UNINTENDED TRAGEDY OF THE COMMONS? AN EVALUATION OF ENERGY USAGE ON HIGHER EDUCATION CAMPUSES WITH CARBON NEUTRALITY GOALS

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Abstract

Climate change is a feedback loop of inequality – both a cause and effect on a global scale. The impacts of which such as rising sea levels, increased incidents of natural disasters, and altered weather patterns disproportionately impact developing countries and vulnerable populations. Climate change is fundamentally caused by consumption – resource-intense lifestyles in rich Western countries. Higher education embraced its role as a leader in the response to climate change through sustainability declarations, such as the Climate Commitment and its carbon neutrality goal. But with a history of failed sustainability declarations, how do we know the Climate Commitment is effective and reduces energy consumption behavior? Using data from 119 higher education institutions in the US, this study builds on behavioral economic energy modelling to predict the likelihood an institution signs onto the Climate Commitment, and how energy usage per capita changes afterward. While the study finds that energy consumption decreases on Climate Commitment campuses between the baseline and performance years, the widespread distribution warrants further investigation into the matter.

KEYWORDS: (Carbon Neutrality, Energy Consumption, Higher Education, Commitment, Climate Change, Implementation Effectiveness)
JEL Codes: (Q4, C5, L390)

ON MY HONOR, I HAVE NEITHER GIVEN NOR RECEIVED UNAUTHORIZED AID ON THIS THESIS

Signature :
____Emily Abbott______________

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Variable Summary Guide

Variable	Description
a	Area of campus (acres)
aw	Area of campus per capita (acres/person)
C	Carbon Neutrality (Dummy)
DIFF	*pecpaw* – *ecbaw* (MMBtu/person)
DIFFN	*pecpaw* – *ecbaw* < 0 (MMBtu/person)
DIFFP	*pecpaw* – *ecbaw* > 0 (MMBtu/person)
eb	Area of LEED certified buildings (sq. ft.)
ebw	Area of LEED certified buildings per capita (sq. ft./person)
ecb	Energy consumption on campus in the baseline year, not including transportation (MMBtu)
ecbw	Energy consumption on campus in the baseline year, not including transportation per capita (MMBtu/person)
ecbaw	Energy consumption on campus in the baseline year, not including transportation per capita when C = 1 (MMBtu/person)
ecp	Energy consumption on campus in the performance year, not including transportation (MMBtu)
ecpw	Energy consumption on campus in the performance year, not including transportation per capita (MMBtu/person)
ecpaw	Energy consumption on campus in the performance year, not including transportation per capita when C = 1 (MMBtu/person)
pecpaw	Predicted energy consumption on campus in the performance year, not including transportation per capita when C = 1 (MMBtu/person)
en	Endowment (USD)
enw	Endowment per capita (USD/person)
ep	Enrollment pressure (enrollment rate)
cdd	Cooling degree days
fcdd	*f* * *cdd*
fcddw	*(f* * *cdd)/n*
hdd	Heating degree days
fhdd	*f* * *hdd*
fhddw	*(f* * *hdd)/n*
fe	Feasibility (Dummy for renewable energy)
f	Area of buildings on campus (sq. ft.)
fw	Area of buildings per capita (sq. ft./person)
l	Leadership (Dummy for sustainability office)
n	People on campus (students, faculty and staff)
rc	Renewable energy generated on campus (MMBtu)
rcw	Renewable energy generated on campus per capita (MMBtu/person)
ro	Renewable energy generated off campus (MMBtu)
row	Renewable energy generated off campus per capita (MMBtu/person)
sca	Social capital variable A (Reverse Princeton Green College Rankings)
scb	Social capital variable B (Princeton Review Green College List)

t	Time since joining Climate Commitment (years)
t^2	$t * t$
varC	Variable when C = 1
varNC	Variable when C = 0

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INTRODUCTION

1.A Climate Change and Higher Education

Climate change is everywhere: it's in the news, on campus, and the hottest topic of conversation for any family gathering. The academic community agrees that global climate change is a major and unprecedented challenge for civilization. Climate change is an anthropogenic phenomenon wherein burned fossil fuels release Greenhouse Gases (GHGs) into the atmosphere, causing a rise in the average global surface temperature (Dow & Downing, 2006, p. 37). Climate change is fundamentally due to consumption – the resource-intense lifestyles in typically richer and Western societies (Shove, 2014). The International Panel on Climate Change (IPCC) determined that the accumulation of GHGs in the atmosphere resulted from the growing use of energy and the expansion of the global economy during the 20th century, mostly by what are now considered developed countries (Fifth Assessment Report, 2014).

Climate change is a feedback loop of inequality – both a cause and an effect on a global scale. While developed countries profit from the expanding global economy, changes such as rising sea levels, increasing incidents of natural disasters, and altered weather patterns disproportionately impact developing countries and vulnerable populations (Flannery, 2005, p. 199). While even the ancient Greeks suspected that humans could change the local environment, academic institutions are influential in climate change research – they posit and prove the phenomenon, and continue to contribute to the discourse (Weart, 2008). As a pioneer of research, and developer of future professionals and leaders, higher education institutions are critical stakeholders in the response to climate change and the development of a more environmentally sustainable society (Dyer & Dyer, 2014, p. 111).

Sustainability refers to a philosophy that emphasizes the connection between human society, the economy and the natural environment (Caradonna, 2014, p. 12). Many colleges first embraced sustainability in the 1960's by fostering environmental education. By the 1990's, higher education institutions broadened their approach, and began to publicize sustainability declarations, which expressed commitments to intergenerational responsibility as, "universities bear profound responsibilities to increase the awareness, knowledge, technology and tools to create an environmentally sustainably future" (Corcoran et al, 2007, p. 8; University Leaders for a Sustainable Future, 1990, p. 1). One sustainability initiative announced in 2006 is the Presidents' Climate Leadership Commitment (formerly known as ACUPCC - American College & University Presidents' Climate Commitment; hereinto referred as the Climate Commitment).

1.B Climate Commitment and Carbon Neutrality

The Climate Commitment is a highly-publicized declaration designed to scale-up sustainability leadership within higher education and establish environmentally-conscious role models for American society. The Commitment represents the addition of sustainable practices within higher education, "the university can both engage students in understanding the institutional metabolism of materials and activities, and have them actively participate to minimize pollution and waste" (USLF, 1990 retrieved from Wright, p. 10). Climate Commitment institutions create environmental action plans, establish an institutional implementation structure responsible for sustainability commitments, and conduct GHG emissions inventories (Dyer & Dyer, 2017, p 112). An integral piece of the Climate Commitment is carbon neutrality, "carbon neutrality and resilience are extremely high priority areas of action for all institutions and we aim to lead the nation in these efforts" ("The Presidents' Climate Leadership Commitments").

Carbon neutrality is a concept in which an organization does not have a net contribution of GHG emissions to the atmosphere through an equal release and sequestration of carbon dioxide. Achieving carbon neutrality involves calculating an organization's total GHG emissions, reducing fossil fuel consumption, implementing renewable energy, and balancing the remaining emissions through carbon offsets (Selman, 2010, p. 158).

As a market-tool, carbon offsets represent the reduction or sequestration of GHG emissions elsewhere through projects such as reforestation or forest conservation. Organizations buy carbon offsets from these projects and use offsets to detract from their own GHG emissions (Trexler & Kosloff, 2006, p. 34). Many established institutions are connected to the grid and source their energy from utility companies, making it difficult to completely discontinue fossil fuel use. This dependence makes carbon offsets instrumental for achieving carbon neutrality (Selman, 2010).

Another tool for achieving carbon neutrality are the multiple scopes of emissions in calculating organizational carbon footprints, established by the World Business Council for Sustainable Development and the World Resource Institute:

- Scope 1: direct sources of emissions that are owned or controlled by an institution.
- Scope 2: emissions associated with the generation of imported sources of energy, such as purchased electricity.
- Scope 3: all other indirect sources of emissions that could result from the activities of an organization, but these sources are owned or controlled by another entity (Willson & Brown, 2008, p. 498).

These distinctions help institutions determine strategic and actionable plans for reduction. By specifying between different emission sources, organizations can determine easy and cost-effective methods for emissions reductions (I. Johnson, personal communication, October 29, 2018). Scope 2 emissions – specifically purchased electricity – are paramount for reductions as they account for nearly half of all emissions on university campuses (Sinha, Schew, Sawat, Kolwait & Strode 2010, p. 570) Scopes 1 and 2 are focal areas for emissions reductions in higher education, as the institution has direct power over those decisions. It is these areas that must be grappled with since Scope 3 is an indirect result of the institution and more difficult to reduce. These tools are essential in the trying to achieve carbon neutrality.

1.C Implementation of Sustainability Declarations

The 1990 Talloires Declaration was the first international declaration to focus on sustainability in higher education. Tallories stressed that universities should 'practice what they preach' by implementing sustainability on campus. A recent sustainability declaration, the 2016 We Are Still In campaign, includes American cities, states, businesses and schools that will try to uphold the international Paris Climate Accord, despite the lack of federal governmental participation[1]. Higher education institutions have joined or declared goals focusing on sustainability in education, research, campus operations, and community outreach (USLF, 1990). Though declarations tackle sustainability issues through these different means, all sustainability declarations address one underlying theme: the unjustifiable levels of consumption in developed countries.

Most sustainability declarations fail. Since sustainability declarations are non-binding and voluntary mechanisms, institutions are not held accountable for the goals that they set. Institutions struggle to set clear goals and/or appropriate implementation strategies to achieve their objectives (Grinsted, 2011, p. 29). Many universities will adopt a pre-established strategy within the network of a specific declaration, even if that strategy is inappropriate for that institution.

[1] https://www.wearestillin.com/about

The 2012 Hallifax Declaration intended to provide long-term goals and action frameworks applicable to colleges and universities. However, analysis indicates that the Hallifax Declaration's suggestions were irrelevant and largely ineffective on individual campuses. In addition, the declaration's network provided little help to institutions that publicized their sustainability goals (Wright, 2004, p. 10).

Although many sustainability declarations differ in terms of objectives and implementation strategies, they attempt to address the true cause of climate change – consumption (Wright, 2004). Like other declarations, the Climate Commitment provides reporting tools and guidance for its member institutions. However, this precedent of highly publicized yet unsuccessful sustainability declarations calls into question the effectiveness of the Climate Commitment and carbon neutrality goals.

While evaluating the results of these declarations, it is necessary to consider the possibility of unintended consequences in signing onto and implementing highly publicized sustainability declarations. Which begs the question: as colleges and universities under the Climate Commitment begin to reduce fossil fuel use, implement renewable energy, and buy carbon offsets, does the institution use more energy per capita? This study aims to investigate if and how energy usage changes on higher education campuses after signing onto the Climate Commitment and declaring a carbon neutrality goal.

1.D Purpose and Significance of Study

This study explores sustainability implementation on higher education campuses. Specifically, the paper sets out to understand why higher education institutions choose to join groups like the Climate Commitment, as well as if and how energy usage changes after joining.

