy on GHG emissions has yet to be widely researched.

Many existing studies on taxation and emissions focus on evaluating the effects of carbon tax policies. Carbon taxes are based on the Pigouvian principle that putting a price on CO2 raises the relative cost of carbon-intensive goods, thereby encouraging companies to reduce emissions (Nordhaus 2013). While a Pigouvian tax is widely recognized as the best policy mechanism to reduce emissions[2], there are also challenges that present a risk to its effectiveness. Some of these include complications in determining tax rates, the means through which they would be collected and how to best utilize the revenue obtained (Marron and Toder 2014). Given these challenges, as well as political

[2] According to the "Economists' Statement on Carbon Dividends", published by The Wall Street Journal in 2019, over 3,600 renowned economists agree that carbon taxes are an effective mechanism to reduce emissions.

barriers to implementing a carbon tax in the U.S., it is important to consider other tax mechanisms that impact emissions. Some examples are tax credits for renewable electricity, accelerated depreciation policies and broad-based tax provisions (Nordhaus et al. 2013).

Policies on accelerated depreciation are particularly relevant for this research because they are one of the largest business tax expenditures in the federal income tax code. They also have a direct effect on the cost of capital for corporations. Essentially, accelerated depreciation allows companies to deduct their investment in certain capital types on a faster schedule than the standard tax lifetime, consequently reducing their tax burden. This lowers the cost of capital for corporations and encourages firms to invest more. A larger capital stock leads to increases in output and, other things equal, higher GHG emissions (Nordhaus et al. 2013).

The proposition that higher output (i.e. economic growth) is responsible for increases in emissions is well reported in literature. This relationship is denominated the scale effect and has been widely observed in different contexts (Grossman 1995; Panayotou 1997; Tsurumi and Managi 2009). More specifically, the scale effect dictates that more resources and inputs are employed to produce more output, consequently increasing the level of emissions. However, the impact of growth on emissions has become progressively nuanced due to the composition and technique effects (Grossman and Krueger 1995). The composition effect states that economic growth causes the structure of the economy to shift towards less polluting economic activities. Moreover, the technique effect dictates that when high income economies allocate more resources for research and development, "old and dirty" technologies are replaced with "new and clean" ones (Liobiekene and Butkus 2018). Therefore, these two effects are expected to have the opposite impact on emissions as the scale effect (Panayotoun 1997; LaPlue and Erickson 2019).

More recent literature argues that the presence of the technique and composition effects contributes towards the decoupling of economic growth and GHG emissions (LaPlue and Erickson 2019). The argument behind decoupling is that economic growth in the U.S and other OECD countries has steadily outpaced the rise in emissions over the past decades (Gupta 2015). This trend would mean that the strong positive correlation between economic output and emissions has started to disappear. Yet, there is a lot of contradicting evidence surrounding the theory of decoupling. On the one hand, there is research from a wide variety of countries supporting this premise. It has been observed, for instance, in the EU-27 countries that the technique and composition effects have begun dominating the scale effect, allowing slight reductions in energy use and emissions between 1999 and 2009, despite increases in GDP (Cruz and Dias 2016). On the other hand, it is well reported by decomposition analyses that GDP is an upward driver of GHG emissions, in most cases overwhelming the technology-induced emission reductions (Duarte et al. 2013; Zu et al. 2014; Streimikiene and Balezentis 2016).

Given this contradictory evidence, there is currently no consensus in literature regarding the trend of decoupling between emissions and economic growth. This paper further studies this question through the lense of corporate-taxation-induced growth. More specifically, my research looks into how corporate taxation's influence on the cost of capital impacts growth and, consequently, emissions. According to Nordhaus, Merrill and Beaton, tax policy changes that decrease the cost of capital for corporations, such as accelerated depreciation, lead to higher investment in capital, thereby increasing output and emissions. This suggests a negative correlation between the cost of capital and GHG emissions. Nevertheless, this theoretical relationship has not been extensively studied in empirical research. My paper investigates this hypothesis and adds to the literature on this topic.

IV. Data

This section contains insights into the data I use in my analysis, which focuses on the 5 years preceding the Tax Cuts and Jobs Act of 2017, and the 2 years following it (before the COVID-19 pandemic). The key statistics on all of the variables discussed in this section are shown in *Appendix I*.

Main Variables

In order to evaluate the impact of changes to corporate taxation on GHG emissions, I use data on two key variables: sectoral emissions and the average industry cost of capital.

Greenhouse Gas Emissions

The main dataset is from the EPA Greenhouse Gas Reporting database. It includes information on annual direct emissions (in tonnes of CO2 equivalents) of all reporting facilities in the United States.[3] These figures are categorized into 9 sectors, which are further divided into 52 subsectors.

For the purpose of this research, all of the subsectors selected from the EPA data have to be compatible with the industry denominations used by the Bureau of Economic Analysis (BEA), since my analysis combines information from both of these sources. This requires me to merge the databases by finding the subsectors in the EPA data that best correspond to the BEA industry denominations (see *Appendix II* for detailed data merging procedure). After this process, the 14 remaining industries included in my analysis are: Oil and gas extraction, Mining, Mineral products manufacturing, Primary metals manufacturing, Fabricated metal products, Computer and electronics manufacturing, Electrical equipment manufacturing, Food processing, Paper and pulp, Petroleum and coal products, Chemical products, Pipeline transportation, Waste, and Educational services.[4] These industries collectively represent about 35% of all emissions reported by U.S. facilities to the EPA between 2012 and 2019.

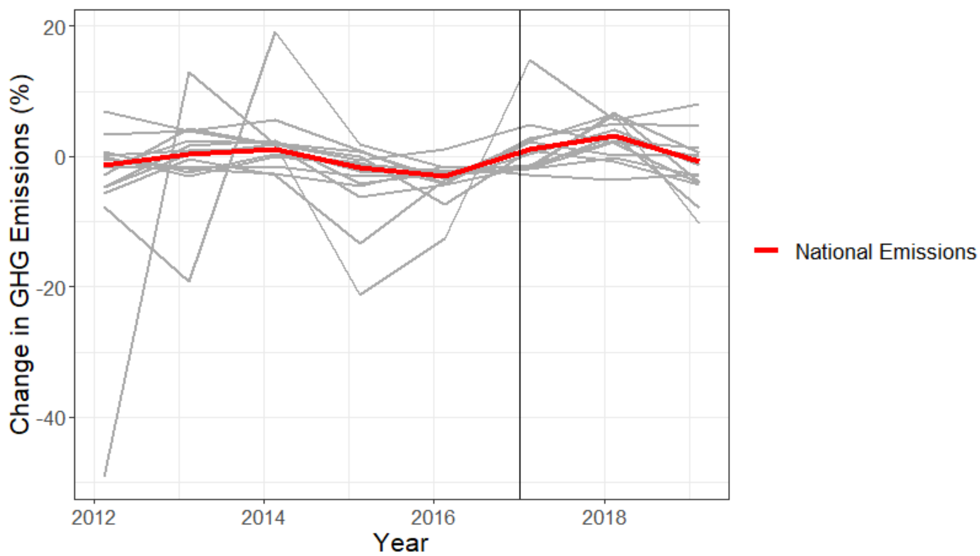
I then compile and summarize the emissions data from the relevant facilities into annual figures for the corresponding sectors. Based on these values, I calculate the annual percent change in industry emissions between 2012 and 2019, which allows for easier interpretation of trends. These annual

[3] The aforementioned data is available in the following link: https://www.epa.gov/enviro/greenhouse-gas-customized-search. It was downloaded on September 14th, 2021.

[4] Of the original 52 EPA subsectors, only 5 were eliminated (Power Plants, Other Manufacturing, Military, Other and Use of Electrical Equipment) due to the absence of a corresponding sector in the BEA data. The remaining 47 subsectors were merged and matched with the 14 corresponding BEA industries.

variations are shown in *Graph 1* below, where the 14 sectors included in the analysis are plotted in gray and the change in aggregate national emissions is plotted in red.

Graph 1 - Time Series of Annual Percent Changes in Sectoral and National GHG Emissions



Note: This graph shows the annual change in emissions for the 14 sectors plotted in gray and the change in aggregated national emissions plotted in red. The vertical line represents the implementation of the TCJA in 2017. It is evident that emissions diverged a lot between the industries over this time period, with only a few sectors showing increases after the TCJA.
Source: EPA.

There are large differences in emissions across the sectors shown in *Graph 1*. This is particularly interesting after the implementation of the TCJA in 2017. While it appears that a few industries experienced noticeable increases in GHG emissions after TCJA, others seem to have continued on their decreasing trend (see *Appendix III* for graphs of the change in emissions of individual sectors). This is somewhat to be expected though, given the vast differences in characteristics across the 14 sectors, such as capital composition, which is discussed later in this section.

Cost of Capital

The cost of capital (ϱ) measure I use in my research follows the Hall and Jorgenson (1967) formulation, due to its widespread use in tax policy and investment literature. The formula for ϱ is shown below.

$$\varrho = \frac{r+\delta-\pi}{1-u}(1-uz)-\delta \tag{1}$$

In equation 1, r designates the discount rate, δ corresponds to the rate of capital depreciation, π is the expected annual inflation, u is the statutory corporate income tax rate and z stands for the net present value of depreciation deductions per dollar of investment. As shown above, tax policy is intrinsically related to the cost of capital, impacting it both through the corporate tax rate and legislation on depreciation deductions.

In order to estimate the sector cost of capital, I use data from a variety of sources. The first step is to calculate the cost of capital per type of investment, as defined by the BEA: equipment, intellectual property (IP) and structures. I then calculate the average sector cost of capital by attributing weights to each capital type, proportional to how intensive their use is in each sector.

To calculate the cost of capital per type of investment, I start by finding the three variables that are independent of capital type (but have annual variations): r, u and π.

The data for r, the discount rate, is from the Federal Reserve Economic Data (FRED) website.[5] The series used contains nominal 10-year treasury constant maturity rates. Given that the data is reported for every weekday, I average and compile it into annual estimates.

The information needed for u, the statutory corporate income tax rate, is from the Internal Revenue Services (IRS) website. Since throughout the period analyzed (2012-2019), there were no changes to the corporate tax rate other than the one implemented by the TCJA, the data for u consists only of two values: 0.35 before 2018 and 0.21 starting in 2018.

The data for π, the expected inflation rate, is calculated by subtracting the value of Treasury Inflation-Protected Security (TIPS) rates from the 10-year treasury constant maturity rates (r). The TIPS rates used consist of bi-annual rates for 10-year TIPS from the Treasury Direct website.[6] I average these values to get annual figures, which are then subtracted from the corresponding values for r. The resulting estimates are used as the annual expected inflation rates.

After finding the annual values for r, u and π, I begin quantifying the two variables that are dependent on the type of investment: δ and z .

For δ, the economic depreciation rate of capital, I extract data from the BEA. First, I use information from their "BEA Rates of Depreciation, Service Lives, Declining Balance Rates and Hulten-Wykoff Categories" table to quantify the economic rates of depreciation for structures and equipment. The table contains depreciation rate estimates for 34 categories of private equipment and 24 categories of private structures. These are averaged and compiled into two general estimates for equipment and structures. Since the table contains no data on intellectual property, I use information from "Depreciation of Business R&D capital", a research paper published by the BEA. The study estimates depreciation rates for 12 different types of IP, which I average to obtain a single estimate. The final figures for the rates of economic depreciation of the three investment types are shown in *Appendix IV.*

The data for z, the net present value of depreciation deductions per dollar of investment, is from an open-source model called B-Tax, which can be accessed through the online "Cost of Capital Calculator".[7] This application contains all of the necessary inputs for years after 2014 and the model

[5] The aforementioned data is available in the following link: https://fred.stlouisfed.org/series/DGS10. It was downloaded on March 18th, 2021.
[6] The aforementioned data is available in the following link: https://www.treasurydirect.gov/instit/annceresult/tipscpi/tipscpi.htm. It was downloaded on April 2nd, 2021.
[7] The Cost of Capital Calculator is available at https://compute.studio/ PSLmodels/ Cost-of-Capital-Calculator/. The data used was downloaded on April 9th, 2021.