The findings of this study are critical for sustainability in higher education, and can inform future implementation of highly publicized declarations.

This paper finds that on average, higher education institutions with carbon neutrality goals use less energy per capita in the performance year than the baseline year. This suggests that carbon neutrality goals, and previous implementation strategies are effective in reducing GHG emissions as well as energy consumption. However, there is a wide distribution: some institutions use less energy, and some institutions use more energy. The schools that use more energy after adopting a carbon neutrality goal tend to be smaller, with fewer total people on campus, and have larger endowments per person.

This study suggests that while the overall trend of energy consumption on Climate Committed campuses is a decreasing one, individual institutions must examine their own unique energy consumptive behaviors and, if necessary, create strategies to tackle wasteful energy consumption.

LITERATURE REVIEW

In the past, higher education has primarily focused on teaching aspects of sustainability, integrating the philosophy into its curriculum. Lozano et al. (2015) found that within sustainability, higher education schools neglected to actually implement practices on campus through actions to reduce consumption and emissions. However, in 2006 the higher education sector embraced their leadership position in addressing climate change by establishing the Climate Commitment, a long-term decision to achieve carbon neutrality (Sinha et al, 2010). Through this, institutions establish their own target date for achieving carbon neutrality and evaluate progress through greenhouse gas emissions inventories (Dyer & Dyer, 2017).

2.A: Higher Education and the Climate Commitment

Young students are more likely to have concern for environmental issues, and pressure their institutions to incorporate sustainability in the school's identity. Heslop, Morian and Courineau (1981) found that consumers who express more concern for conservation are likely to be white, younger, educated, with higher incomes and socioeconomic statuses.

In his investigations of moral philosophy, Haidt (2012) found that college students in the US are WEIRD (western, educated, industrialized, [globally] rich and democratic) compared to other communities around the world. WEIRD societies have narrow moral domains. This suggests that there is very little leeway for the "right" opinions and actions on campus (Haidt, 2012). Applying this to environmental issues, conservation behaviors are deemed "right" and wasteful behaviors are "wrong".

Cultural psychology suggests that "culture and psyche make each other up", so that a school is developed and shaped by the students, while the students are developed and shaped by the school (Haidt, 2012, p. 113)**.** Students want their institutions to embrace their moral values, such as environmental concern. Jameleske et al (2015) found that that 76.2% of US college students believe that climate change is real, and expressed the need for a substantial coordinated response. Students want their schools to reflect their values through sizable actions (Jacob et al, 2019). Schools are willing to invest in these actions by voluntarily joining sustainability commitment groups.

Higher education leaders attempting to address complex issues, such as climate change, are aware that multiple stakeholders need to be engaged in a cross disciplinary systems approach. Son (2016) found that organizations, like individuals, join groups to achieve common goals. The Climate Commitment group provides an opportunity for institutions to collaborate, "the ACUPCC [Climate Commitment] founders understood that individual institutional action is necessary, but not sufficient to address climate change and other global sustainability challenges. Collaboration is required both within and between sectors" (Dyer & Dyer, 2017, p. 113). Organizational groups, such as the Climate Commitment, are useful for communicating complex knowledge and promote diverse and innovative thinking between members (Tekansi & Chesmore, 2003). Higher education institutions join these associations because they foster creative thinking and collaboration among institutions, who are working toward a common goal.

Many organizations are incentivized to join associations because of the services provided to members (Bennett, 2000). Groups provide high levels of structure and support to members while representing the collective interests of the whole (Battisti, 2015). Associations give member enterprises legitimacy with external parties, and provide expertise to members (Dalziel, 2006; Spillane, Healey & Chong, 2010). Structured groups provide a sustainable network and increase accountability for institutions (Coburn, Choi & Mata, 2010). Like others, sustainability associations provide these services for higher education institutions.

Second Nature and AASHE, the two organizations that facilitate the Climate Commitment, play a unique role in promoting and implementing sustainability within the higher education sector. These organizations consult with Climate Commitment institutions, provide expertise, and create a transparent social network for colleges and universities to communicate through to tackle environmental issues. The Climate Commitment legitimizes institutional commitments to carbon neutrality, provides organization, support, and opportunities for networking and collaboration to members. By mandating annual GHG inventories, the Climate Commitment attempts to provide structure, ensure transparency, and hold institutions accountable for their carbon neutrality goals.

2.B: Modelling Energy Consumption

Much of the economic literature that models energy consumption uses a neoclassical approach at the household level. Control variables are limited to physical and extrinsic factors such as area of a house, number of rooms, number of family members, price of energy and other financial incentives (Van Raaij & Verhallen, 1983)**.** This rational choice model assumes that individuals objectively weigh the costs and benefits of alternatives before choosing the optimal course of action (Frederiks, Stenner & Hobman, 2015). This neoclassical approach models for *Homoeconomicus,* a theoretical entity that resembles the textbook image of humans offered by economics, which assumes that people think and choose rationally and well (Thaler & Sustein, 2009). Following the rational choice model, consumers will only perform energy conservation behaviors when they are economically advantageous (Costanzo, Archer, Aronsen & Pettigrew, 1986). However, the academic community agrees that people do not behave like this in reality; there are other intrinsic factors that motivate behavior (Thaler and Sustein, 2009). Therefore, the model of energy consumption should reflect this, and incorporate social-psychological processes (Costanzo et al, 1986).

A purely attitudinal model of energy consumption assumes that conservation behavior follows from favorable attitudes towards sustainability (Constanzo et al, 1986). However, studies show that programs intending to promote sustainable behavior by disseminating information are ineffective. Blake (1999) theorizes that this is due to a Knowledge- and Value-Action Gap. In that an individual's actions are not informed by their knowledge or values (Blake, 1999). This disconnect supports the notion that attitudes and actions do not have a strong, direct or consistent relationship (Costanzo et al, 1989). Ohler and Billger (2014) argue that in energy usage, consumers must choose between self-interests, motivated by production and consumption of private goods (ex: concern over comfort and electricity costs) and social-interests, motivated by common goods (ex: concern over clean air and climate change mitigation). Due to these competing interests, scholars have found that pro-environmental attitudes do not consistently lead to pro-environmental behaviors, especially in regards to energy conservation (Ohler and Billger, 2014).

So if an individual's attitude and beliefs do not impact their behavior, what does? Financial incentives? Setting specific intentions? The academic community has determined that communicating descriptive norms through social diffusion changes individual consumer behavior. Descriptive norms inform consumers about the prevalence of certain behaviors among their peers and provide suggestions about effective adaptive behavior to motivate change (Schubert, 2017; Frederiks et al, 2015). Schultz el al (2007) suggest that descriptive norms act as a standard from which others do not wish to deviate. Individuals evaluate their own performance by comparing themselves to others, and conform to the prevailing descriptive norm (Frederiks et al, 2015). Social diffusion models effective behavior, and produces reinforcements and payoffs for that behavior (Costanzo et al, 1989). Social comparisons thus encourage a competition that rewards those who score best in light of that descriptive norm (Costanzo et al, 1989).

However, descriptive norms act as a magnet of behavior, drawing from below and above the norm to the average, which causes a Boomerang Effect (Schultz et al, 2007). When given information about a gray behavior, such as energy consumption, people increase their own propensity for what they perceive to be the average for that behavior (Schubert, 2017). The Boomerang Effect suggests that when given information about energy consumption among their peers, an individual's behavior will converge to that norm. So, individuals with high initial consumption would decrease their usage, and individuals with low initial consumption would increase their usage – both sides change their behavior to the average (Allcot, 2011).

The limited modelling of energy consumption in the higher education sector follows a neoclassical approach. This methodology, similar to the rational behavior model for individual energy consumption, factors in physical and extrinsic explanatory variables for energy consumption. This method includes explanatory variables such as the gross internal area of residential and nonresidential buildings, heating degree days, and price of energy (Wadud et al, 2019). This study is the first to explicitly apply individual energy usage behavior to higher education institutions to create a more realistic model of energy consumption on college campuses.

Anyone who has ever joined a gym knows that membership does not directly lead to working out more often. Several studies have shown that signing onto a commitment does not actually lead to any sort of follow-through (Della Vigna & Malmendier, 2006). Bekessey et al. (2007) found that signing a sustainability declaration does not ensure that it is fully implemented.

Theoretically, a higher education institution could achieve carbon neutrality by implementing renewable energy, purchasing carbon offsets and utilizing energy efficiency technologies without changing their energy consumption behavior. This paper aims to fill a gap in the literature, by utilizing behavioral theory in a model of energy consumption to determine the effect of declared carbon neutrality goals on higher education campus energy usage.

THEORY AND MODEL

This section discusses the economic theory employed in developing the following model. The model determines the likelihood a higher education institution joins the Climate Commitment, as well as the energy usage on campuses after joining that group. The Climate Commitment group is used to represent a network of institutions that have established carbon neutrality and climate resiliency goals. Drawing from Ohler and Billger's (2014) study of conservation behaviors and residential energy consumption, this paper uses Heckman Two-Step Selection to model energy consumption at higher education campuses with carbon neutrality goals. The Heckman Model is utilized for estimating regression models that suffer from selection bias.

Stage One is a probit equation based on a normal distribution. Stage One models the likelihood that an institution joins the Climate Commitment. This analysis is carried out for institutions with and without carbon neutrality goals, and is necessary to avoid selection bias. Selection bias is present in the sample as the higher education institutions who declare carbon neutrality goals are self-selecting rather than random. If left uncorrected, selection bias skews the model, as the coefficients for explanatory variables, which represent the relationships of explanatory variables with the dependent variable, would be incorrect. These skewed coefficients would not accurately represent the significance of each explanatory variable in relation to energy consumption on Climate Commitment campuses.

Stage Two of this model calculates energy usage per capita on higher education campuses that have joined the Climate Commitment. The second stage utilizes the Inverse Mills Ratio, a statistical term calculated in Stage One, that can be added to a multiple regression model to remove sample selection (Woolridge, 2009).

The Inverse Mills Ratio is added as an explanatory variable in Stage Two, and adjusts the coefficients of other explanatory variables appropriately. Heckman utilized the Inverse Mills Ratio to correct for selection bias by treating selection bias as omitted-variable bias. Omitted variable bias occurs when a model fails to include one or more relevant explanatory variables. By adding the Inverse Mills Ratio (which represents a decreasing function of the probability that an institution is selected into the sample for Stage Two) as an explanatory variable, we seek to correct for censoring (Heckman, 1979). The results of Stage Two are informative for the self-selecting sample through this treatment.

3.A. Variable Section

3.A.I Stage One: Probability of Declaring Carbon Neutral Goals

The probability of a higher education institution declaring a carbon neutrality goal is represented by the probability that an institution joins the Climate Commitment. Given that there are a variety of factors that influence the likelihood that an institution declares a carbon neutrality goal, the probit is modeled as follows:

$$Prob\ (C = 1|Z) = \Phi(Z\gamma)$$

Where C indicates the institution's relationship to the Climate Commitment, Z represents a vector of explanatory variables, γ is a vector of unknown parameters, and Φ is the cumulative distribution function of a standard normal distribution. This probability is calculated into a value of 1 or 0: 1 represents an institution that has joined the Climate Commitment (and declared a carbon neutrality goal) and 0 represents an institution that has not joined the Climate Commitment (and does not have a declared carbon neutrality goal). The vector of explanatory variables can be expanded to:

$$Z = g\ (en, sp, ep, l, fe, ce, sca, scb)$$

This vector of explanatory variables suggests that the decision for a higher education institution to join the Climate Commitment and subsequently declare a carbon neutrality goal is dependent on multiple factors including the institution's endowment (en), student pressure (sp), enrollment pressure (ep), leadership (l), feasibility (fe), cost of energy (ce) and two variables for social capital (sca and scb). Incorporating these explanatory variables into the probit, the expanded function is:

$$Prob\ (C = 1 | g\ (en, sp, ep, l, fe, ce, sca, scb)) = \Phi[g\ (en, sp, ep, l, fe, ce, sca, scb)\gamma]$$

So that the probability an institution joins the Climate Commitment is based on the explanatory variables in vector Z, unknown parameters (γ) and the cumulative distribution function (Φ). The cumulative distribution function is later used to calculate the Inverse Mills Ratio.

3.A.II Stage Two: Energy Usage on Higher Education Campuses in Climate Commitment

Stage Two of the model calculates energy usage on higher education campuses that joined the Climate Commitment group – institutions that when modeled in Stage One, result in 1. Drawing from the precedent set by Heckman (1979), the model that represents energy usage per capita may be specified as:

$$e^* = H\beta + u$$

Where $e^*$is the energy usage that is not observed if institutions do not join the Climate Commitment group, H is a vector of explanatory variables and u represents the unobserved determinants of energy usage. Drawing from Wadud, Royston and Selby (2019) the vector of explanatory variables for Stage Two can be expanded to:

$$H = [h\ (ebw, fw, aw, rcw, row, t, t^2, fhddw, fcddw)]$$

Vector H is a function where ebw is the energy efficiency of buildings on campus per capita, fw is the total area of building space in square feet per capita, aw is the area of campus in acres per capita, rcw is renewable energy generated on campus per capita, row represents renewable energy generated off-campus but utilized on campus per capita, t is time in years since joining the Climate Commitment, t^2 is a quadratic function of the time in years since an institution has joined the Climate Commitment, f$hddw$ is an interaction variable between the area of building space and the number of heating degree days for the school per capita, and $fcddw$ is an interaction variable between the area of building space and the number of cooling degree days for the school per capita. This paper evaluates energy usage per capita to ensure that increases in energy consumption cannot be attributed to factors such as a growing student body or institutional expansion.

The expectation of energy usage is conditional to the institution's status with the Climate Commitment, which is shown as the following:

$$E[e|H, C = 1] = H\beta + E[u|H, C = 1]$$

Since the energy usage is conditional upon an institution's relationship with the Carbon Commitment, the unobserved determinants of energy usage (u) is conditional upon an institution's Climate Commitment Status as well. Assuming that the error terms are jointly normal:

$$E\,[e|H, C = 1] = H\beta + \rho\sigma_u\lambda(Z\gamma)$$

Where ρ represents the correlation between the unobserved determinants of the propensity to use energy (ε) and the unobserved determinants of energy usage (u), σ_u is the standard deviation of u, and λ is the Inverse Mills Ratio calculated at $Z\gamma.$

The Inverse Mills Ratio is calculated as follows:

$$\lambda_{i,} = \phi(C)/\Phi(C)$$

The Inverse Mills Ratio, generated from Stage One, is the ratio of the probability density function (ϕ) to the cumulative distribution function (Φ). The Inverse Mills Ratio is incorporated as an explanatory variable in Stage Two to correct the coefficients of other explanatory variables.

Fully expanded, the equation for calculating energy usage on campus is:

$$E\ [e|H, C = 1] = h\ (ebw, fw, aw, rcw, row, t, t^2, fhddw, fcddw) +\ \rho\sigma_u\lambda(Z\gamma)$$

So that energy consumption on campuses that have joined the Climate Commitment are a function of the explanatory vector H, the correlation between the unobserved determinants of the propensity to use energy and the unobserved determinants of energy (ρ), the standard deviation of the unobserved determinants of energy (σ_u), and the Inverse Mills Ratio (λ).

DATA & METHODOLOGY

This section discusses the data and methodology used in this econometric analysis. The data used in this analysis were compiled from the following sources: AASHE, Second Nature, Princeton Review Green College Rankings, Princeton Review Green College List, Princeton Review Complete Book of Colleges, and Weather Data Depot. Some additional data were collected from individual institution websites as well. This dataset contains observations for 119 higher education institutions in the United States. Several variables and proxy variables were constructed and refined for the purpose of this analysis. This section will outline how the dataset was compiled, manipulated, tested and analyzed given several assumptions.

4.A Institutions

This data set contains non-panel data. The schools included in this dataset are all members of and report to AASHE. The data was refined by deleting duplicates, schools located outside of the United States, and schools with incomplete data. Some institutions reported twice for the same performance year with different values. In this case, a third "institution" was created, and averaged data from the two unique responses. The first two entries were then removed from the dataset so as to not over-represent specific institutions. This dataset contains information for schools of all institution types ranging from Associates to Doctoral and Research programs. 73% of these schools are members of the Climate Commitment and have carbon neutrality goals. Table 4.1 breaks down the distribution of institution types, and their Climate Commitment status. As shown in Table 4.1, 46% of Climate Commitment institutions have Doctoral and Research programs. With the exception of Baccalaureate institutions, there is a fairly even distribution among institution types in terms of Climate Commitment status.

Table 4.1

Institution Type and Climate Commitment

Carbon Neutrality	Associate	Baccalaureate	Doctoral	Master	Grand Total
0 (No Climate Commitment)	3	19	38	14	74
1 (Climate Commitment)	5	33	53	24	115
Grand Total	**8**	**52**	**91**	**38**	**189**

This dataset contains explanatory variables and data for the performance year. However, data for explanatory variables for the baseline year were not available. The baseline year represents the year that each institution began reporting to AASHE. Each institution began reporting at different points in time, so that the difference in years between performance year and baseline year are unique for each school.

4.B Stage One Variables

The first stage of the Heckman model calculates the decision a higher education institution makes to join the Climate Commitment. As there is limited econometric modelling for this specific type of decision, the following explanatory variables were determined by the author, with the guidance of Professor Daniel Johnson.

The explanatory variables employed in Stage One are: an institution's endowment, the cost of energy, student pressure, enrollment pressure, leadership, feasibility, and social capital. Variables such as enrollment pressure, student pressure, leadership, feasibility and social capital do not have intuitive values. Proxies were constructed for these variables and are explained further in the section.

The dataset does not have information for the cost of energy. This variable is included in the model as it may motivate schools to invest in technologies such as energy efficiency, renewable energy and perhaps the Climate Commitment. However, data for this variable were not available, and could not be included in neither the dataset, nor the regression.

An institution's endowment represents a pool of money and financial assets that are invested and grow in principal to provide additional income for future investing or expenditures (Phung, 2017). The endowment (*en*) was included in this model as a means of expressing the school's monetary resources which could be available for investing in sustainability. Table 4.2 shows that the average endowment for an institution in this dataset is approximately $1.3 billion USD. Table 1 in Appendix A breaks down the endowment variable by Climate and Non-Climate institutions, and shows that the median endowment for a Non-Climate institution is larger than the median Climate endowment. 188 out of the 189 institutions in the dataset reported their endowment value. We then found and employed per capita endowment (*ecw*) to represent the wealth and potential financial assets for institutions to invest per person.

The enrollment pressure variable (*ep*) is included in this model as it represents the stress an institution may feel if it is unable to fill classrooms. *ep* is proxied by an institution's enrollment rate, which is the percentage of admitted students that enroll at the institution collected from the Princeton Review's Complete Guide to Colleges. The average and median enrollment rates are higher at Non-Climate institutions (Table 1, Appendix A).

The student pressure variable, *sp,* represents the influence of student advocacy on administrative decisions. *sp* is proxied by a dummy variable for active environmental action student groups: 1 represents an institution with an active group on campus, and 0 represents an institution without an active group. This data was compiled from the AASHE database, as well as individual institution websites. *sp* is included in the model, as environmental student groups may persuade the administration to join the Climate Commitment. As demonstrated in Table 4.3, over 90% of institutions in the dataset have active sustainability student groups. As shown in Descriptive Statistics 3 of Appendix A, this is split evenly between Climate and Not Climate Institutions.

The leadership variable, *l*, represents the effect leadership has on the decision to join the Climate Commitment. *l* is proxied by a dummy variable, which represents if an institution has at least one sustainability office that includes more than one full-time employee. An institution is assigned the value of 1 if they meet this criteria, and assigned 0 if they do not. *l* is intended to represent if the institution has the leadership capabilities that are required to join the Climate Commitment and hopefully implement the carbon neutrality goal. Table 4.3 demonstrates that 87% of institutions in the dataset have sustainability offices.

The feasibility variable (*fe*), like leadership, is included in the model to represent if an institution has the capabilities to join the Climate Commitment and make a carbon neutrality goal. *fe* is proxied by a dummy variable, which indicates if an institution owns renewable energy generators on or off campus. This is an appropriate proxy, as an institution that has already invested in renewable energy may be more likely to join the Climate Commitment than an institution that has not. Over 80% of institutions in this dataset have already invested in renewable energy.

Social capital represents what an institution would receive (services, publicity, etc.) from joining the Climate Commitment. In this model, social capital is proxied by two variables: *sca* and *scb.* These are appropriate proxy variables as they represent the recognition that schools receive when they join sustainability initiatives such as the Climate Commitment.

Social capital variable A, (*sca*) is proxied by the Princeton Review's Top 50 Green College Ranking. The rankings are informed by institutional data and survey questions that cover factors such as the health and sustainability of campus life, the preparation of employment for students in a green economy, and the environmental responsibility of school policies ("Top 50 Green Colleges Methodology). The proxy variable was constructed by reverse ordering the college rankings and adding one to that value. One was added to differentiate between the last school on the list, and schools in the dataset that did not appear on that list. For example, the school that was ranked first of the Green College Rankings, was assigned a value of 51, while the school that was ranked 50^{th} on the list was assigned a value of 1. Schools in the dataset that did not appear on the list were assigned values of 0. Most of these ranked schools are Climate Commitment institutions. Some of the higher ranked schools are not Climate Commitment Institutions (Table 1, Appendix A).