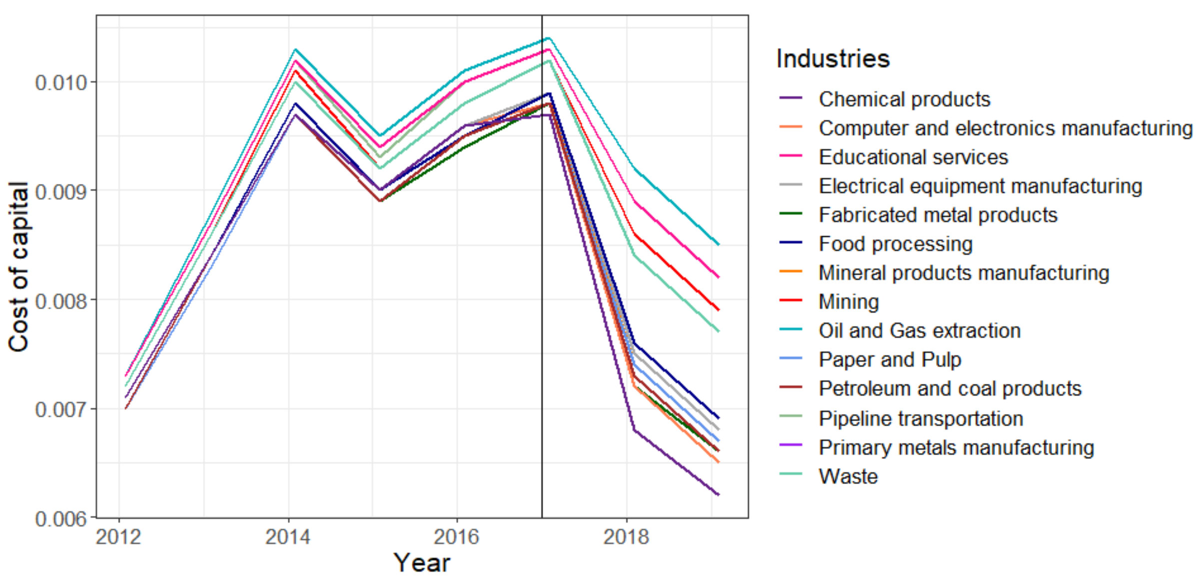
output includes annual values of z for a variety of assets, which are categorized by investment type following the BEA standards. I average the values of z to find annual estimates for the three capital types. It is important to note that the z values provided by the tool assume a mix of debt and equity to fund corporate investment.

Since the online application does not contain the input values for years before 2014, I manually adjust these inputs by making appropriate changes to the rate of return and the depreciation schedule.[8] However, there is little variation in the values of z between 2012 and 2014, since the policies on deductions remained somewhat unchanged over this period.

It is important to note that the online application also generates estimates for the average cost of capital for different types of investment and for different industries. These values are not utilized in my research because they make simplifying assumptions that are not compatible with my analysis. For instance, the application uses the nominal interest rate of business debt and the real return on corporate equity as replacements for the real rate of return *r*. These assumptions explain the differences in the cost of capital estimates calculated by my research and the ones directly from the online calculator. A more detailed description of the tool and the data decisions made can be found in *Appendix V*.

Finally, I combine the information collected on the different parameters to create estimates for the average cost of capital of structures, equipment and IP. I then weigh these figures for each of the 14 sectors according to their average capital composition, which is described in the next subsection. The resulting values represent the average sector cost of capital, which are plotted in *Graph 2* to allow for a comparison between trends before and after the TCJA.

Graph 2 - Time Series of the Average Annual Cost of Capital per Industry



Note: The data plotted in the graph above was calculated following the Hall and Jorgenson cost of capital formulation and using data from a variety of sources, as described above. The colorful lines represent the average annual cost of

[8] These changes were made with the assistance of the creator of the application, Dr. Jason DeBacker, from the University of South Carolina.

capital for the industries indicated in the legend. The vertical line marks the implementation of the TCJA in 2017. It is evident from the graph that the cost of capital decreased substantially across all sectors after TCJA.

It is clear from the graph that the average cost of capital experienced a substantial decrease after TCJA, which appears to have been stronger for some sectors, such as Chemicals and Mineral products manufacturing. Yet, the cost of capital was relatively similar between the 14 industries before 2017. This is not because the sectors have comparable capital compositions, however. Rather, it is because the calculated cost of capital figures did not diverge much across the three types of investment over this time period. While it seems counterintuitive to find similar cost of capital estimates for structures, equipment and IP, this is explained by how the two parameters in ϱ that vary by investment, δ and z, are aggregated and averaged for all capital types within the three categories. This represents a data limitation of my research, however the same issue has been faced by previous studies. In fact, the cost of capital figures estimated by the online Cost of Capital Calculator also vary little between investment types, despite making different assumptions from the ones made in my research.

Supporting variables

In addition to the two main variables, I collect data on other industry characteristics that are relevant to estimate the impact of changes in the cost of capital on emissions. These include capital composition, industry gross output and sectoral investment. I also collect information on U.S. gross domestic product (GDP).

Capital Composition

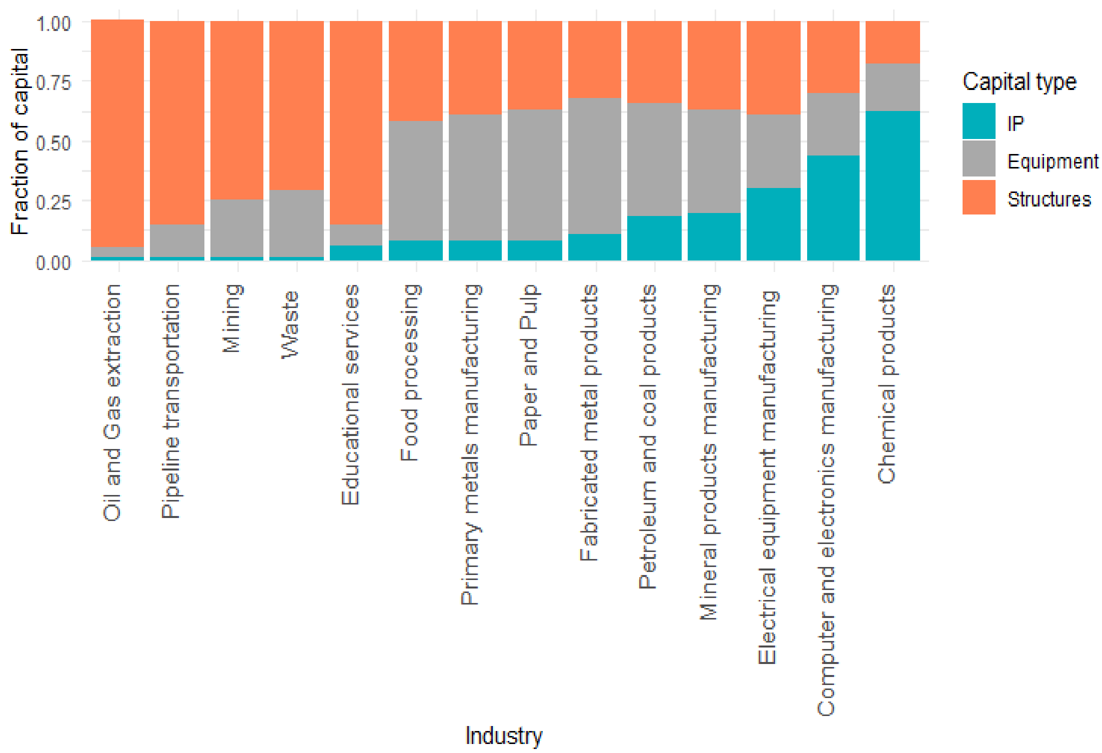
In order to better understand the capital composition of each sector, I use data on annual capital stock of structures, equipment and intellectual property between 2012 and 2019. This information is from the BEA Fixed Asset Tables. Tables 3.1S, 3.1E and 3.1I provide information regarding the current-cost net stock of private structures, equipment and intellectual property in billions of U.S. dollars.[9] I compile these figures into annual estimates for the 14 industries by following the sector matching guidelines described in *Appendix II*. I then adjust the estimates for inflation by using the Consumer Price Index for all items in the United States, which I retrieve from FRED in the form of previous period growth rates.[10] Lastly, I average these annual figures into sectoral estimates for each of the three capital types, which are then translated into trillions of dollars to facilitate interpretation of regressions results.

In order to better understand the capital composition of the industries studied, the average capital stock figures are used to calculate the relative fraction of each investment type across the 14

[9] The aforementioned data is available in the following link: https://apps.bea.gov/iTable/iTable.cfm?ReqID=10&step=2. It was downloaded on November 16, 2021.
[10] The aforementioned data is available in the following link: https://fred.stlouisfed.org/series/CPALTT01USQ657N. It was downloaded on January 8th, 2022.

sectors. This information is summarized in *Graph 3*, which shows a clear difference in capital intensities across the industries analyzed.

Graph 3 - Bar Graph of Capital Composition Across Industries



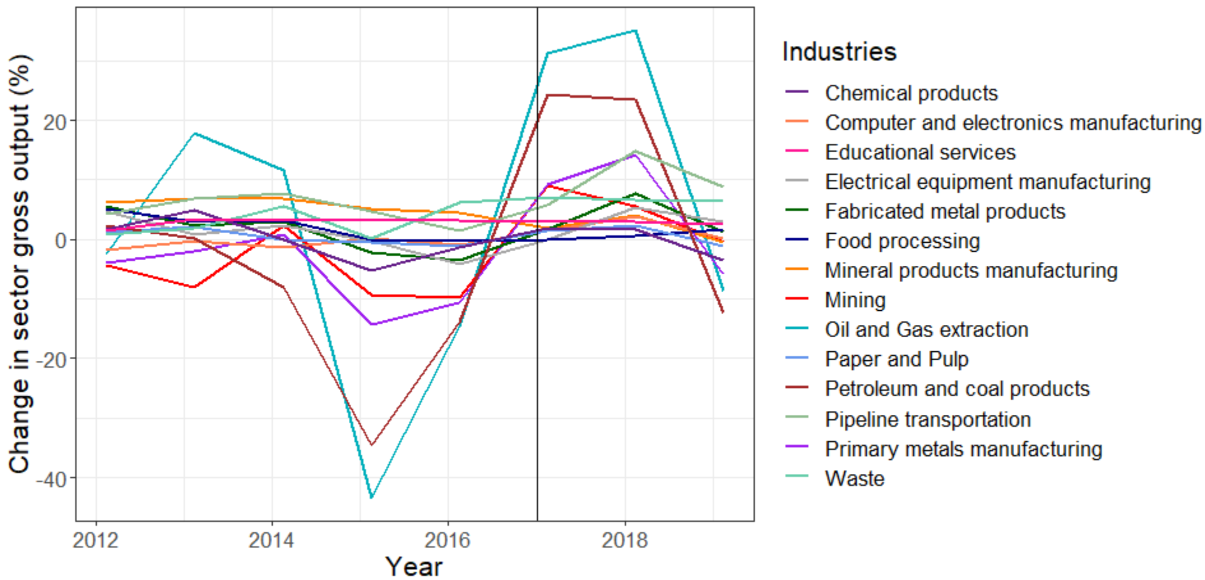
Note: Each bar in this graph represents the capital composition of a different sector, as indicated by the horizontal axis title. The capital composition is divided into the three BEA investment categories: IP, equipment and structures. It is evident that average capital structure varies a lot across the industries analyzed.
Source: BEA.