Social capital variable B, (*scb*) is proxied by a dummy variable for the Princeton Review's List of Green Colleges. The list features 322 out of 2,000 schools evaluated. The schools were determined using the methodology above as well, and are listed in alphabetical order but not ranked. If institutions in the dataset are on the List of Green Colleges, they are assigned a value of 1, if they are not they are assigned a value of 0. Approximately 83% of institutions in this dataset appear on the list.

Table 4.2
Stage One Continuous and Discrete Variables

Variable	Description	Mean	Median	Std. Dev.	Min	Max
en	Dollar amount of endowment	1.32e+9	2.68e+8	3.55e+9	9,899	2.64e+10
ep	Admission enrollment rate	0.3306	0.29	0.1843	0.11	0.95
sca	Reverse order Green College Ranking	4.28	0	11.371	0	51

Table 4.3
Stage One Dummy Variables, Vector Z

Variable	Description	Mean	Std. Dev.	Frequency (%)	
				1	0
sp	Value = 1 if active group, 0 if otherwise	0.926	0.263	92.60	7.40
l	Value = 1 if sustainability staff, 0 if otherwise	0.862	0.345	86.20	13.80
fe	Value = 1 if own renewable energy, 0 if otherwise	0.809	0.394	80.90	19.10
scb	Value = 1 if on Green College List, 0 if otherwise	0.831	0.831	83.10	16.90

4.C Stage Two Variables

The second stage of the Heckman model calculates energy consumption for Climate Commitment institutions in the performance year. This stage of the model is informed by behavioral theory of individual energy consumption and neoclassical models of higher education energy usage.

The model shows that energy consumption in the performance year for institutions with carbon neutrality goals includes vector *H,* a function of explanatory variables. Institutions reported data on energy consumption excluding transportation in the performance year, area of buildings in square feet, area of campus in acres, renewable energy generated on campus owned by the institution, and renewable energy generated off campus, utilized on campus and owned by the institution. These variables were then divided by the reported number of students, faculty and staff (*n*), creating the explanatory variables used in the model which are measured per capita of each institution. Two interaction variables were created for the purpose of this model: *fhddw* and *fcddw*.

Degree days (*dd*) are a measurement that quantifies the energy needed to heat or cool a building. Degree days are a measure of the outside temperature on a given day or period of days. This is then compared to a standard temperature, typically 65° F – the more extreme the outside temperature, the higher number of heating or cooling degree days ("Energy Units and Calculators Explained – Degree Days", 2018).

The variable *fhddw* is an interaction variable between the area of buildings on campus and the number of heating degree days. Data for heating degree days was collected by entering an institution's zip-code into the Weather Data Depot website. We decided to interact the number of heating degree days with the area of building space, as a high number of heating degree days results in higher energy usage for space heating. We then divided this expression by *n*, to express this interaction variable per capita.

The variable *fcddw* is an interaction variable between the area of buildings on campus and the number of cooling degree days. Data for cooling degree days was collected from Weather Data Depot as well. We decided to interact the number of cooling degree days with the area of building space, as a high number of cooling degree days results in higher energy usage for space cooling. We divided this expression by *n* to express the interaction as per capita.

The Boomerang Effect is incorporated into the model by adding a quadratic variable for time. The variable *t* represents the time in years since an institution has joined the Climate Commitment. Institutions that have not joined the Climate Commitment were assigned the value 0 for this variable, as they have spent 0 years in the group. The Boomerang Effect suggests that

Climate Commitment institutions will decrease their usage initially, then gradually increase their energy consumption over the years.

Table 4.4
Stage Two Variables

Variable	Description	Mean	Std. Dev.	Min	Max
ecbw	Energy consumption per capita baseline year (MMBtu/person)	42.31	28.67	0.631	151.05
ecpw	Energy consumption per capita performance year (MMBtu/person)	40.082	26.070	2.483	140.49
fw	Area of buildings per capita (sq. ft/person)	371.38	376.59	176.33	1,352.77
ebw	Area of LEED certified buildings per capita (sq. ft./person)	18.09	32.14	0	378.02
aw	Area of campus per capita (acres/person)	0.206	0.828	0.0004	9.564
rcw	Renewable energy on campus per capita (MMBtu/person)	0.407	1.82	0	22.79
row	Renewable energy off campus per capita (MMBtu/person)	0.272	1.282	0	11.09
fhddw	Area of buildings * heating degree days (sq ft *dd/person)	2.01e+10	2.53e+10	1.60e+8	1.99e+11
fcddw	Area of buildings * cooling degree days (sq ft * dd/person)	2.57e+10	2.29e+10	3.19e+7	1.48e+11
t	Time since joining the Climate Commitment (years)	4.989	4.943	0	12
t^2	Time (years) squared	49.201	55.484	0	144

4.D: Correlation Testing

All variables used in this analysis were tested and evaluated using a Pearson pairwise correlation matrix (see Appendix B). Most of the variables show correlation coefficients less than 0.1 at the 99% confidence level. None of the correlation values are equivalent to 0.7 or 0.8, which is when models begin to exhibit multicollinearity problems. None of the values for Stage One of the model show signs of multicollinearity (shown in Matrix 1, Appendix B). Some of the values for variables in Stage Two of the model approach multicollinearity, and for which we will explain.

The variables *fw* and *fhddw* are highly correlated with the dependent variable *ecpw,* with values of 0.629 and 0.502 respectively. This correlation is explanatory in nature, in that *fw* and *fhddw* are highly significant in explaining *ecpw*. The variables *fw* and *fhddw* are correlated in themselves, with a value of 0.7597. This is because *fhddw* is an interaction variable calculated by multiplying *f* and *hdd* and dividing the result by *n.* Matrix 2 also shows that *t* and t^2 are correlated with a value of 0.9848. This is unsurprising, as they are the same variable represented in a linear and quadratic form.

ECONOMETRIC RESULTS AND ANALYSIS

In this section, we examine the results of our econometric exploration of energy consumption behavior in higher education institutions with carbon neutrality goals. We first address the limitations of this paper, and subsequent alterations to the model that were needed in order to run our final analysis. We then look at each stage of the Heckman model individually.

5.A: Limitations and Model Alterations

There are two known forms of selection bias present in the data. The group of institutions joining the Climate Commitment are self-selecting within the dataset, which we are able to correct for using Heckman 2-Step Selection. As a whole, the dataset is biased. We can assume that institutions reporting their information to AASHE, the primary source of data for this analysis, are more focused on sustainability than institutions who are not. This can be seen as over 80% of institutions in the dataset appear on the Green Colleges Lis, whereas only 16% of institutions evaluated were chosen. Therefore, we cannot directly apply this model to the higher education sector as a whole.

The first model run through Stata was the theoretically-based model developed in Section 3. However, as shown in Model 1 of Appendix C, Stata was unable to generate and implement lambda, (λ, the Inverse Mills Ratio) as well as inferential statistics of the coefficient values within the probit model. We hypothesize that this is because the variables and data collected for the probit are mostly statistically insignificant. We acknowledge that this model may be suffering from omitted variable bias. However, in response to the difficulties with the Heckman command, we conducted the model in three steps: a probit model, generating the Inverse Mills Ratio, and a regression.

5.B: Stage One Probit:

The explanatory variables in the theoretical model were not statistically significant. Due to this, t-tests were run on all variables in the dataset with respect to *C*, the carbon neutrality dummy variable, to determine what within the dataset was statistically significant for the Stage One Probit. For the sake of transparency, the results of these t-tests can be found in Appendix D.

The t-test is used to determine if there is a significant difference between the means of two groups. In this case, the t-test was used to test the difference in means of potential explanatory variables for the Stage One Probit. A significant difference is considered a t-value of approximately 1.8 or higher. The difference between the two groups suggests that the variable might help to explain why an institution would join the Climate Commitment group. For the t-tests run, variables with a t-value that approached 1.8 or higher were included in the probit model. The t-tests tested all variables in the dataset. Some variables represent the same factor, but are measured differently, such as *f* and *fw*, which are the total measurement and the measurement per capita respectively. In these instances, we chose the variable that had the highest t-value of the two.

After the t-tests were conducted, we determined that variables *f, ep, ecbw, en, l* and *fhdd* were to be initially included in the Probit. From there, we narrowed the model by what was statistically significant and concluded that *ep, ecbw* and *l* were explanatory variables. This process is shown in Appendix D. Variables such as *t* and t^2 have high t-values in relation to C, however were not included. We chose not to include these variables as they represent time since joining the Climate Commitment. While there is a large difference between the means of these two groups when C =1 and C =0, this is an effect rather than a cause of joining the Climate Commitment.

As a pre-cautionary measure, an additional Pearson pairwise correlation matrix was created with these variables, which showed no signs of multicollinearity. This matrix can be found in Matrix 3, Appendix C. The following equation is derived from Table 5.1:

$$Prob(C = 1) = -1.014(ep) - 0.00897(ecbw) + 0.5196(l) + 0.55217$$

This suggests that the probability that an institution joins the Climate Commitment (C=1) is negatively influenced by enrollment pressure and energy consumption per capita in the baseline year, and positively influenced by leadership.

Table 5.1
Probit Model Results

Variable	Coefficient	z	P > |z|
ep	-1.014	-1.99	0.046
ecbw	-0.009	-2.63	0.0009
l	0.519	1.91	0.056
__*cons*	0.552	1.69	0.092

The probit suggests that an institution with a higher enrollment rate is less likely to join the Climate Commitment. Institutions with high enrollment rates may be seen as more desirable to incoming students. Schools with lower enrollment rates may join the Climate Commitment as a way of marketing to future students, and incentivizing them to apply and enroll in the institution.

The probit model shows that energy consumption per capita in the baseline year has a negative relationship with the probability that an institution joins the Climate Commitment. Higher education institutions with high values for energy consumption in the baseline year are less likely to join the Climate Commitment than institutions with low baseline energy consumption. Overall though, this has a small impact on the probability that an institutions joins.

The equation determines that leadership has a positive relationship with the probability of joining the Climate Commitment. The variable for leadership, *l,* represents if an institution has a sustainability office. According to the model, institutions with sustainability staff are more likely to join the Climate Commitment.

5.C Calculating Inverse Mills Ratio:

As can be seen in Model 1 of Appendix C, the Heckman command using Stata did not generate a lambda, (λ, Inverse Mills Ratio). We then used the above probit model to calculate the Inverse Mills Ratio. The following described process can be seen in Appendix C.

After running the probit model in Stata, we obtained the linear predictors from the model with the command:

"predict phat, xb"

We then generated the variable *mills* (the Inverse Mills Ratio), using the command:

"gen mills = exp(-.5*phat*phat)/(sqrt(2*_pi)*normprob(phat))"[2]

This command generated a variable for the Inverse Mills Ratio, which was then implemented in our Stage Two Regression as an explanatory variable.