Industry Gross Output

The data for the sector-level gross output is from the BEA Industry Economic Account Data Tables. The "Gross Output by Industry" table provides annual output in billions of U.S. dollars for the different BEA sectors.[11] I summarize these figures for the 14 industries by following the matching guidelines specified in *Appendix II*. The resulting estimates are then adjusted for inflation by using the same methods applied to the capital stock figures. These values are shown in *Graph 4* in the next page.

[11] The aforementioned data is available in the following link: https://apps.bea.gov/iTable/iTable.cfm?reqid=150&step=2&isuri=1&categories=gdpxind. It was downloaded on January 8th, 2022.

Graph 4 - Time Series of Annual Percent Change in Industry Gross Output



Note: This graph shows the annual percent change in gross output for the industries indicated in the legend. The vertical line represents the implementation of the TCJA in 2017. It is evident that the majority of industries don't show considerable increases in gross output after TCJA. The two exceptions are Petroleum and Coal products, and Oil and Gas extraction.
Source: BEA.

According to the graph, gross output doesn't show unusual growth for most industries after TCJA. This could explain the small increase in emissions experienced by the majority of sectors after 2017. However, it isn't clear why many industries didn't experience higher gross output following TCJA. While this could have been caused by external factors that limited increases in production after 2017, it could also be explained by a weak relationship between the cost of capital, investment and gross output. These relationships are further investigated in section V.

Investment

The data on investment is from the BEA Fixed Asset Accounts Tables. I use information from Table 3.7 ESI, which contains annual "Investment in Private Fixed Assets by Industry" in billions of dollars, from 2012 to 2019.[12] I summarize these figures for the 14 relevant industries by using the matching guidelines specified in *Appendix II*.

Gross Domestic Product

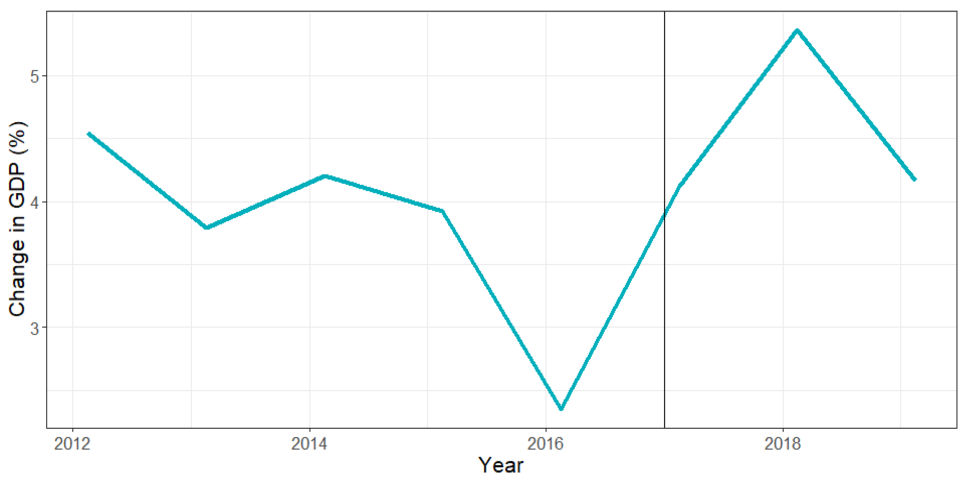
In addition to industry specific data, I collect information on the United States gross domestic product from the FRED website. The dataset consists of a seasonally adjusted quarterly time series of

[12] The aforementioned data is available in the following link: https://apps.bea.gov/iTable/iTable.cfm?ReqID=10&step=2. It was downloaded on January 16, 2022.

nominal GDP in billions of U.S. Dollars.[13] To obtain estimates for the annual GDP, I use an average of the four quarters for each year between 2012 and 2019. These figures are then adjusted for inflation by using the methods previously described.

The annual percent changes in U.S. GDP are plotted in *Graph 5* to better visualize patterns before and after the TCJA. While GDP presents positive changes throughout the entire period analyzed, there is a clear increase in the rate of GDP growth immediately after 2017. This is to be expected given the policies implemented by the TCJA, which included a decrease in the corporate tax rate. However, this trend is interesting given that most sectors in the analysis didn't experience large increases in gross output after 2017, as shown by *Graph 4*. This raises the question of whether this increase in GDP growth was driven only by a few industries that are not fully captured by my research.

Graph 5 - Time Series of Annual Percent Change in U.S. GDP



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Note: This graph shows the annual percent change in U.S. GDP between 2012 and 2019. The vertical line represents the implementation of the TCJA in 2017. It is evident that the rate of GDP growth increased after TCJA.
Source: FRED.

V. Empirical Approach

Initial Analysis and Assessment

Before introducing a regression equation into my analysis, I evaluate the mechanisms through which the TCJA corporate tax policies affected greenhouse gas emissions across the industries in my research.

[13] The aforementioned data is available in the following link: https://fred.stlouisfed.org/series/GDP. It was downloaded on January 8th, 2022.

I begin by investigating whether there was a significant change in corporate emissions after 2017. To do so, I use a linear regression of the annual percent change in emissions for all sectors on a TCJA dummy, which is equal to 1 starting in 2018. It is important to note that there are limitations to this regression, given that it does not infer causality. Additionally, since the data ranges from 2012 to 2019, the coefficient only reflects the changes experienced in the two years following the TCJA, which limits the interpretation of results. Nevertheless, this is a good starting point to analyze whether GHG emissions experienced relevant changes after TCJA. The regression specification and coefficient obtained are summarized below.

Specification: $\Delta GHG_{st} = \beta 1 * TCJA_t + u_{st}$

Table 1 - Coefficient for the Regression of Change in GHG Emissions on a TCJA Dummy

	All Sectors	Pr (> |t|)
TCJA dummy	0.021 (0.01)	0.17
Number of observations	112	
R^2	0.017	
Standard errors are shown in parentheses	· p < 0.1 *p < 0.05 ** p < 0.01 *** p<0.001	

Note: This table shows the coefficient and p-value from the regression of annual change in GHG emissions on a TCJA dummy, which is equal to 1 starting in 2018. It is evident that the annual change in emissions increased by a non-significant amount after TCJA.
Source: EPA.

According to *Table 1*, the annual percent change in emissions does not show a statistically significant increase after TCJA. However, this is partially explained by the vast differences across the 14 sectors, some of which did not experience any increase in emissions after 2017 due to external factors[14]. In order to better understand this result, I assess a series of regressions that evaluate the empirical relationship between the TCJA policies, the cost of capital, investment, gross output and GHG emissions. It is important to mention that these regressions use the annual percent change (as decimals) of the variables of interest, in order to facilitate interpretation.

First, I investigate the relationship between the TCJA policies and the average industry cost of capital. According to economic theory, the policies implemented in 2017 should decrease the cost of capital, both through the reduction of the corporate tax rate and the full expensing of capital types with a shorter depreciable life. To confirm whether this behavior is observed in the data, I use a regression of the annual percent change in the sector cost of capital on the TCJA dummy. The following table shows the regression specification and the results obtained.

[14] *Appendix VIII* shows the individual sector regressions of annual change in GHG emissions on the TCJA dummy.

Specification: $\Delta Q_{st} = \beta 1 * TCJA_t + u_{st}$

Table 2 - Coefficient for the Regression of Change in Sector Cost of Capital on a TCJA Dummy

	All Sectors	Pr (> |t|)
TCJA dummy	-0.177 (0.03)	< 0.001***
Number of observations	112	
R^2	0.243	
Standard errors are shown in parentheses	· p < 0.1 *p < 0.05 ** p < 0.01 *** p<0.001	

Note: This table shows the coefficient and p-value from the regression of annual change in sector cost of capital on a TCJA dummy, which is equal to 1 starting in 2018. The cost of capital figures were calculated following the Hall and Jorgenson formulation, using the data described in section IV. It is evident from the results that the average industry cost of capital decreased significantly after TCJA.

These results confirm the hypothesized behavior with a highly significant negative coefficient. Therefore, it can be concluded that the cost of capital per industry decreased by an average of 17.7 percentage points after the TCJA. This coefficient supports the conclusions from *Graph 2*, which also demonstrates a clear reduction in the cost of capital after 2017.

Next, I examine whether the theoretical negative relationship between the cost of capital and investment is observed in the data. To do so, I use a linear regression of annual change in sector-level investment on the annual variation in industry cost of capital. The regression specification and the results obtained are shown below.

Specification: $\Delta I_{st} = \beta 1 * \Delta Q_{st} + u_{st}$

Table 3 - Coefficient for the Regression of Change in Investment on the Change in Cost of Capital

	All Sectors	Pr (> |t|)
Change in the cost of capital	-0.205 (0.10)	0.046*
Number of observations	112	
R^2	0.035	
Standard errors are shown in parentheses	· p < 0.1 *p < 0.05 ** p < 0.01 *** p<0.001	

Note: This table shows the coefficient and p-value from the regression of annual change in investment on the change in sector cost of capital. The cost of capital figures were calculated following the Hall and Jorgenson formulation, using the data described in section IV. It is evident from the results that there is a statistically significant negative correlation between the industry cost of capital and sector-level investment in the sample.
Source: BEA.

Based on these results, a 1 percentage point decrease in the cost of capital is correlated with a statistically significant increase in investment of 0.205 percentage points, on average. This coefficient confirms the negative relationship between the cost of capital and investment. Since the mean annual investment for all sectors over this time period was 41.33 billions of dollars, such a change would be substantial. This is especially true when coupled with the results from the previous regression, which indicate that the cost of capital decreased by an average of 17.7 percentage points after TCJA.

Next, I look into the relationship between investment and sector-level gross output. Past literature argues that increases in investment lead to higher sectoral output (Nordhaus et al. 2013). To investigate if this claim holds in the data, I use a linear regression of the change in industry gross output on the change in sector-level investment. The regression specification and coefficients are shown in the table below.

Specification: $\Delta GO_{st} = \beta 1 * \Delta I_{st} + u_{st}$

Table 4 - Coefficients for the Regression of Changes in Industry Gross Output on Changes in Investment

	All Sectors	Pr (> |t|)
Change in investment	0.207 (0.05)	< 0.001***
Number of observations	112	
R^2	0.143	
Standard errors are shown in parentheses	· p < 0.1 *p < 0.05 ** p < 0.01	*** p<0.001

Note: This table shows the coefficient and p-value from the regression of annual change in industry gross output on the change in sector-level investment. It is evident from the results that increases in sectoral investment are correlated with highly significant growth in industry gross output.
Source: BEA.

The results obtained, which are highly significant, support that investment and sectoral gross output are positively correlated. In fact, an increase of 1 percentage point in sector-level investment would correspond to an increase of 0.207 percentage points in industry gross output, on average.

Lastly, I investigate how changes in industry gross output impact sectoral emissions. To do so, I use a linear regression of annual change in GHG emissions on industry gross output. The regression specification and results are summarized below.

Specification: $\Delta GHG_{st} = \beta 1 * \Delta GO_{st} + u_{st}$

Table 5 - Coefficient for the Regression of Changes in GHG Emissions on the Change in Industry Gross Output

	All Sectors	Pr (> |t|)
Change in industry gross output	0.103 (0.07)	0.15
Number of observations	112	
R^2	0.019	
Standard errors are shown in parentheses	· p < 0.1 *p < 0.05 ** p < 0.01 *** p<0.001	

Note: This table shows the coefficient and p-value from the regression of annual change in sectoral GHG emissions on the change in industry gross output. It is evident from the results that increases in gross output are correlated with non-significant growth in industry emissions.
Sources: EPA, BEA.

The magnitude and direction of the coefficient suggest that increases in industry gross output are correlated with positive changes in corporate greenhouse gas emissions. This relationship is not statistically significant at a 5% level, which is likely attributed to other factors that impacted emissions over this time period, as further studied in the following subsection. Nevertheless, it can be concluded from this series of regressions that the hypothesis developed by Nordhaus, Merrill and Beaton holds and is roughly observed in the data — tax policy changes responsible for decreasing the sector cost of capital, such as the TCJA, are correlated with higher investment and gross output, thereby increasing GHG emissions.

However, the results shown so far are only suggestive of direction, given that bivariate regressions don't demonstrate causality. In the following subsection, I present a more theoretical approach based on a multivariate regression that investigates causality between these elements.

Regression Equation

The regression equation below estimates how changes in corporate tax policy affect a sector's annual emissions through the industry's average cost of capital. In order to achieve this, the multiple linear regression uses the GHG data from the 14 selected industries between 2012 and 2019.

$$\Delta GHG_{st} = \beta 1 * \Delta_{Q_{st}} + \beta 2 * B_s + \beta 3 * E_s + \beta 4 * \Delta_{Q_{st}} * B_s + \beta 5 * \Delta_{Q_{st}} * E_s + \Theta X_{st} + u \qquad (2)$$

In equation 2, ΔGHG_{st} designates the annual percent change in U.S. greenhouse gas emissions for a sector s at year t. The independent variable $\Delta_{Q_{st}}$ represents the annual percent change in the average cost of capital for a sector $\boldsymbol{s}$ at year $\boldsymbol{t}$. The variables $\boldsymbol{B_s}$ and $\boldsymbol{E_s}$ designate the average capital stock of buildings (structures) and equipment in trillions of U.S. dollars for a sector $\boldsymbol{s}$. Furthermore, $\boldsymbol{X_{st}}$ designates the vector on possible controls for the regression and $\boldsymbol{\Theta}$ represents the coefficient on said controls. Lastly, the term $\boldsymbol{u}$ incorporates any unobservable factors that impact the dependent variable.

The coefficients of interest in the equation are the ones for the variables $\Delta\rho_{st}$, ($\Delta\rho_{st}$* $\boldsymbol{B_s}$) and ($\Delta\rho_{st}$* $\boldsymbol{E_s}$). The change in the average sector cost of capital ($\Delta\rho_{st}$) is the focus of this paper, because it is the main mechanism by which corporate taxation impacts variations in GHG emissions. However, changes in the cost of capital have differing effects on emissions depending on the sector. The magnitude of this influence is a function of the capital composition of each industry and how emissions intensive the capitals used are. For instance, many industries that rely heavily on IP as a form of capital, such as Technological Services, have a smaller impact on emissions than industries that rely heavily on machinery and factory buildings. The interactive variables ($\Delta\rho_{st}$* $\boldsymbol{B_s}$) and ($\Delta\rho_{st}$* $\boldsymbol{E_s}$) are intended to capture this joint impact.

Even though the change in sector cost of capital is hypothesized to have a significant impact on industry emissions, there are many external factors to be considered. To account for these other influences, I incorporate $\boldsymbol{\Theta X_{st}}$ into the regression equation. As it is further explained in the results section, there are two main controls used in my research: the $\Delta\boldsymbol{GDP_t}$ variable, which represents the annual percent change in real U.S. gross domestic product at year $\boldsymbol{t}$; and $\Delta\boldsymbol{GOP_{st}}$, which designates the annual percent change in real gross output for a sector $\boldsymbol{s}$ at year $\boldsymbol{t}$. The annual variation in GDP incorporates overall economic trends that affect emissions in all sectors, such as economic contraction and political instability. The annual change in sectoral gross output, on the other hand, accounts for the industry-specific trends that affect emissions, such as changes in the price of inputs or the introduction of sector-specific environmental regulation.

The $\Delta\boldsymbol{GDP_t}$ and $\Delta\boldsymbol{GOP_{st}}$ variables serve an important role in the analysis, because when included as controls in the regression, they jointly account for the scale effect. As previously mentioned, the scale effect represents the direct impact of economic growth on GHG emissions, which in this case can be divided into economy-wide growth ($\Delta\boldsymbol{GDP_t}$) and sector-specific growth ($\Delta\boldsymbol{GOP_{st}}$). This will be further explained in the next section.

This breakdown of the equation allows for an in-depth analysis of the mechanisms by which corporate taxation impacts emissions. Most importantly, it enables inferences about causality. Since the equation controls for industry characteristics ($\boldsymbol{B_s}$ and $\boldsymbol{E_s}$) and relevant external factors ($\boldsymbol{\Theta X_{st}}$), the coefficients on $\Delta\rho_{st}$ and the interactive variables estimate the causal effect of tax policy changes to the cost of capital on sectoral GHG emissions.

VI. Results

The regression analysis in this paper uses the R Statistical Package (see *Appendix VI* for the commands employed). This section summarizes the main findings from the multivariate regression and pertinent conclusions.

Table 6 - Regression Results

Equation number	(1)	(2)	(3)	(4)	(5)
Dependent Variable	ΔGHG_{st}	ΔGHG_{st}	ΔGHG_{st}	ΔGHG_{st}	ΔGHG_{st}
Change in cost of capital ($\Delta_{Q st}$)	0.1542 (0.116)	0.1606 (0.116)	0.2226 (0.113)·	0.2226 (0.113)·	-0.0615 (0.115)
Structures (B_s)	0.0115 (0.011)	0.0095 (0.010)	0.0106 (0.009)	0.0106 (0.009)	0.0106 (0.009)
Equipment (E_s)	0.0777 (0.151)	0.1069 (0.151)	0.0871 (0.147)	0.0871 (0.147)	0.0946 (0.146)
Interaction between structures and change in the cost of capital ($\Delta_{Q st} * B_s$)	-0.0943 (0.061)	-0.1213 (0.062)·	-0.1213 (0.057)*	-0.1213 (0.057)*	-0.0982 (0.053)·
Interaction between equipment and change in the cost of capital ($\Delta_{Q st} * E_s$)	-1.1386 (1.010)	-1.1226 (1.007)	-0.9859 (0.995)	-0.9859 (0.995)	-0.8665 (0.900)
Change in sectoral gross output (ΔGOP_{st})		0.121 (0.042)**	0.0463 (0.037)	0.1204 (0.034)***	0.0048 (0.040)
Change in gross domestic product (ΔGDP_t)			2.6917 (0.619)***		
Residuals from regression of change in GDP on change in sectoral gross output				2.6917 (0.619)***	
Number of observations	112	112	112	112	112
R^2	0.037	0.061	0.117	0.117	0.191
Year fixed effects	No	No	No	No	Yes
Sector fixed effects	No	No	No	No	No
Net effect of changes in the cost of capital on emissions (by type of capital stock)					
Intellectual Property	0.15	0.16	0.22	0.22	-0.06
Structures	0.13	0.13	0.19	0.19	-0.08
Equipment	0.06	0.07	0.14	0.14	-0.13

Robust standard errors are shown in parenthesis. · $p < 0.1$ * $p < 0.05$ ** $p < 0.01$ *** $p<0.001$

Note: This table shows the coefficients, robust standard errors and other details regarding the five regressions specifications analyzed in my research. The lower part of the table uses the relevant coefficients to calculate the net effect of changes in the cost of capital on emissions by type of capital stock. The details of this calculation are provided in *Appendix VII*. The regressions in column 1 through 5 follow the specification $\Delta GHG_{st} = \beta 1 * \Delta_{Q st} + \beta 2 * B_s + \beta 3 * E_s + \beta 4 * \Delta_{Q st} * B_s + \beta 5 * \Delta_{Q st} * E_s + \Theta X_{st} + u$, where ΘX_{st} varies based on the column. It is evident from the results that equations 1 through 4 show a positive and slightly significant relationship between the change in the cost of capital and GHG emissions. Yet, given the coefficient from column 5, this relationship

remains ambiguous. Additionally, the results offer robust evidence of the differential impact of capital types on greenhouse gasses, and of a significant positive relationship between economic growth and emissions.
Sources: EPA, BEA, FRED, Treasury Direct, IRS, the Cost of Capital Calculator.

Table 6 presents the five main regression specifications this paper analyzes. The bottom portion of the table shows the net effect of changes in the cost of capital on emissions, which is calculated from the coefficients on ΔQ_{st} and its interactions with the structure and equipment capital stocks (see *Appendix VII* for calculation details). This is the effect of interest for my research, since it comprehensively measures how corporate taxation influences emissions through the cost of capital.

Equation 1 exemplifies the baseline regression explained in the previous section, where the control factors ($\boldsymbol{\Theta X_{st}}$) are omitted. Given the omission of relevant external factors, the coefficients from this regression are biased. Nevertheless, the results in column 1 allow for important conclusions to be drawn.

First, the coefficient on the annual change in the cost of capital reveals a positive relationship with variations in GHG emissions. While this coefficient is not statistically significant, the sign and magnitude indicate that a decrease in the cost of capital, *ceteris paribus*, leads to a decrease in emissions. A positive correlation between these two variables opposes the original hypothesis, however, it is important to acknowledge that such hypothesis took into account only the scale effect and disregarded the impact of the technique and composition effects. This relationship is later investigated by the results of equations 2 and 3.

The positive sign on the coefficients of structures and equipment are directionally suggestive that investments in these two types of capital tend to increase greenhouse gas emissions. However, given the large standard errors, these coefficients are inconclusive.

Another relevant discovery concerns the negative coefficients on the interactive terms between the sector's capital stock and the changes in the cost of capital. While these coefficients are not statistically significant, their negative sign offers an important conclusion — decreases in the cost of capital and consequent higher investment in structures and equipment, as compared to intellectual property, contribute to a relative increase in GHG emissions. This is suggestive evidence of the differential impact of capital types on emissions, which can also be observed in the net effects table. Intuitively, this difference is explained by how certain capital types, such as structures, are more emissions-intensive than others, like intellectual property. This is especially true because investing in intellectual property likely expands the impact of the technique effect (e.g. through patents for cleaner technologies), thereby decreasing emissions more than investments on structures and equipment would.

While the baseline model offers valuable insights into the role of the cost of capital and sectoral capital composition in estimating changes in emissions, the lack of control variables creates limitations. The omission of relevant external factors both raises problems with biased estimates and constrains the interpretation of the scale effect on emissions. The next subsection will attempt to better distinguish between the scale, technique and composition effects by analyzing equations 2 and 3 from *Table 6*.

Separating scale, technique and composition effects

Given that equation 1 does not include the $\boldsymbol{\Delta GDP_t}$ and $\boldsymbol{\Delta GOP_{st}}$ variables, scale is not separately measured by any of the covariates. Instead, the scale effect is captured by the net impact of changes in the cost of capital on GHG emissions, alongside the technique and composition effects. This figure is positive for all capital types in column 1, which indicates that the combined impact on emissions of the scale, technique and composition effects moves in the same direction as changes in the cost of capital. Therefore, a decrease in the cost of capital leads to a net decrease in emissions.

This result contradicts the original hypothesis regarding this behavior, which claims that a change in corporate taxation responsible for decreasing the cost of capital should lead to higher investment in said capital and, consequently, higher output. According to the scale effect, this growth in output would increase GHG emissions. Therefore, changes in the cost of capital were expected to be negatively correlated to changes in emissions, holding other effects constant. Yet, the net impact figures in column 1 are all positive, which indicates that there must be a simultaneous opposing factor that dominates the scale effect. Previous literature argues that this is explained by the technique and composition effects (Panayotou 1997; Liobiekene and Butkus 2018; Sugiawan and Managi 2016).

In order to investigate whether the scale effect does behave differently than the technique and composition effects, equation 2 separately accounts for scale by including changes in sector-level gross output ($\boldsymbol{\Delta GOP_{st}}$). However, since it does not incorporate the impact of macroeconomic phenomena on sectoral emissions ($\boldsymbol{\Delta GDP_t}$), equation 2 also experiences bias due to the omitted variable. Specification 3 eliminates this bias by including both variables in the regression.