5.D Stage Two Regression:

The theoretical model discussed in Section 3 for Stage Two produced a regression that accounted for only 61.37% of the variation in the dataset. This model implements the dependent variable, *ecpaw,* which represents energy consumption per capita in the performance year for Climate Commitment institutions. Through various attempts, and trial and error, we determined the model that best predicts *ecpaw*. Similar to the Stage One probit, an additional Pearson pairwise correlation matrix was made for the new explanatory variables in this regression. This matrix did not show evidence for any multicollinearity problems, and can be found in Matrix 4,

[2] https://www.stata.com/support/faqs/statistics/mills-ratio/

Appendix C. The model below explains over 72% of the variation in the data set, and is represented in Table 5.2.

Table 5.2
Regression Model Results

Variable	Coefficient	t	P > |t|
fw	0.0667	4.54	0.000
t	-2.51	-1.01	0.315
t^2	0.1978	1.07	0.285
fhddw	7.57e-7	0.42	0.677
fcddw	6.32e-6	0.43	0.670
enw	-1.74e-5	-1.14	0.259
l	30.458	6.31	0.000
aw	-2.107	-1.52	0.131
ebw	0.0978	1.46	0.148
mills	84.41	9.19	0.000
_cons	-62.16	-5.84	0.000

This model then gives way to the following equation:

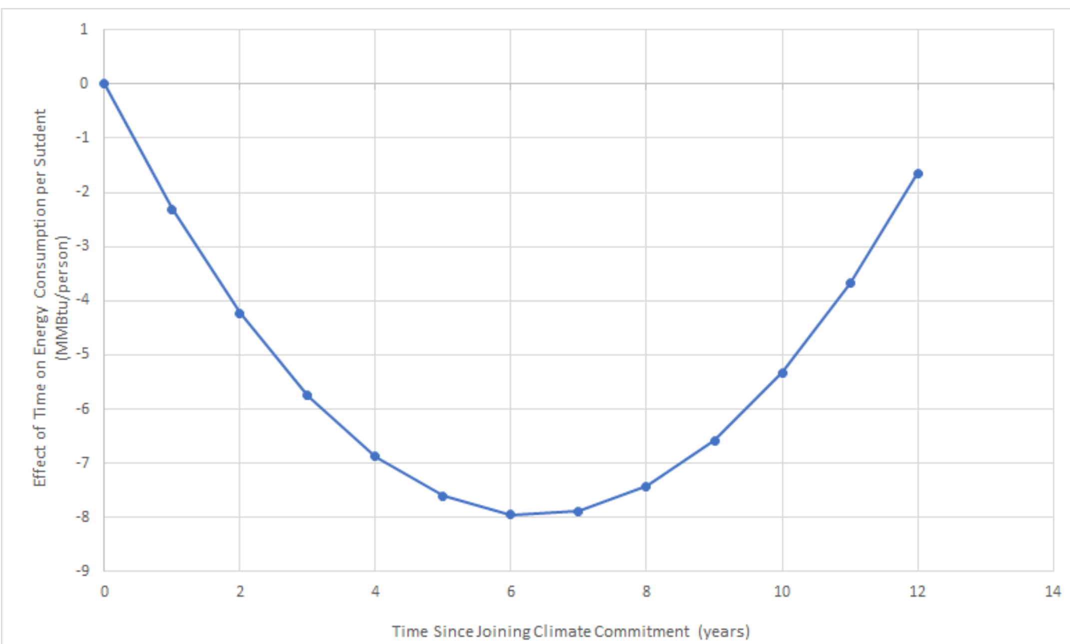
$$ecpaw = 0.0667(fw) + 0.198(t^2) - 2.5(t) + 0.00000076(fhddw) +$$
$$0.00000063(fcddw) - 0.0000174\,(enw) + 30.36\,(l) - 2.11\,(aw) + 0.978\,(ebw) +$$
$$84.41\,(mills) - 62.16$$

This regression shows that for every additional foot of building per capita, energy consumption per capita in the performance year increases by approximately 0.0667 MMBtus/capita. As discussed in Section 1, purchased electricity is the biggest use of energy on campus, and the larger area of buildings leads to more lighting, heating and cooling throughout the year. Since energy consumption is measured in MMBtu/person, it is sound that the impact that an additional square foot of building/person, would have such a small, yet positive and statistically significant impact on energy consumption.

The interaction variables *fhddw* and *fcddw* have a very small and positive impact on energy consumption per capita in the performance year. Comparing these to variable *fw* above, the extra energy needed to heat and cool a building in extreme weather contributes significantly less to energy consumption per capita, than another square foot of building space per person.

The model shows energy consumption per capita initially decreases after joining the Climate Commitment. So, after a certain period of time, the longer an institution has been in the Climate Commitment, the more energy they will use. Figure 5.1 shows how time impacts the predicted energy consumption for a Climate Commitment institution. All other factors held constant, the energy consumption per capita decreases between years 1-6, and begins to increase afterwards. The longest period of time that an institution could possibly be a signatory of the Climate Commitment was 12 years, which is why this graph stops at that point.

Figure 5.1:
Predicted Energy Consumption per Capita over Time



According to Table 5.2 and the subsequent model, *enw* has a small and negative impact on *ecpaw*. The variable *enw* represents the total amount of the endowment in USD divided by *n*. The model shows that institutions with larger endowments per capita, use less energy per capita. For every dollar per capita increase in *enw,* energy consumption decreases by 0.0000174

MMBtu/capita. This may be because institutions with larger endowments have more financial resources to invest in sustainability and technologies such as energy efficiency and renewable energy.

The model shows that leadership has a significant impact on energy consumption as well as Climate Commitment status. Remember, in the probit model a sustainability office increased the probability that an institution declared a carbon neutrality goal. However in this model, the presence of a sustainability office is shown to increase the energy consumption per capita in the performance year by 30.45 MMBtu/capita. This may be the amount of energy that the office physically consumes during the year. It may also be an effect that a sustainability staff has on student, staff and faculty usage.

The variable for campus area, *aw,* is shown to have a negative impact on energy consumption per capita. For every 1 acre per capita, the energy consumption decreases by 2.107 MMBtu/capita. This may be for institutions that have less building area but larger campus area, such as institutions in rural areas.

According to Table 5.2 and the subsequent model, *ebw* has a small and positive impact on *ecpaw*. For an increased area of 1 square foot of LEED certified building per capita, energy consumption increases by approximately 0.0978 MMBtu/capita. Energy efficient buildings, such as LEED certified buildings, require less energy to produce the same amount of lighting, heating, cooling etc. Although LEED certified buildings are more energy efficient than others, they still demand energy for these activities, which is why we see this increase in energy consumption.

Inverse Mills Ratio (mills):

This model suggests that the variable for the Inverse Mills Ratio, *mills,* has a very large and significant impact on energy consumption per capita in the performance year. The variable *mills* was calculated earlier in the section, and was added as an explanatory variable for Stage Two to correct for selection bias. The variable *mills* does not actually have an impact on energy consumption, but adjusts the coefficients of other explanatory variables.

5.E: Effect of Carbon Neutrality Goals on Energy Consumption

We used the above model to determine if and how a carbon neutrality goal changes energy consumption at higher education institutions. We used the regression to determine the variable *pecpaw,* which represents the predicted energy consumption in the performance year for Climate Commitment institutions, essentially $\widehat{ecpaw}$. We then generated the variable *DIFF,* which is calculated as the difference between *ecbaw* and *pecpaw*.

$$DIFF = pecpaw - ecbaw$$

This process of generating DIFF is documented in Appendix F. *DIFF* is the difference between energy consumption per capita in the baseline year, and predicted energy consumption per capita in the performance year for Climate Commitment institutions. We include the exact equation used in calculating DIFF, to show that negative values of DIFF represent a decrease in energy consumption, and positive values represent an increase in energy. Table 5.3 demonstrates that Climate Commitment institutions, on average, decreased their energy consumption by 1.57 MMBtu/capita. However, as we can see in Figure 5.2, there is range of values for DIFF. Table 5.3 shows that *DIFF* ranges from an institution that decreased their energy consumption by over 40 MMBtu/capita to an institution that increased their energy consumption by 28.8541 MMBtu/capita. This indicates that while many institutions were predicted to decrease their energy consumption per capita between the baseline and performance year, some institutions were also predicted to increase their energy consumption.

Table 5.3
Energy Consumption Baseline, Predicted Performance and Difference

Variable	Obs	Mean	Std. Dev.	Min	Max
pecpaw	115	36.736	19.345	0.993	83.5
ecbaw	115	38.303	25.112	5.038	109.322
DIFF	115	-1.566	12.587	-40.985	28.854

Figure 5.2 shows the distribution of schools based on their *DIFF* value. Institutions represented on the left side of the histogram decreased their energy consumption, and institutions on the right side of the figure increased their energy consumption. Of the 115 schools with carbon neutrality goals, 56% of the institutions were predicted to decrease their energy consumption while 44% were predicted to increase their energy consumption. We then examined these schools further.

Two variables were created in this process: *DIFFN* and *DIFFP*. *DIFFN* represents the institutions with negative *DIFF* values, meaning that they decreased their energy consumption per capita from the baseline to the performance year. *DIFFP* represents institutions with positive *DIFF* values, so that they were predicted to increase their energy consumption per capita.

Figure 5.2
DIFF Histogram

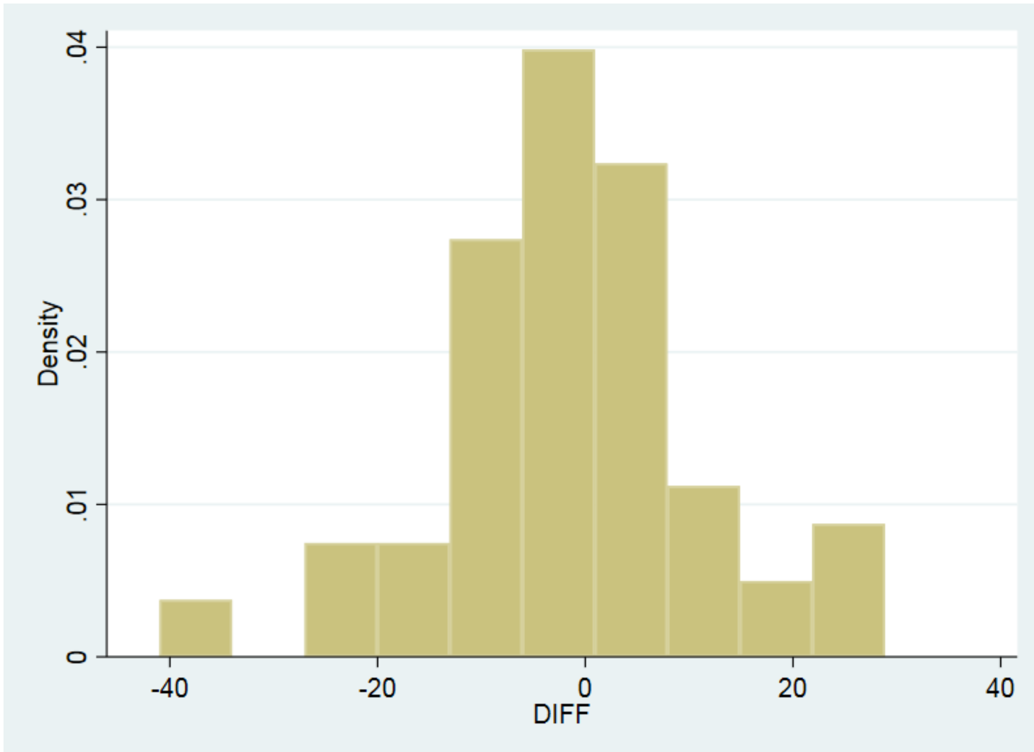


Table 5.4 shows that among the 65 *DIFFN* institutions, the average school were modeled to decrease their energy consumption by 9.39 MMBtu/person. While there is a wide range among these schools as well, a majority of the schools were predicted to reduce between 1-10 MMBtu/capita. This can be seen in Figure 5.3, which shows the distribution of *DIFFN* schools by the predicted difference of energy consumption per capita between their baseline and performance years. Table 5.5 summarizes some characteristics of the *DIFFN* schools. Of the 65 institutions, 0 were Associates, 17 were Baccalaureate, 13 were Masters and 34 had Doctoral and Research programs. The average size of these institutions was a total of 20,610 people including students, faculty and staff, and the average endowment per capita is $66,900/person.