While the results in column 3 do not allow us to decompose the scale, technique and composition effects, they do enable the separation of the scale effect from the two others. Since equation 3 separately controls for scale by including both the $\boldsymbol{\Delta GDP_t}$ and $\boldsymbol{\Delta GOP_{st}}$ variables, its calculated net impact does not capture the influence of the scale effect, unlike equation 1. Therefore, the difference between the net figures from columns 1 and 3 is indicative of the scale effect of cost of capital changes on emissions. From *Table 6*, it is evident that these figures are lower for equation 1 than for equation 3, pointing to a negative scale effect. Thus, it can be concluded that, holding constant the impact of the technique and composition effects, there is a negative relationship between changes in the cost of capital and changes in emissions. This comparison also offers suggestive evidence that the technique and composition effects dominate the impact of the scale effect in this context, therefore contributing to an overall positive net effect of changes in the cost of capital on emissions.

In addition to pertinent insights regarding the scale effect, equations 2 and 3 provide an opportunity to validate some of my findings. The two columns largely corroborate the conclusions from the baseline regression, presenting coefficients of similar magnitude and sign. There are also new inferences that can be deducted from the combination of these results. For example, the coefficient on the change in the cost of capital is significant at a 10% level in equation 3, but not in equations 1 and 2. This is likely because a portion of the time series variation in GHG emissions caused by macroeconomic factors is incorrectly attributed to the $\Delta_{Q_{st}}$ covariate in the first two columns. By adding the $\boldsymbol{\Delta GDP_t}$ control in equation 3, this no longer happens. Another relevant observation is that the interaction between changes in the cost of capital and structures appears to be statistically significant in equations 2 and 3, which provides further evidence of the differential impact of capital types on emissions.

Lastly, these specifications offer important information regarding the impact of economic growth on emissions. The coefficient on the change in sectoral gross output from equation 2 is positive and statistically significant. The same is true for the coefficient on the annual change in GDP from equation 3. Therefore, these results offer robust evidence of a statistically significant positive relationship between growth and emissions, as previously evidenced in literature (Panayotou 1997). It is important to mention that, while the $\boldsymbol{\Delta GOP_{st}}$ coefficient from equation 3 is also positive, it is not statistically significant given the multicollinearity with the $\boldsymbol{\Delta GDP_t}$ variable. This is further explained in the next subsection, along with other methods to validate the robustness of my conclusions.

Robustness

Despite offering pertinent conclusions, equations 1 through 3 experience limitations due to omitted variables and multicollinearity. In specifications 1 and 2, the omission of relevant external factors creates biased estimates. However, by including both $\boldsymbol{\Delta GDP_t}$ and $\boldsymbol{\Delta GOP_{st}}$, equation 3 introduces a problem with multicollinearity, since the change in gross domestic product is causally related to the change in sector-level gross output. This is true because the change in GDP is equal to the sum of variations in gross output of the different sectors in the economy. To resolve this issue, equation 4 substitutes $\boldsymbol{\Delta GDP_t}$ with the residuals from the regression of $\boldsymbol{\Delta GDP_t}$ on $\boldsymbol{\Delta GOP_{st}}$. The residuals represent broader economic growth after controlling for the influence of sector-specific trends on GDP, thus ensuring that there are no longer two covariates measuring the same effect on emissions. Instead, the coefficient on the residuals captures how the variation in GDP that is not explained by changes in sectoral gross output impacts GHG emissions. Equation 5 utilizes a different approach to resolve the issue of multicollinearity. It substitutes the annual change in GDP with fixed year effects, since both aim to control for annual external factors and macroeconomic trends that impact emissions.

Equation 4 offers the same conclusions as equation 3 since they are mathematically identical, with the exception of the coefficients on change in sectoral gross output and the residuals. These two offer robust evidence that, after eliminating problems with multicollinearity, both $\boldsymbol{\Delta GDP_t}$ and $\boldsymbol{\Delta GOP_{st}}$ are statistically significant factors in estimating changes in emissions.

While equation 5 presents, for the most part, coefficients of the same sign and magnitude as the previous equations, it shows much less statistically significant estimates. This is likely because the fixed year effects capture a portion of the impact of different covariates on emissions, since some of the change in these variables is time series variation. However, the coefficient on the change in sector cost of capital is vastly different from the ones obtained by the previous specifications, indicating that this effect remains ambiguous. Consequently, the joint effect of the composition, technique and scale effects is also left ambiguous, as shown by the negative figures from equation 5 in the net effects table.

The difference observed between the $\boldsymbol{\Delta Q_{st}}$ coefficient from equation 5 and the remaining specifications is not very surprising, however. As shown in *Graph 2*, most of the change in the cost of capital over this period can be attributed to time series variation and not cross-sector specificities. Therefore, the substitution of changes in GDP by fixed year effects controls for such time-series variation, leaving only the sector differences to be captured by the ΔQ_{st} coefficient. Consequently, the negative sign of the coefficient in equation 5 can be interpreted as a negative correlation between sectoral variations in the cost of capital and changes in GHG emissions. In this case, sectors with an overall lower cost of capital would be expected to have a higher impact on emissions, which is in agreement with this research paper's underlying hypothesis.

Therefore, specifications 1 through 5 largely offer the same conclusions, with the exception of the ΔQ_{st} coefficient. This contributes to the robustness of the results presented by my research.

VII. Conclusion

The analysis in this paper suggests that changes in corporate taxation have an impact on sectoral greenhouse gas emissions through their effect on the cost of capital. Nevertheless, this impact appears to not be statistically significant at a 5% level, based on the regression analysis. This is likely due to limitations introduced by the use of aggregated industry-level data, which is the best available alternative to firm-level data that is not publicly disclosed.

The effect of taxation on emissions is difficult to estimate at the industry level, given its dependence on characteristics that vary a lot by firm, such as capital composition. Additionally, conducting the analysis at the sector level introduces complexities regarding the external factors that impact emissions. While there is a measurable number of variables that affect a single firm's change in GHG generation, at the aggregated sector level, there are countless external factors to be taken into account. These can only be represented by a more general metric, such as the change in sectoral gross output, which still doesn't encompass all the relevant effects. Given these limitations, the use of aggregated sector data is likely the largest contributor to the low statistical significance of the results.

Nonetheless, my research still allows for relevant conclusions to be drawn. For instance, the analysis contradicts the theory of decoupling between economic growth and GHG emissions mentioned in section III. The results show a statistically significant positive correlation between growth and emissions, as supported by previous literature (Duarte et al 2013; Zu et al 2014; Streimikiene and Balezentis 2016). On the other hand, this paper also finds evidence that the technique and composition effects complicate the impact of growth on emissions. The results from 4 out of the 5 regression specifications show a positive net effect of changes in the cost of capital on GHG emissions. The positive sign indicates that the presence of technique and composition effects dominates the impact of the scale effect in this context, thus allowing corporations to respond to a decrease in the cost of capital without contributing to increases in emissions. Yet, the results from the 5th regression contradict these findings with a negative net effect figure, which supports the idea that a decrease in the cost of capital would lead to higher GHG emissions through increases in sector-level gross output. Given these contrasting results, it is crucial for future research to investigate the evolving nature of this relationship.

Nevertheless, the analysis does present robust evidence of a trade-off between economic growth and GHG emissions, raising questions of how policy makers should account for this relationship when developing new legislation. Literature argues that this trade-off would largely disappear through the implementation of Pigouvian carbon pricing (The Wall Street Journal 2019). Yet, while such mechanisms are not implemented in the U.S., policy makers need to consider the implications of all types of growth-driven legislation on emissions, including corporate tax policy. The TCJA of 2017 serves as a case study of the impact of growth-oriented tax policy on greenhouse gasses. While my results show that overall U.S. emissions increased by a non-significant amount after TCJA, it does appear that this impact was statistically significant for a small number of sectors (details are in *Appendix VIII*). The exact reasons why some industries experienced higher increases in emissions than others remains unclear based on my results. Therefore, it is crucial that the relationship between changes in corporate taxation and GHG emissions be further studied and taken into account by U.S. legislators.

Future research on this topic should continue to study my results by using different data sources or different methodology. As previously mentioned, the biggest shortcoming of this paper is limited access to detailed firm-level data, which is not publicly available. If given access to this information, researchers would better understand the relationship between the cost of capital and emissions. Additionally, the GHG emissions figures used in my analysis also face limitations, since the EPA only collects data on facilities that emit more than 25,000 metric tons of carbon equivalents per year. This means that smaller facilities are not obligated to report and are consequently not included in this research. Furthermore, future studies could investigate how corporate taxation affects GHG emissions in countries other than the United States. This question is not addressed by my paper due to my inability to access detailed data from other countries.

In regards to methodology, future research could look into other strategies to merge the datasets used. Given the incompatibility of the sector nomenclatures from the BEA and the EPA, the information from both sources is manually merged, likely resulting in measurement error. The use of firm-level data would likely resolve this issue, thus minimizing bias. Lastly, if able to access firm data, further studies could look into refining the variables chosen for the regression equation. For instance, the chosen external factors could be substituted by detailed variables, such as the firm's annual consumption of renewable energy. However, in the absence of firm-level data, later research would likely be constrained by the same factors presented in my paper.

VIII. Appendix

Appendix I - Key Statistics on Research Variables

Table A.1 below contains important statistics on the GHG emissions data for each of the 14 analyzed sectors, between 2012 and 2019.

Table A.1 - Summary Statistics on Annual GHG Emissions (in tCO_2)

Industry	Mean	Median	Min	Max	Standard Deviation
Chemical products	144,892,287	143,133,917	139,516,102	153,666,247	5,082,193
Computer and electronics manufacturing	6,061,469	6,192,216	5,192,572	6,426,532	397,821
Educational services	9,101,615	9,104,707	8,716,855	9,497,764	253,043
Electrical equipment manufacturing	174,955	174,041	140,520	204,229	21,390
Fabricated metal products	11,914,843	12,045,182	10,803,081	12,828,463	672,177
Food processing	33,305,647	33,269,145	32,175,634	34,417,733	734,364
Mineral products manufacturing	79,693,935	80,889,428	74,349,021	82,405,637	2,689,222
Mining	73,597,714	72,655,751	68,702,274	77,528,094	3,144,457
Oil and Gas extraction	82,610,130	82,173,994	78,094,784	88,324,041	3,062,608
Paper and Pulp	152,904,040	151,844,609	142,062,366	164,069,253	7,882,833
Petroleum and coal products	339,485,615	337,024,644	323,409,204	360,146,937	13,331,423
Pipeline transportation	14,070,995	13,989,868	12,672,334	15,455,672	1,001,262
Primary metals manufacturing	84,027,194	79,654,533	76,536,993	94,649,145	8,024,944
Waste	127,980,983	128,023,251	123,469,088	133,551,175	3,092,495

Note: This table shows the summary statistics (mean, median, minimum, maximum and standard deviation) on the annual GHG emissions figures for each of the 14 industries analyzed, in tonnes of CO_2 equivalents (tCO_2).
Source: EPA.

Table A.2 summarizes key statistics for the data collected on all of the research variables described in section IV. The metrics are on the combined data from the 14 industries analyzed between 2012 and 2019.

Table A.2 - Summary Statistics on Variables of Interest

	Mean	**Median**	**Min**	**Max**	**Standard Deviation**
Cost of capital	0.0086	0.0089	0.0062	0.01042	0.0012
Structures capital stock (billions of dollars)	246.08	108.10	27.50	1,893.60	422.52
Equipment capital stock (billions of dollars)	84.48	78.85	22.20	206.00	50.61
GDP (billions of dollars)	18,540.93	18,398.62	16,178.06	21,265.78	1,646.76
Sectoral gross output (billions of dollars)	341.72	268.51	36.23	962.14	267.66
Investment (billions of dollars)	41.33	20.70	4.90	204.60	45.82

Note: This table shows the summary statistics (mean, median, minimum, maximum and standard deviation) on all of the data collected for my research. The metrics are on the combined information from the 14 sectors. The units are described in parenthesis under the data type.
Sources: BEA, FRED.

Appendix II - Industry Matching Methodology between EPA and BEA Data

In order to conduct my analysis, I combine data from the EPA's Greenhouse Gas Reporting database, the BEA's Fixed Asset Account Tables and the BEA's Industry Economic Account Tables. Given that the EPA and the BEA categorize sectors differently, it is necessary to develop a matching process between the two industry categorizations.

The EPA dataset contains information on 9 different sectors, which are broken down into 52 subsectors. The BEA classification is composed of 19 sectors, which are divided into 56 subsectors. The industry matching process consists of first finding the BEA parent industry that each EPA subsector best fits under, and then further looking into the BEA subsector descriptions to find the most compatible one. For instance, "Natural Gas Processing" best fit under the "Mining" parent industry, and within that category, it is most compatible with the "Oil and Gas extraction" sub-industry. *Table A.3* shows the results from this process in detail.

Of the original 52 EPA subsectors, only 5 are eliminated (Power plants, Other manufacturing, Military, Other and Use of electrical equipment) due to the absence of a corresponding sub-category in the BEA data. There is also one instance where 2 BEA industries are matched with the same EPA subsectors — "Paper products" and "Printing and related support activities" from the BEA classifications are matched with "Pulp and Paper" and "Other paper producers" from the EPA data.

The remaining 47 subsectors are merged together and matched with the 14 BEA industries they are the most compatible with. After this process, the remaining 14 subsectors are renamed for simplicity and included in the analysis as: Oil and Gas extraction, Mining, Mineral products manufacturing, Primary metals manufacturing, Fabricated metal products, Computer and electronics manufacturing, Electrical equipment manufacturing, Food processing, Paper and Pulp, Petroleum and coal products, Chemical products, Pipeline transportation, Waste and Educational services.

Table A.3 - BEA Subsectors and Corresponding EPA Subsectors

BEA Parent Industry	BEA Subsector	Corresponding EPA Subsectors
Agriculture, forestry, fishing, and hunting	Farms	
	Forestry, fishing, and related activities	
Mining	Oil and gas extraction	• Natural Gas Processing • Natural Gas Transmission/Compression
	Mining, except oil and gas	
	Support activities for mining	• Lime Manufacturing • Underground Coal Mines • Other Minerals
Utilities		
Construction		
Manufacturing	Wood products	
	Nonmetallic mineral products	• Cement Production • Glass Production • Soda Ash Manufacturing
	Primary metals	• Iron and Steel Production • Aluminum Production • Zinc Production • Lead Production • Magnesium
	Fabricated metal products	• Other Metals • Ferroalloy Production

Manufacturing	Machinery	
	Computer and electronic products	• Electronics Manufacturing
	Electrical equipment, appliances, and components	• Electrical Equipment Manufacturers
	Motor vehicles, bodies and trailers, and parts	
	Other transportation equipment	
	Furniture and related products	
	Miscellaneous manufacturing	
	Food and beverage and tobacco products	• Food Processing
	Textile mills and textile product mills	
	Apparel and leather and allied products	
	Paper products Printing and related support activities	• Other Paper Producers • Pulp and Paper
	Petroleum and coal products	• Petrochemical Production • Petroleum Refineries • Offshore Petroleum & Natural Gas Production • Onshore Petroleum & Natural Gas Production
	Chemical products	• Ethanol Production • Other Chemicals • Hydrogen Production • Nitric Acid Production • Ammonia Manufacturing • Adipic Acid Production • HCFC-22 Prod./HFC-23 Dest. • Titanium Dioxide Production • Silicon Carbide Production • Fluorinated GHG Production • Phosphoric Acid Production
	Plastics and rubber products	
Wholesale trade		

Retail trade		
Transportation and warehousing	Air transportation	
	Railroad transportation	
	Water transportation	
	Truck transportation	
	Transit and ground passenger transportation	
	Pipeline transportation	• Natural Gas Local Distribution Companies
	Other transportation and support activities	
	Warehousing and storage	
Information		
Finance and insurance		
Real estate and rental and leasing		
Professional, scientific, and technical services		
Management of companies and enterprises		
Administrative and waste management services	Administrative and support services	
	Waste management and remediation services	• Wastewater Treatment • Municipal Landfills • Solid Waste Combustion • Industrial Landfills
Educational services		• Universities
Health and social assistance		
Arts, entertainment, and recreation		
Accommodation and food services		
Other services, except government		

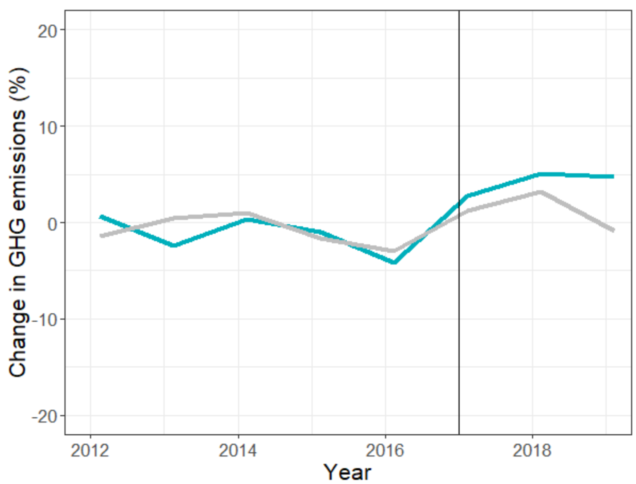
Note: This table shows the results of the data combination process utilized in this paper. The first column indicates the BEA parent industry, which is divided into subindustries (shown in column 2). The last column names the EPA

subsectors that correspond to the BEA subindustries shown in column 2. The empty rows in column 2 represent BEA parent industries that are not further divided into subindustries. The empty rows in column 3 represent BEA industries and subindustries that don't have a corresponding EPA subsector. The 5 EPA subsectors that were not included in the research do not appear in the table above.
Sources: EPA, BEA.

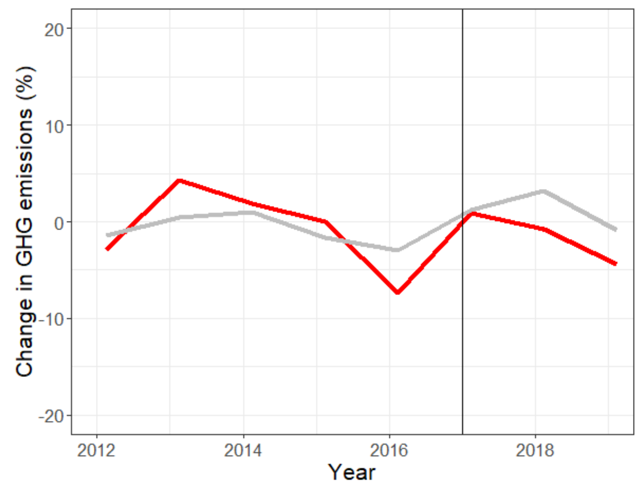
Appendix III - Time Series Graphs of Annual Percent Change in GHG emissions Across Sectors

The following graphs show the annual percent changes of GHG emissions in each of the 14 sectors included in this paper. The gray line represents the annual change in aggregate national emissions over the same time period.

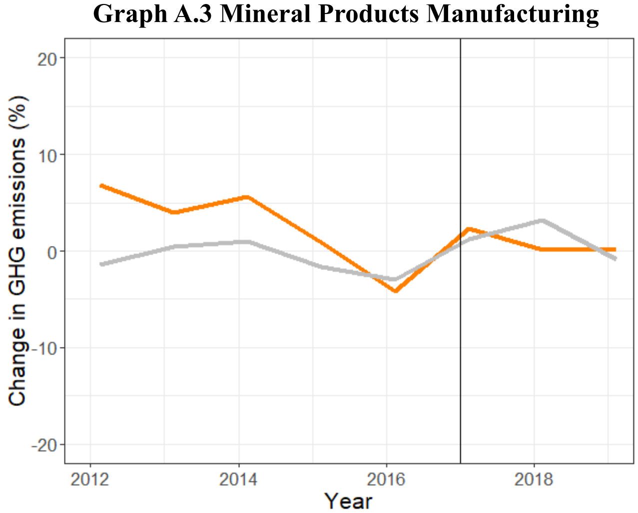
Graph A.1 Oil and Gas Extraction



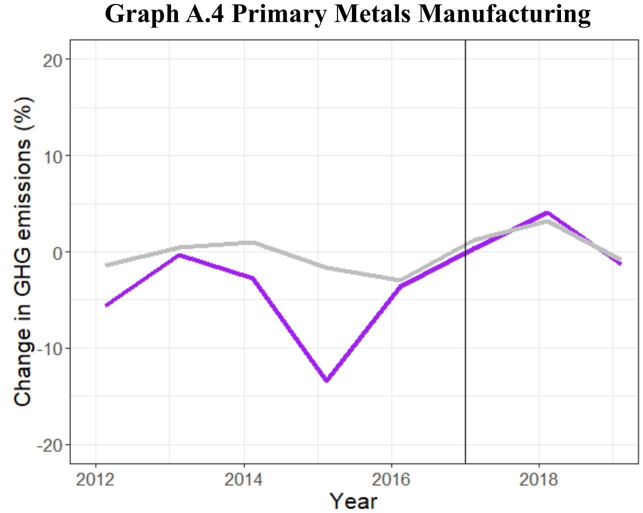
Graph A.2 Mining



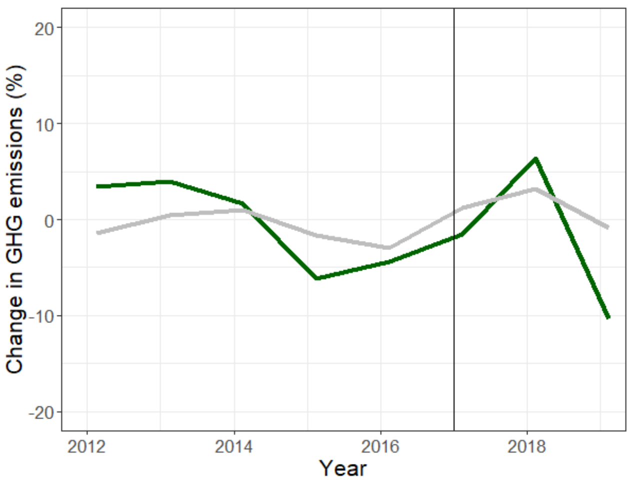
Graph A.3 Mineral Products Manufacturing