Table 5.4

***DIFFN* Institutions**

Variable	Obs	Mean	Std. Dev.	Min	Mx
DIFFN	65	-9.398	9.149	-40.984	-0.195
nN	65	20,610.71	19,462.15	737	112,377
enwN	65	66,900.61	117,320.8	178.76	661,416.7
AssocN	0	0	0	0	0
BacN	17	1	0	1	1
MasN	13	1	0	1	1
DRN	34	1	0	1	1

Figure 5.3

***DIFFN* Histogram**

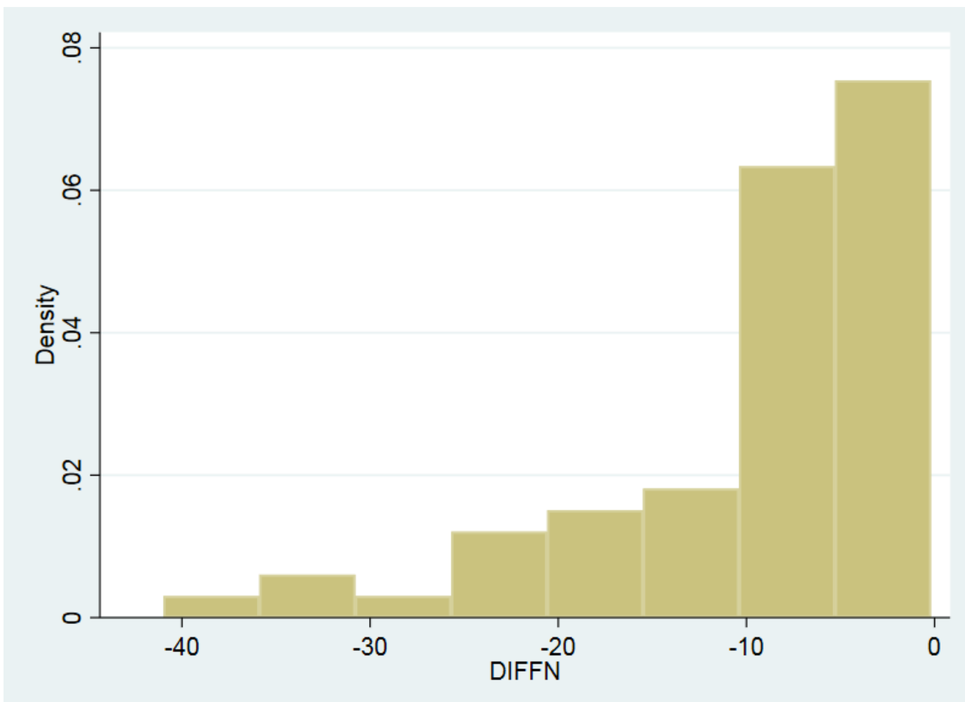


Table 5.5 shows that 49 institutions with carbon neutrality goals increased their energy consumption per capita from the baseline to the performance year. On average, these institutions increased their consumption by 8.85 MMBtu/person, however there is a wide range of energy increases from 0.53 to 28.9 MMBtu/person. This distribution is shown in Figure 5.4, which shows that most institutions increased their energy consumption from 1-10 MMBtu/person. However, compared to Figure 5.3, the institutions who increased their energy consumption are

more evenly distributed. Of these 49 institutions, 5 are Associates, 16 are Baccalaureate, 10 are Masters and 18 are Doctoral and Research programs. The average size of *DIFFP* schools include 16,939 people, which is smaller than average of *DIFFN* schools. We also found that the average *enw* of *DIFFP* schools was larger than *DIFFN* schools, with a value of $67,659/person.

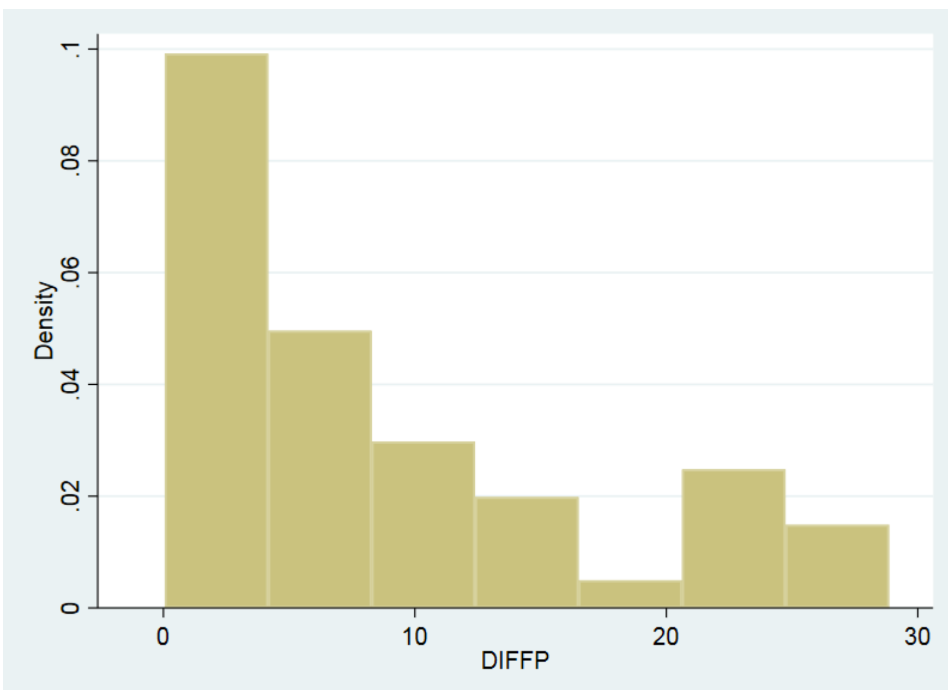
Table 5.5

***DIFFP* Institutions**

Variable	Obs	Mean	Std. Dev.	Min	Mx
DIFFP	49	8.849	8.4133	0.0528	28.854
nP	49	16,939.79	19,498.16	442	92,721
enwP	49	67,659.88	109,267.6	121.486	467,260
AssocP	5	1	0	1	1
BacP	16	1	0	1	1
MasP	10	1	0	1	1
DRP	18	1	0	1	1

Figure 5.4

***DIFFP* Histogram**



Comparing all the institutions, we find that college campuses with carbon neutrality goals that were modeled to increase their energy consumption per capita between the baseline and performance years (*DIFFP* institutions) were more wide-spread among institution types, had smaller bodies of students, faculty and staff on campus, and larger endowments per capita than *DIFFN* campuses.

Colorado College has demonstrated its commitment to sustainability through multiple declarations. In 2009, President Tiefentaler signed onto the Climate Commitment with the objective of reaching carbon neutrality by 2020. More recently in 2018, the school joined the We Are Still In pledge[3]. Colorado College is one the 115 institutions in this dataset with a declared carbon neutrality goal. Colorado College is a *DIFFP* institution, meaning that the model predicted that the school would increase their energy consumption per capita between the baseline and performance years. However, Table 5.6 shows that in reality, Colorado College decreased energy consumption per capita by 16.374 MMBtu/person.

Figure 5.5 compares Colorado College to similar institutions with carbon neutrality goals. Compared to schools such as Haverford College and Dickinson College, Colorado College has one of the smaller predicted energy consumption per capita increases. However, some of the schools chosen are *DIFFN*. Table 5.6 outlines where Colorado College fits within *DIFFP* schools, and shows that Colorado College has a significantly smaller population and larger endowment per person.

[3] http://reporting.secondnature.org/institution/detail!655##655

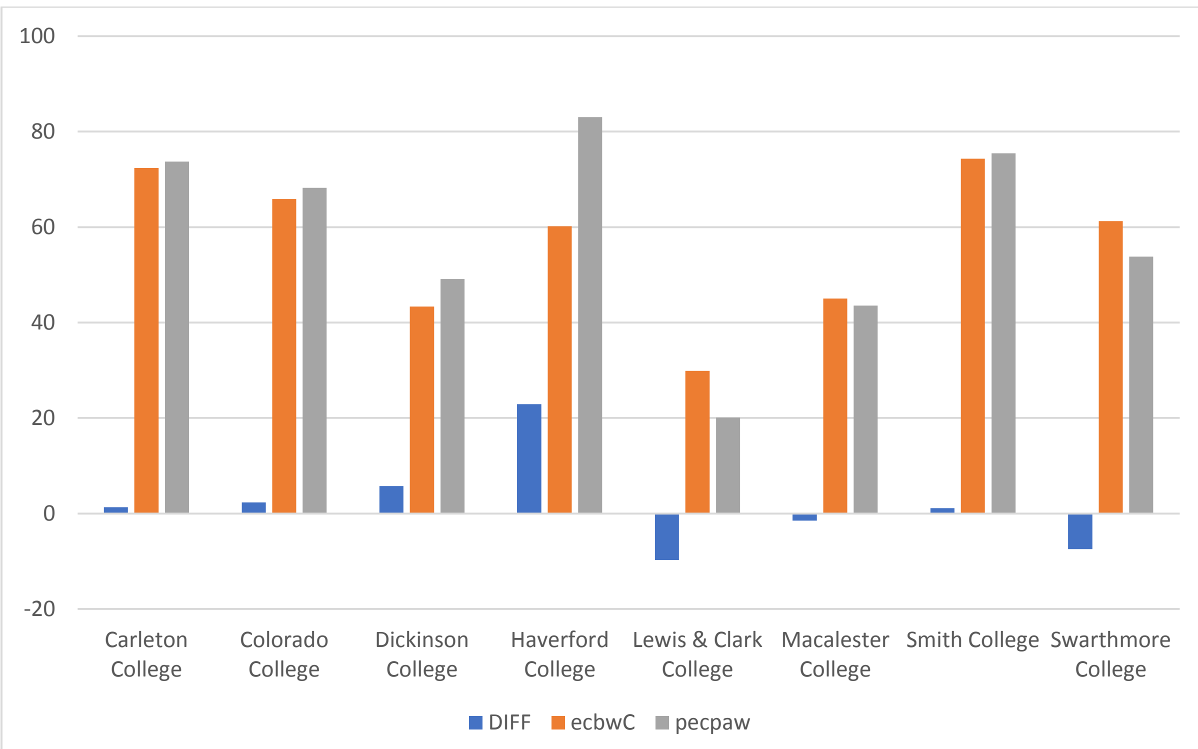
Table 5.6

DIFFP Avg. v. Colorado College

Variable	DIFFP Avg.	Colorado College
ecbw	27.856	65.904
ecpw	27.577	49.53
pecpw	36.413	68.239
DIFF	8.849	2.335
nP	16,939.79	3,208
enwP	67,659.88	224,465.40

Figure 5.5

Colorado College and Similar Institutions



CONCLUSION

In conclusion, this examination has successfully evaluated the impact of carbon neutrality goals on energy consumption behavior in higher education. Our results suggest that certain factors impact the decision for an institution to join the Climate Commitment. In addition, our results suggest that there is a general trend in that Climate Commitment schools decrease their energy usage per capita. However, we implore that the exact impacts of carbon neutrality goals on campus energy usage are different for each specific institution.