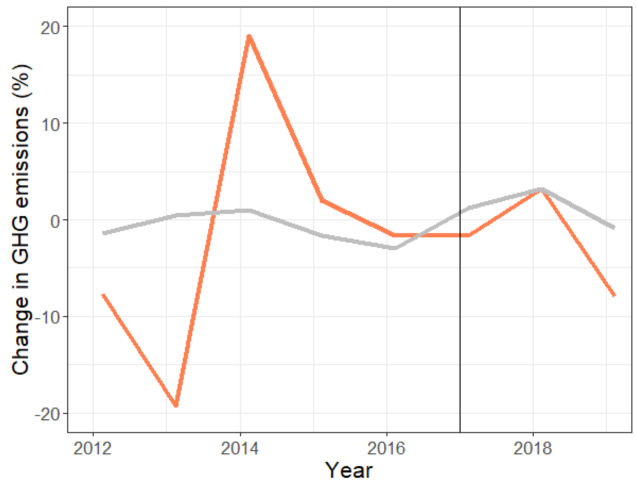
Graph A.4 Primary Metals Manufacturing



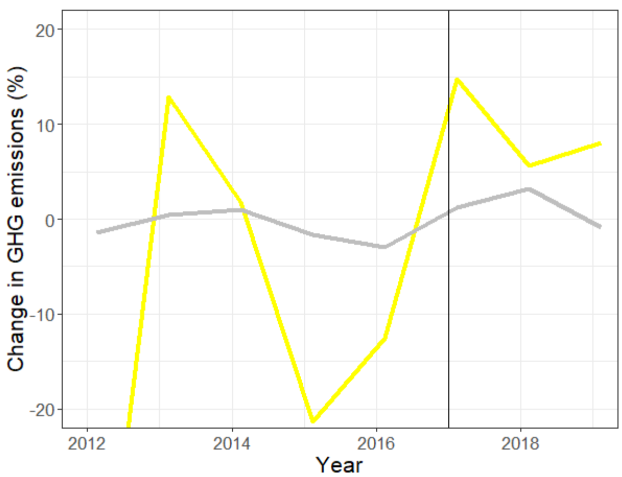
Graph A.5 Fabricated Metal Products



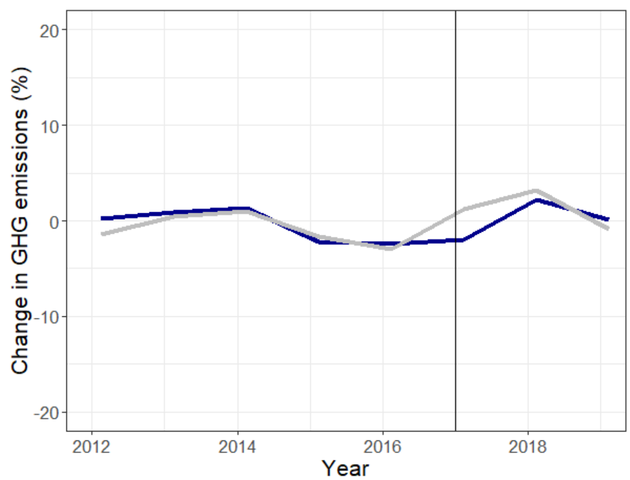
Graph A.6 Computer and Electronics Manufacturing



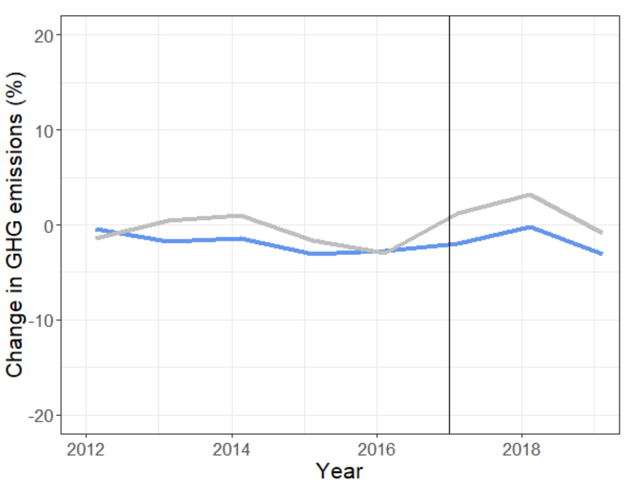
Graph A.7 Electrical Equipment Manufacturing



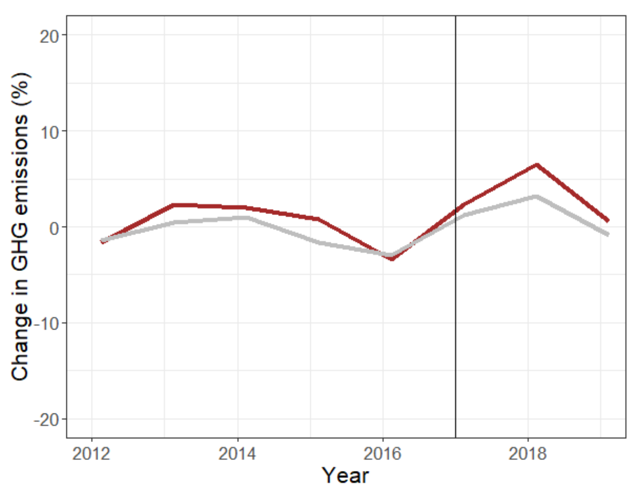
Graph A.8 Food Processing



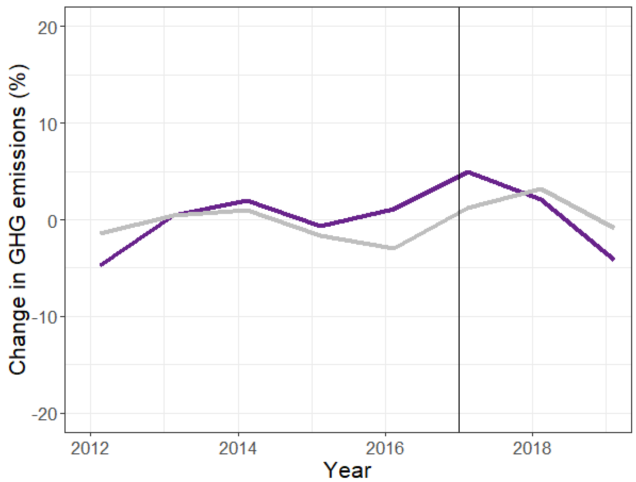
Graph A.9 Paper and Pulp



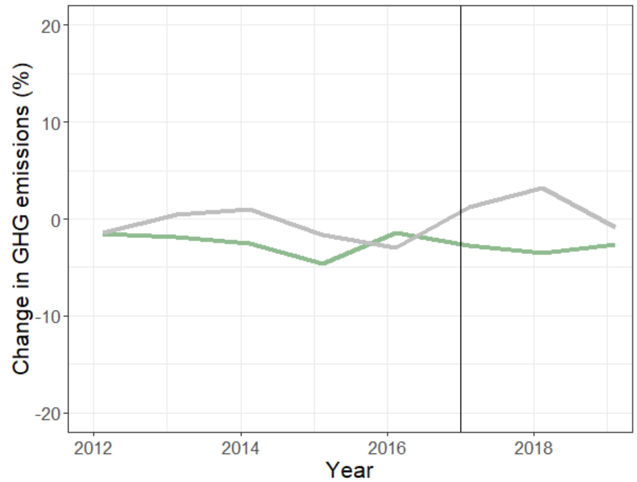
Graph A.10 Petroleum and Coal Products



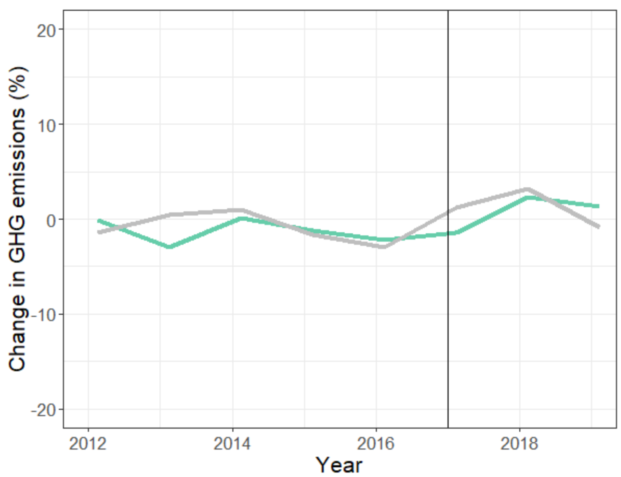
Graph A.11 Chemical Products



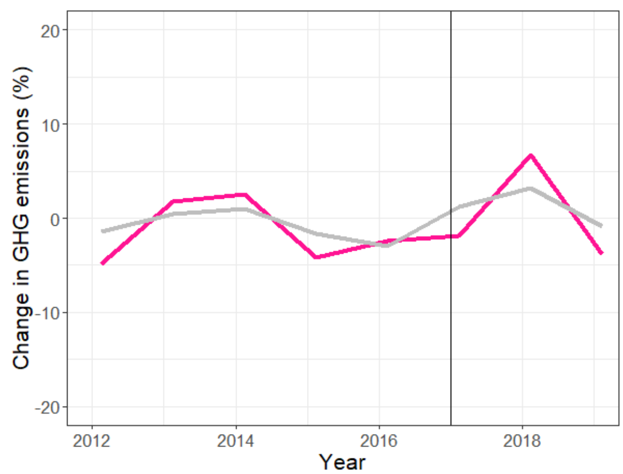
Graph A.12 Pipeline Transportation



Graph A.13 Waste



Graph A.14 Educational Services



Note: The 14 graphs above show the annual percent change in GHG emissions (in color) for each of the industries indicated in the graph titles. The gray line in all of the graphs represents the annual change in aggregate national emissions over the same time period. The vertical line marks the implementation of the TCJA in 2017. It is evident based on the graphs that the trend in emissions varied a lot across the sectors included in this paper between 2012 and 2019.
Source: EPA.

Appendix IV - Rates of Economic Depreciation by Capital Type

The following table contains the estimates for the rates of economic depreciation by capital type used in the calculation of the cost of capital.

Table A.4 - Average Rates of Economic Depreciation by Capital Type

Capital Type	Rate of Economic Depreciation
Equipment	0.139
Structures	0.029
Intellectual Property	0.297

Note: This table shows the average rates of economic depreciation for the three capital types (in decimals). These values are used in the calculation of the cost of capital per investment type.
Source: BEA.

Appendix V - Cost of Capital Calculator Details and Data Decisions

Data decisions for the net present value of depreciation deductions (z)

The calculation of z, the net present value of depreciation deductions, is obtained using the B-Tax model through the online Cost of Capital Calculator application. The calculator takes inputs on business tax parameters, such as business-entity level taxes, deductions and limitations on financing, as well as individual and payroll tax parameters. These inputs are automatically updated for the years between 2014 and 2029, according to past and current provisions, but can also be manually altered to test for changes in legislation or adapt inputs to fit previous years. Based on these values, the application runs simulations to calculate the net present value of depreciation deductions (z), the effective average tax rate (EATR), the marginal effective tax rate (METR) and the cost of capital (ϱ). Each of these measures is calculated three times, taking into account different forms of financing: all debt, all equity and a mix of both. These outputs are calculated for each industry and equipment, categorized using BEA standards.

While the outputs of the calculator aren't a perfect match for my analysis given the different assumptions made, the values for z are the most comprehensive and updated measures available. Since the role of financing does not play a role in my analysis, I utilize the values for z assuming a mix of debt and equity. I also opt for using the values of z per type of capital investment (equipment, structures and intellectual property). I make this decision because it better matches my calculation methodology, which consists of first calculating the cost of capital per type of investment and, later on, converting these values to industry-level cost of capital by using the sector's capital composition.

It's important to note that the values for z before 2014 are not available through the online application. They were obtained directly from the author of the online Cost of Capital Calculator, Jason DeBacker. Dr. DeBacker kindly offered to do the calculations for z-mix, based on the deduction policies from previous years, as well as other updated parameters. He provided the output for z-mix values between 2010-2013 categorized by type of investment. I combine these values with the direct output retrieved from the application for 2014-2019 to serve as the final z-values in my manual calculations of the cost of capital.

Cost of capital assumptions

The Cost of Capital Calculator provides estimates for the cost of capital per industry, which differ from the ones calculated in my research. This can be attributed to the different assumptions utilized by the application. Two important distinctions that explain the divergence in magnitude of the cost of capital estimates are the values used for the rate of return (*r*) and the rate of inflation (π). The model retrieves information for these parameters from the Congressional Budget Office's forecasts. While the values for the expected inflation don't vary much from the ones in my research, the estimates used for the rate of return are quite different. The application utilizes the following formula to calculate the after-tax rate of return:

$$r'_{m,j}-\pi=f_{m,j}[i-\pi]+(1-f_{m,j})E_j \quad (3)$$

In the formula above, $f_{m,j}$ represents the fraction of the marginal investment financed with debt by firms in industry m and of tax entity type j. Since this formula for the real rate of return is composed of the return on equity and return on corporate debt, the parameter ends up being much higher than the one used in my analysis. Consequently, the final estimates for the cost of capital are also much higher than the ones I utilize in my research.