6.B Discussion:

The results of our Stage One probit show that schools are more likely to join the Climate Commitment if they have a sustainability office. This office offers the leadership, feasibility and conceptual competence necessary to join and hopefully implement sustainability commitments made. Along the same lines, schools with initially high energy consumption per capita are less likely to join the Climate Commitment. This may be because these schools are less sustainably minded to begin with, indicated by the high baseline consumption rate. Schools with low enrollment rates are more likely to join, which conveys that schools may use the Climate Commitment as a marketing tool to incentivize potential students to apply and enroll. The Climate Commitment could expand their group, and subsequent environmental impact, by targeting schools that fit these criteria. Some of these schools identified in the dataset are Berea College, Elon University, Loyola Marymount University, and our neighbors at University of Colorado at Colorado Springs.

There are other factors that influence the decision to join the Climate Commitment which were not included in the Stage One probit model. However, these could inform the Climate Commitment in their institutional targeting as well.

Stage Two of this model found that institutional energy consumption per capita was dependent on a myriad of explanatory variables, such as area of buildings, the presence of a sustainability office and area of campus. The results that this model predicted were then used to find that on average, schools with carbon neutrality goals will decrease their energy consumption per capita between the baseline and performance year.

However, there is a wide range of responses to carbon neutrality goals. This study suggests that the significant factor may not be the declaration of the goals in themselves, but how those goals are implemented. Higher education institutions should be held accountable for the goals they set and how the strategies to achieve those goals are implemented. If higher education institutions are attempting to achieve carbon neutrality without addressing their energy consumption behavior, they could be wasting valuable resources, time, and ultimately, they will not achieve the goal they wish to.

All of the Associates programs with carbon neutrality goals were predicted to increase their energy consumption. Schools that were predicted to increase their energy usage are smaller, and have larger endowments per capita. Some of these schools identified in the dataset are College of Lake County, Haverford College and Southern Oregon University. It is important to target and track schools with these characteristics to ensure that they successfully implement their carbon neutrality goals, without the unintended consequence of increasing their per capita energy consumption.

6.C Implications and Future Studies:

Professor Jim Parco of Colorado College often says, “all models are bad, but some models are useful.” This model cannot and should not be implemented to the higher education sector as a whole. The two known forms of selection bias in the dataset prevents this model from being useful to all of higher education in the United States. However, this model could be implemented for sustainability-focused higher education institutions, or to evaluate other sustainability declarations that involve energy consumption.

This model could be improved with a dataset that included explanatory variables for the baseline year, a wider range of institutions, and more statistically significant independent variables for the Stage One probit. Future studies should look to compare how energy usage changes on campuses with carbon neutrality goals compared to campuses that do not have carbon neutrality goals.

While this model may not be good (or useful), it could inspire other models that aim to critically and creatively evaluate sustainability and address the root of climate change – consumption.

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APPENDIX A

Descriptive Statistics 1
Stage One Probit:

```
. summarize en l sp ep  fe sca scb
```

Variable	Obs	Mean	Std. Dev.	Min	Max
en	188	1.32e+09	3.55e+09	9898.969	2.64e+10
l	189	.8624339	.3453589	0	1
sp	189	.9259259	.262587	0	1
ep	189	.3306402	.1842845	.11	.95
fe	189	.8095238	.3937197	0	1
sca	189	4.275132	11.37085	0	51
scb	189	.8306878	.3760235	0	1

.

Descriptive Statistics 2
Stage Two Regression:

```
. summarize ecbw ecpw fw ebw aw rcw row fhddw fcddw t t2
```

Variable	Obs	Mean	Std. Dev.	Min	Max
ecbw	189	42.30999	28.66588	.630884	151.046
ecpw	189	40.08228	26.07002	2.482497	140.4991
fw	189	376.5883	176.3344	51.69941	1352.774
ebw	189	18.08763	32.14217	0	378.0244
aw	189	.2055552	.8281249	.0003618	9.563887
rcw	189	.4067962	1.815455	0	22.7886
row	189	.2719897	1.282429	0	11.09409
fhddw	189	1506210	1132457	5524.479	5968437
fcddw	189	838389.9	797592.9	3265.104	8415025
t	189	4.989418	4.943284	0	12
t2	189	49.20106	55.48387	0	144

.

Descriptive Statistics 3
Descriptive Statistics: Climate v. Not Climate Institutions

```
. summarize enC enNC enwC enwNC epC epNC spC spNC lC lNC feC feNC scaC scaNC scbC scbNC ecbwC ecbwNC ecpwC ecpwNC fwC
> fwNC ebwC ebwNC awC awNC rcwC rcwNC rowC rowNC fhddwC fhddwNC fcddwC fcddwNC, separator(4)
```

Variable	Obs	Mean	Std. Dev.	Min	Max
enC	114	8.44e+08	1.86e+09	1300000	1.08e+10
enNC	73	2.05e+09	5.13e+09	9898.969	2.64e+10
enwC	116	65798.17	112359.2	0	661416.7
enwNC	74	120375.3	249680.7	19.30048	1568154
epC	115	.3095739	.1671228	.11	.95
epNC	74	.3633784	.2050812	.11	.95
spC	115	.9217391	.2697571	0	1
spNC	74	.9324324	.2527157	0	1
lC	115	.8956522	.3070491	0	1
lNC	74	.8108108	.3943323	0	1
feC	115	.8086957	.3950495	0	1
feNC	0				
scaC	115	5.052174	12.23946	0	51
scaNC	74	3.067568	9.829131	0	46
scbC	115	.8521739	.3564808	0	1
scbNC	74	.7972973	.404757	0	1
ecbwC	115	38.30313	25.11151	5.037631	109.3218
ecbwNC	74	48.53686	32.6633	.630884	151.046
ecpwC	115	36.73691	22.7615	3.716139	102.2046
ecpwNC	74	45.28116	29.93705	2.482497	140.4991
fwC	115	36.73691	22.7615	3.716139	102.2046
fwNC	74	396.9172	192.6467	51.69941	1352.774
ebwC	115	17.74608	19.41629	0	105.1849
ebwNC	74	18.61842	45.51306	0	378.0244
awC	115	.2000607	.9197864	.0003618	9.563887
awNC	74	.2140939	.6669806	.0034294	3.907651
rcwC	115	.4916521	2.224422	0	22.7886
rcwNC	74	.2749256	.8555338	0	5.143089
rowC	115	.3325407	1.566539	0	11.09409
rowNC	0				
fhddwC	115	1451080	1119847	5524.479	5421849
fhddwNC	74	1591886	1154189	7223.651	5968437
fcddwC	115	816009.1	914118.3	3265.104	8415025
fcddwNC	74	873170.8	575648.7	46012.47	3460327

.

Appendix B: Pairwise Correlation Matrices

Matrix 1:

Pairwise Correlation Matrix – Stage One:

```
. pwcorr C en sp ep l fe sca scb
```

	C	en	sp	ep	l	fe	sca
C	1.0000						
en	-0.1667	1.0000					
sp	-0.0199	0.0361	1.0000				
ep	-0.1429	0.2782	-0.1023	1.0000			
l	0.1202	0.1067	-0.0543	-0.0220	1.0000		
fe	-0.0026	0.0990	0.0171	-0.0943	0.1975	1.0000	
sca	0.0854	0.0767	0.1066	-0.0873	0.0883	0.0165	1.0000
scb	0.0714	0.1139	0.1417	-0.0613	0.2702	0.1044	0.1702

	scb
scb	1.0000

.

Matrix 2:

Pairwise Correlation Matrix – Stage Two:

```
. pwcorr ecpw ebw fw aw rcw row t t2 fhddw fcddw
```

	ecpw	ebw	fw	aw	rcw	row	t
ecpw	1.0000						
ebw	0.1765	1.0000					
fw	0.6293	0.3610	1.0000				
aw	0.0300	0.4101	0.2595	1.0000			
rcw	0.0318	0.0400	0.0611	0.0669	1.0000		
row	0.0096	0.0788	0.0112	-0.0284	-0.0194	1.0000	
t	-0.0705	-0.0239	-0.0358	-0.0698	-0.0276	0.0185	1.0000
t2	-0.0407	-0.0280	-0.0203	-0.0741	-0.0412	0.0115	0.9848
fhddw	0.5018	0.1848	0.7597	0.2576	0.0748	-0.0097	-0.0663
fcddw	0.2984	0.1943	0.3898	0.0492	-0.0139	0.2095	-0.0469

	t2	fhddw	fcddw
t2	1.0000		
fhddw	-0.0607	1.0000	
fcddw	-0.0473	0.0522	1.0000

.

Matrix 3:

Pairwise Correlation Matrix – Regression Stage One:

```
. pwcorr C ep ecbw l
```

	C	ep	ecbw	l
C	1.0000			
ep	-0.1429	1.0000		
ecbw	-0.1747	-0.0140	1.0000	
l	0.1202	-0.0220	0.1109	1.0000

.

Matrix 4:

Pairwise Correlation Matrix – Regression Stage Two:

```
. pwcorr ecpaw fw t t2 fhddw fcddw enw l aw ebw mills
```

	ecpaw	fw	t	t2	fhddw	fcddw	enw
ecpaw	1.0000						
fw	0.6619	1.0000					
t	0.1505	-0.0358	1.0000				
t2	0.1547	-0.0203	0.9848	1.0000			
fhddw	0.4932	0.7597	-0.0663	-0.0607	1.0000		
fcddw	0.1854	0.3898	-0.0469	-0.0473	0.0522	1.0000	
enw	0.5091	0.4695	-0.0550	-0.0320	0.2399	0.2587	1.0000
l	0.0469	-0.1358	0.1487	0.1519	-0.0873	-0.1120	0.0071
aw	0.0217	0.2595	-0.0698	-0.0741	0.2576	0.0492	0.0157
ebw	0.1111	0.3610	-0.0239	-0.0280	0.1848	0.1943	-0.0109
mills	0.6124	0.4131	-0.1903	-0.1618	0.2993	0.2314	0.5637

	l	aw	ebw	mills
l	1.0000			
aw	-0.0661	1.0000		
ebw	-0.0812	0.4101	1.0000	
mills	-0.4371	0.0659	0.1152	1.0000

.

Appendix C

Model 1:

Theoretical Heckman Model:

```
. heckman ecpaw ebw fw aw rcw row t t2 fhddw fcddw, select(C en sp ep l fe sca scb) twostep

Heckman selection model -- two-step estimates   Number of obs      =       188
(regression model with sample selection)              Selected     =       114
                                                      Nonselected  =        74

                                                Wald chi2(9)       =    103.06
                                                Prob > chi2        =    0.0000

------------------------------------------------------------------------------
       ecpaw |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ecpaw        |
         ebw |   .1856762   .0901143     2.06   0.039     .0090555     .362297
          fw |   .0751363   .0160366     4.69   0.000     .0437051    .1065675
          aw |  -2.511097   1.818562    -1.38   0.167    -6.075414     1.05322
         rcw |   .5261668   .7026504     0.75   0.454    -.8510026    1.903336
         row |   -.415746   1.069166    -0.39   0.697    -2.511273    1.679781
           t |  -2.668236   3.347502    -0.80   0.425    -9.229219    3.892747
          t2 |   .2500287    .247667     1.01   0.313    -.2353896    .7354471
       fhddw |   3.18e-06   2.28e-06     1.40   0.163    -1.29e-06    7.65e-06
       fcddw |   9.15e-07   2.03e-06     0.45   0.653    -3.07e-06    4.90e-06
       _cons |   2.734646   8.632179     0.32   0.751    -14.18411    19.65341
-------------+----------------------------------------------------------------
select       |
           C |   12.14906          .        .       .            .           .
          en |   2.89e-26          .        .       .            .           .
          sp |   1.71e-15          .        .       .            .           .
          ep |   4.74e-15          .        .       .            .           .
           l |  -3.46e-15          .        .       .            .           .
          fe |  -5.37e-16          .        .       .            .           .
         sca |   1.32e-17          .        .       .            .           .
         scb |  -7.75e-17          .        .       .            .           .
       _cons |  -6.051655          .        .       .            .           .
-------------+----------------------------------------------------------------
/mills       |
      lambda |          0  (constrained)
-------------+----------------------------------------------------------------
         rho |    0.00000
       sigma |  16.449316
------------------------------------------------------------------------------

.
```

Appendix D:

T-Test Results for All Variables in Relation to "C":

Variable	t
f	1.29
ep	1.97
ecbw	2.43
enw	2.02
fw	1.27
fhdd	1.69
fcdd	0.80
en	2.30
ecb	2.00
a	-0.79
l	-1.67
sp	0.27
t	-19.01
rc	-0.86
ro	-0.79
fe	0.04
sca	-1.17
scb	-0.98
hdd	-0.02
cdd	-0.19
aw	0.11
rcw	-0.80
row	-0.81
t^2	-13.91
ebw	0.18
fhddw	0.83
fcddw	0.48

Appendix E

Probit 1 (Theoretical):

```
. probit C en sp ep l fe sca scb

Iteration 0:   log likelihood = -126.02365
Iteration 1:   log likelihood = -118.56969
Iteration 2:   log likelihood = -118.51058
Iteration 3:   log likelihood = -118.51046
Iteration 4:   log likelihood = -118.51046

Probit regression                                 Number of obs     =        188
                                                  LR chi2(6)        =      15.03
                                                  Prob > chi2       =     0.0201
Log likelihood = -118.51046                       Pseudo R2         =     0.0596
```

C	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
en	-6.78e-11	3.56e-11	-1.90	0.057	-1.38e-10	2.05e-12
sp	-.2298642	.3936629	-0.58	0.559	-1.001429	.541701
ep	-.9256565	.5611022	-1.65	0.099	-2.025397	.1740835
l	.5264473	.2905353	1.81	0.070	-.0429915	1.095886
fe	-.1289896	.2488393	-0.52	0.604	-.6167056	.3587264
sca	.0091566	.0092049	0.99	0.320	-.0088846	.0271979
scb	.2237172	.2669123	0.84	0.402	-.2994213	.7468557
_cons	.3016587	.5343609	0.56	0.572	-.7456694	1.348987

.

Probit 2 (Informed by ttests):

```
. probit C f ep ecbw en l fhdd

Iteration 0:   log likelihood = -126.02365
Iteration 1:   log likelihood =  -117.6147
Iteration 2:   log likelihood = -117.55669
Iteration 3:   log likelihood = -117.55664
Iteration 4:   log likelihood = -117.55664

Probit regression                                 Number of obs     =        188
                                                  LR chi2(4)        =      16.93
                                                  Prob > chi2       =     0.0020
Log likelihood = -117.55664                       Pseudo R2         =     0.0672
```

C	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
f	8.96e-09	2.68e-08	0.33	0.738	-4.35e-08	6.14e-08
ep	-1.090303	.5558309	-1.96	0.050	-2.179711	-.0008941
ecbw	-.0063241	.0040564	-1.56	0.119	-.0142744	.0016263
en	-2.69e-11	4.18e-11	-0.64	0.519	-1.09e-10	5.50e-11
l	.6423663	.2829319	2.27	0.023	.08783	1.196903
fhdd	-5.50e-12	6.13e-12	-0.90	0.370	-1.75e-11	6.52e-12
_cons	.4387906	.347865	1.26	0.207	-.2430122	1.120593

.

Probit 3 (minus f):

```
. probit C ep ecbw en l fhdd

Iteration 0:   log likelihood = -126.02365
Iteration 1:   log likelihood =  -117.6623
Iteration 2:   log likelihood = -117.61295
Iteration 3:   log likelihood = -117.61293
Iteration 4:   log likelihood = -117.61293

Probit regression                                 Number of obs     =        188
                                                  LR chi2(3)        =      16.82
                                                  Prob > chi2       =     0.0008
Log likelihood = -117.61293                       Pseudo R2         =     0.0667
```

C	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ep	-1.097457	.5554895	-1.98	0.048	-2.186196	-.0087172
ecbw	-.006396	.0040525	-1.58	0.115	-.0143387	.0015468
en	-2.24e-11	3.89e-11	-0.57	0.566	-9.87e-11	5.40e-11
l	.6524896	.2811397	2.32	0.020	.1014659	1.203513
fhdd	-4.03e-12	4.25e-12	-0.95	0.343	-1.23e-11	4.29e-12
_cons	.4538147	.3450667	1.32	0.188	-.2225037	1.130133

Probit 4 (minus en):

```
. probit C ep ecbw l fhdd

Iteration 0:   log likelihood = -126.52217
Iteration 1:   log likelihood = -119.16491
Iteration 2:   log likelihood =  -119.1401
Iteration 3:   log likelihood =  -119.1401

Probit regression                                 Number of obs     =        189
                                                  LR chi2(3)        =      14.76
                                                  Prob > chi2       =     0.0020
Log likelihood =  -119.1401                       Pseudo R2         =     0.0583
```

C	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ep	-.9810039	.5090905	-1.93	0.054	-1.978803	.0167952
ecbw	-.0076313	.0036154	-2.11	0.035	-.0147173	-.0005453
l	.5703574	.2750514	2.07	0.038	.0312666	1.109448
fhdd	-4.55e-12	4.12e-12	-1.10	0.270	-1.26e-11	3.53e-12
_cons	.5333317	.3276607	1.63	0.104	-.1088714	1.175535

.

Probit 5 (Final):

```
. probit C ep ecbw l

Iteration 0:   log likelihood = -126.52217
Iteration 1:   log likelihood = -119.79363
Iteration 2:   log likelihood = -119.76919
Iteration 3:   log likelihood = -119.76919

Probit regression                               Number of obs     =        189
                                                LR chi2(3)        =      13.51
                                                Prob > chi2       =     0.0037
Log likelihood = -119.76919                     Pseudo R2         =     0.0534
```

C	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ep	-1.014279	.5088895	-1.99	0.046	-2.011684	-.0168738
ecbw	-.0089694	.0034152	-2.63	0.009	-.0156631	-.0022758
l	.519619	.271375	1.91	0.056	-.0122663	1.051504
_cons	.5521797	.3274702	1.69	0.092	-.0896501	1.19401

.

Appendix F

Stage Two Regression:

```
. regress ecpaw fw t t2 fhddw fcddw enw l aw ebw mills
```

Source	SS	df	MS			
				Number of obs	=	115
				F(10, 104)	=	27.06
Model	42663.2399	10	4266.32399	Prob > F	=	0.0000
Residual	16398.5391	104	157.678261	R-squared	=	0.7223
				Adj R-squared	=	0.6957
Total	59061.779	114	518.085781	Root MSE	=	12.557

ecpaw	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
fw	.0666107	.0146835	4.54	0.000	.0374927	.0957287
t	-2.511123	2.487863	-1.01	0.315	-7.444648	2.422402
t2	.1978362	.1840728	1.07	0.285	-.167187	.5628595
fhddw	7.57e-07	1.81e-06	0.42	0.677	-2.84e-06	4.35e-06
fcddw	6.32e-07	1.48e-06	0.43	0.670	-2.30e-06	3.56e-06
enw	-.0000174	.0000153	-1.14	0.259	-.0000477	.000013
l	30.45766	4.82588	6.31	0.000	20.88776	40.02756
aw	-2.10722	1.383617	-1.52	0.131	-4.850986	.6365452
ebw	.0978494	.0670717	1.46	0.148	-.0351562	.230855
mills	84.40717	9.18353	9.19	0.000	66.19589	102.6185
_cons	-62.15789	10.64023	-5.84	0.000	-83.25787	-41.05792

Generating and Summarizing DIFF:

```
. drop DIFF

. gen DIFF = pecpaw - ecbaw
(74 missing values generated)

. summarize DIFF
```

Variable	Obs	Mean	Std. Dev.	Min	Max
DIFF	115	-1.56622	12.58667	-40.98452	28.8541

```
. summarize pecpaw ecbaw DIFF
```

Variable	Obs	Mean	Std. Dev.	Min	Max
pecpaw	115	36.73691	19.34526	.992769	83.50008
ecbaw	115	38.30313	25.11151	5.037631	109.3218
DIFF	115	-1.56622	12.58667	-40.98452	28.8541