Appendix VI - R-Package Commands for Multiple Linear Regression Variations

```
require(car)
source("http://www-personal.umich.edu/~hagem/data/summaryR.R")

alt <- read.csv("RALTDATA.csv")
#RALTDATA.csv contains 10 columns of data, including Year, Industry, GHG
#emissions, GHGP (annual percent change in GHG emissions), C (the average sector
#cost of capital), CP (annual percent change in sector cost of  capital), B (sector
capital
#stock of structures in trillions of USD), E (sector capital stock of equipment in trillions
#of USD), GOP (the annual change in sector gross output), GDP (the annual change in
#US Gross Domestic Output), I (the annual investment in capital per sector) and TCJA
#(a dummy that equals to 1 after 2017)

modelf1 <- lm(GHGP  ~ CP + B + E + I(CP*B)+ I(CP*E))
summary(modelf1)
summaryR(modelf1, type="hc0")

modelf2 <- lm(GHGP  ~ CP+ B + E + I(CP*B)+ I(CP*E) + GOP)
summary(modelf2)
summaryR(modelf2, type="hc0")

modelf3 <- lm(GHGP  ~ CP + B + E + I(CP*B)+ I(CP*E) + GOP + GDP)
summary(modelf3)
summaryR(modelf3, type="hc0")
```

```
#Residuals model 4
modelr<- lm(GDP ~ GOP)
summary(modelr)
res <- modelr$resid

modelf4 <- lm(GHGP  ~ CP + B + E + I(CP*B)+ I(CP*E) + GOP + res)
summary(modelf4)
summaryR(modelf4, type="hc0")

modelf5 <- lm(GHGP  ~ CP + B + E + I(CP*B)+ I(CP*E) + GOP + factor(Year))
summary(modelf5)
summaryR(modelf5, type="hc0")
```

Appendix VII - Calculation of the Net Effect of Changes in the Cost of Capital on Emissions

According to the regression equation developed, the total impact of changes in the average sector cost of capital on emissions is a function of two separate effects: the direct influence of policy changes to the cost of capital ($\Delta\varrho_{st}$) and its interactive impact with sector-specific characteristics (I($\Delta\varrho_{st} * B_s$) and I($\Delta\varrho_{st} * E_s$)).

$$\Delta GHG_{st} = \beta 1 * \Delta\varrho_{st} + \beta 2 * B_s + \beta 3 * E_s + \beta 4 * \Delta\varrho_{st} * B_s + \beta 5 * \Delta\varrho_{st} * E_s + X_{st}\, \Theta + u \qquad (2)$$

By taking the partial derivative of the equation above in terms of $\Delta\varrho_{st}$, it can be concluded that the effective impact of a change of 1 percentage point in the sector cost of capital varies by capital type, as shown in the table below.

Table A.5 - Net Effect of Changes in Average Cost of Capital on Emissions, per Capital Type

Capital Type	Net effect
Structures	$\beta 1 + \beta 4 * B_m$
Equipment	$\beta 1 + \beta 5 * E_m$
Intellectual Property	$\beta 1$

Note: This table shows the net effect of changes in the average cost of capital on emissions, for each of the three capital types. These values were calculated by taking the partial derivative of equation 2 in terms of $\Delta\varrho_{st}$.

In this case B_m and E_m represent the mean value of structures and equipment across all sectors and years, where B_m = 0.2365 and E_m = 0.0827. Based on the formulas shown in *Table A.5*, I calculate the net effect for each capital type across the 5 regression specifications. These results are further explained and interpreted in section VI.

Appendix VIII - Individual Sector Analysis of Changes in Emissions after TCJA

Table A.6 shows the coefficients and p-values for the regressions of each individual sector's annual change in emissions on a TCJA-dummy. While the bivariate regressions are not causal, they do show whether or not individual sectors experienced significant increases in emissions after TCJA.

Specification: $\Delta GHG_{st}= \beta 1 * TCJA_t + u_{st}$

Table A.6 - Results on Regressions of Annual Change in GHG Emissions on a TCJA-dummy, by Sector

Industry	Coefficient	Pr (> |t|)
Chemical products	-0.0157	0.59
Computer and electronics manufacturing	-0.0084	0.93
Educational services	0.0292	0.42
Electrical equipment manufacturing	0.1579	0.42
Fabricated metal products	-0.0147	0.78
Food processing	0.0182	0.23
Mineral products manufacturing	-0.0248	0.43
Mining	-0.0205	0.54
Oil and Gas extraction	0.0560	0.02*
Paper and Pulp	0.0028	0.78
Petroleum and coal products	0.0312	0.22
Pipeline transportation	-0.0065	0.50
Primary metals manufacturing	0.0561	0.20
Waste	0.0313	0.01*

Standard errors are shown in parentheses · $p < 0.1$ *$p < 0.05$ ** $p < 0.01$ *** $p<0.001$

Note: This table shows the coefficient and p-value for the regressions of annual change in sectoral GHG emissions on a TCJA dummy, which is equal to 1 starting in 2018. I used separate regressions for each of the 14 sectors. It is evident from the results that only 2 sectors experienced statistically significant increases in emissions after TCJA.
Source: EPA.

IX. References

Bureau of Economic Analysis. n.d. “Table 3: BEA Rates of Depreciation, Service Lives, Declining-Balance Rates and Hulten-Wykoff Categories.” Accessed March 12, 2021. https://apps.bea.gov/scb/account_articles/national/0797fr/table3.htm.

Bureau of Economic Analysis. n.d. “Fixed Asset Account Tables.” Accessed March 12, 2021. https://apps.bea.gov/iTable/iTable.cfm?ReqID=10&step=2.

Bureau of Economic Analysis. n.d. “Industry Economic Account Data: GDP by Industry.” Accessed April 3, 2021. https://apps.bea.gov/iTable/iTable.cfm?reqid=150&step=2&isuri=1&categories=gdpxind.

Bureau of Economic Analysis. 2016. “Depreciation of Business R&D Capital.” Accessed March 14, 2021. https://www.bea.gov/system/files/papers/WP2016-5.pdf.

Cruz, Luis, and José Dias. 2016. “Energy and CO2 intensity changes in the EU-27: decomposition into explanatory effects.” *Sustain.* Cities Soc. 26 486–95.

Duarte, Rosa, Alfredo Mainar, and Julio Sánchez-Chóliz. 2013. “The role of consumption patterns, demand and technological factors on the recent evolution of CO2 emissions in a group of advanced economies.” *Ecol. Econ.* 96 1–13.

Federal Reserve Bank of St. Louis. 2021. “10-Year Treasury Constant Maturity Rate.” Accessed March 16, 2021. https://fred.stlouisfed.org/series/DGS10.

Federal Reserve Bank of St. Louis. 2021. “Gross Domestic Product.” Accessed March 16, 2021. https://fred.stlouisfed.org/series/GDP.

Grossman, Gene, and Alan Krueger. 1995. “Economic Growth and the Environment.” *The Quarterly Journal of Economics*, 110(2), 353–377. https://doi.org/10.2307/2118443.

Grossman, Gene. 1995. *Pollution and Growth: What do we know?*. Cambridge: Cambridge University Press, pp 19–47.

Gupta, Shilpi. 2015. “Decoupling: a step toward sustainable development with reference to OECD countries.” *Int. J. Sustain. Dev. World Ecol.* 22 510–19.

Hall, Robert E., and Dale W. Jorgenson. 1967. “Tax Policy and Investment Behavior.” *The American Economic Review* 57 (June): 391–414.

Jones, Nicola. 2017. “How the World Passed a Carbon Threshold and Why It Matters.” *Yale Environment 360,* January 26, 2017. https://e360.yale.edu/features/how-the-world-passed-a-carbon-threshold-400ppm-and-why-it-matters.

LaPlue, Lawrence, and Christopher A. Erickson. 2019. “Outsourcing, trade, technology, and greenhouse gas emissions.” *Environmental Economics and Policy Studies* 22:217–245.

Liobiekene, Genovaite, and Mindaugas Butkus. 2018. “Scale, composition, and technique effects through which the economic growth, foreign direct investment, urbanization, and trade affect greenhouse gas emissions.” *Renewable Energy* 132 1310-1322.

Mankiw, Gregory. 2013. “A Carbon Tax That America Could Live With.” *New York Times*, August 31, 2013. https://www.nytimes.com/2013/09/01/business/a-carbon-tax-that-america-could-live-with.html.

Marron, Donald, and Eric Toder. 2014. “Tax Policy Issues in Designing a Carbon Tax.” *The American Economic Review* 104(5), 563-568.

Metcalf, Gilbert. 2021. “Carbon Taxes in Theory and Practice.” *Annual Review of Resource Economics* 13. https://doi.org/10.1146/ annurev-resource-102519-113630.

NASA. 2013. “Graphic: Carbon Dioxide hits new high.” Accessed February 7, 2022. https://climate.nasa.gov/climate_resources/7/graphic-carbon-dioxide-hits-new-high/.

Nordhaus, William D., Stephen A. Merrill, and Paul T. Beaton. *Effects of U.S. Tax Policy on Greenhouse Gas Emissions*. Washington, D.C.: National Academies Press, 2013.

Nordhaus, William D. *The Climate Casino: Risk, Uncertainty, and Economics for a Warming World*. New Haven: Yale University Press, 2013.

Panayotou, Theodore. 1997. “Demystifying the environmental Kuznets curve: turning a black box into a policy tool.” *Environment and Development Economics* 2:465–484.

Streimikiene, Dalia, and Tomas Balezentis. 2016. “Kaya identity for analysis of the main drivers of GHG emissions and feasibility to implement EU ‘20-20-20’ targets in the Baltic States.” *Renew. Sustain. Energy Rev.* 58 1108–13.

Sugiawan, Yogi, and Shunsuke Managi. 2016. “The environmental Kuznets curve in Indonesia: exploring the potential of renewable energy.” *Energy Pol.,* 98 187-198.

Tax Foundation. 2021. “Details and Analysis of President Biden’s American Jobs Plan.” Accessed January 7, 2022. https://taxfoundation.org/american-jobs-plan/.

Treasury Direct. 2021. “TIPS/CPI data.” Accessed March 31, 2021. https://www.treasurydirect.gov/instit/annceresult/tipscpi/tipscpi.htm.

Tsurumi, Tetsuya, and Shunshuke Managi. 2009. “Decomposition of the environmental Kuznets curve: scale, technique, and composition effects.” *Environmental Economics and Policy Studies* 11: 19–36.

United States Environmental Protection Agency. 2018. “Greenhouse Gas Customized Research.” Accessed February 5, 2021. https://www.epa.gov/enviro/greenhouse-gas-customized-search.

United States Environmental Protection Agency. 2017. "Global Emissions by Economic Sector." Accessed February 15, 2021. https://www.epa.gov/ghgemissions/global-greenhouse-gas-emissions -data.

United States Environmental Protection Agency. 2021. "Inventory of U.S. Greenhouse Gas Emissions and Sinks." Accessed February 7, 2022. https://www.epa.gov/ghgemissions/inventory -us-greenhouse-gas-emissions-and-sinks.

Wall Street Journal. 2019. "Economists' Statement on Carbon Dividends." Accessed February 7, 2022. https://clcouncil.org/economists-statement/.

Xu, Xianshuo, Tao Zhao, Nan Liu, and Jidong Kang. 2014. "Changes of energy-related GHG emissions in China: an empirical analysis from sectoral perspective." *Appl. Energy* 132 298–307.

Yale School of the Environment. 2021. "The Social Cost of Carbon is Still The Best Way to Evaluate Climate Policy." Accessed February 7, 2022. https://environment.yale.edu/news/article/social-cost-of-carbon-still-best-way-to-evaluate-climate-policy.