University Air Travel & Internal Carbon Taxation

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Abstract

This paper evaluates university air travel behavior and decisions, specifically department price responsiveness, to analyze the possibility of implementing an internal air travel tax at the University of Oregon (UO). The university's price elasticity of demand is estimated through regression analysis. These estimates are then utilized in sensitivity analysis to predict how specific units, and the entire university, would be impacted by a given internal tax on air travel. Our elasticity estimates suggest that university demand is not very sensitive to changes in air travel price. Consequently, an internal tax on air travel would need to be set well above the social cost of carbon to see a significant reduction in university emissions.

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Introduction

The idea of UO internal carbon tax was first brought to our attention by UO's Office of Sustainability, who had previously proposed an internal tax on air travel but were met with strong opposition from the university. Their proposed tax sought to lower department carbon emissions through an internal tax on air travel that was not revenue neutral by design. The proposers originally thought opposition to their proposal stemmed from their target, air travel. We believe that it was not the target of the tax, but the lack of revenue neutrality in design, that caused opposition. Our analysis will focus on potential implementation of an internal tax on university air travel, but it will be revenue neutral at the department level. This design deters behavior by making air travel more expensive relative to other activities, and has a net effect of zero on department budget.

The UO Office of Sustainability shared their proposal with us in Winter 2016, which presented internal carbon taxation as a means for the university to take responsibility for its' carbon footprint. The signing of the Paris Agreement happened to coincide with these efforts to tax carbon emissions internally. With recent U.S. withdrawal from the agreement, the harmony of internal carbon taxation and the country's stance on mitigating greenhouse gas emissions is disrupted. This turn of events does not make internal carbon taxation less relevant. Instead, self-imposed mechanisms to internalize the cost of carbon emissions are arguably more important now that the U.S. has stepped back from international policy efforts.

Momentum has been building within the public and private sector to reduce carbon emissions, and economists generally favor market based solutions like internal carbon taxes to accomplish this goal. Domestic and international corporations, as well as public institutions like universities, are adopting internal carbon taxation policies.

The economic argument for taxation stems from the properties and consequences of externalities. Externalities occur when involved parties do not account for the full costs and benefits of a transaction. Failure to account for full costs and benefits brings inefficient allocations. Carbon consumption results in a negative externality in the form of greenhouse gas emissions and global warming. Taxation is a mechanism of moving from an inefficient to an efficient level of consumption by forcing individuals to internalize the social costs associated with their own consumption. Theoretically, a tax should be set as the difference between the marginal social cost and marginal private cost of carbon to yield an efficient allocation.

An internal tax is one that an institution or body levies upon itself, as opposed to an external tax which would be imposed upon the institution by some external source. Internal taxes are implemented by and levied upon the same body. These defining characteristics may result in lower tax rates than is optimal due to the self-interest of the implementers.

When tasked with evaluating the potential of an internal carbon tax on the University of Oregon, two potential areas of interest stuck out—taxing department energy usage or department air travel. As of 2012, 40% of UO carbon emissions stemmed from heating university buildings making building usage a key target for carbon taxation.[1] However, the University of Oregon often houses multiple departments with individualized budgets in a singular building. Unless costly sophisticated metering systems are installed, multi-departmental buildings make it

[1] Carlson, Sonya. Mital, Steve. *UO Carbon Pricing Proposal*. Slide Deck (11).

impossible to measure usage by individual, or even individual department. The inability to track usage to individual actors renders taxation infeasible for influencing behavior.

Given these challenges, air travel is a more realistic target of internal carbon taxation at UO. Unlike building usage, air travel offers the opportunity to effect behavior of individual actors. The ability to track air travel expenditure at both the department and the individual level lends a better shot at influencing behavior. Additionally, air travel uses the least sustainable inputs of all university carbon emitting activities. It accounts for only 13% of carbon emitting activity and nearly 57% of university emissions.[2] Air travel is a key contributor to the university's carbon footprint, and therefore, a relevant activity to target.

[2] Carlson, Sonya. Mital, Steve. Slide Deck (11).

Literature Review

Internal Carbon Tax Overview

While many national and regional government bodies have implemented formal mechanisms to price carbon usage, many have been slow to form or unreliable due to the global political complexity of the issue. The United States has not yet, and won't likely soon, implement a national mechanism to place a price on carbon. Firms and organizations, however, have taken voluntary measures to internalize the costs of their emissions. The World Bank's Carbon Disclosure Project states that "at least 150 companies use an internal carbon price, with disclosed prices ranging from $6 to $89 per ton of CO_2".[3] Firms use internal carbon taxes primarily as a means of risk management and promoting an environmentally friendly image to the public. Additionally, internal carbon taxation allows public and private organizations to prepare for potential and probable future taxation. Imposing an internal carbon tax allows firms to observe the impact mandatory regulation would have on operations. Additionally, internal carbon taxation is used as a method of encouraging investment in low-carbon revenue opportunities while identifying cost savings.[4]

Yale University Internal Carbon Tax

Methods of structuring an internal carbon taxation program are largely borrowed from the precedent set by William Nordhaus' carbon program at Yale University. Adopting environmentally friendly policies is a trend spreading throughout U.S. universities. Yale University's William Nordhaus has led the way in internal carbon taxation research for higher

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[3] Kossoy, Alexandre et al. 2015. *State and trends of carbon pricing 2015*. State and trends of carbon pricing. Washington, D.C. World Bank Group. (p. 48) http://documents.worldbank.org/curated/en/636161467995665933/State-and-trends-of-carbon-pricing-2015

[4] Kossoy, Alexandre et al. 2015. (p.14)

education institutions. University buildings are a key contributor to the carbon footprint of higher education. Lighting and heating the school's buildings account for 70-76% of Yale University's total annual carbon emissions.[5] For the 2015-2016 academic year, Nordhaus implemented an internal carbon tax on 20 individual school departments. In his pilot program, he separated participating departments into four separate groups—varying their degrees of carbon pricing.

1. Energy usage <u>report only</u>, no tax
2. Energy usage report, 1% <u>monthly reduction</u> or incur a $40/ton tax
3. Energy usage report, <u>revenue neutral</u> $40/ton tax
4. Energy usage report, flat <u>baseline reduction</u> or incur a $40/ton tax

Nordhaus concluded that the most effective tax schema to lower emissions, without significantly affecting department budget, was the revenue neutral tax. This tax program rewarded departments that beat usage targets and penalized those that did not. Those that met targets were rewarded monetarily with collections from the penalized, who incurred a $40/ton tax. By design the net change for the university is $0; it rewards the departments who managed to keep their energy below the tax threshold and punishes the departments who overuse electricity through redistribution of collected tax revenue. Nordhaus's survey of Yale department heads revealed that they were more willing to participate in the future due to a sense of transparency from the administration that accompanied rewarding those who complied with the tax.[6] The other taxation options, such as the 1% monthly reduction, led to perverse incentives. For example, departments were incentivized to use excessively in the first month, setting higher base emissions and thereby creating a threshold easy to beat.

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[5] Nordhaus, William. *Yale University's Carbon Charge: Preliminary Results from Learning by Doing* (2016): n. pag. Yale University, 10 Oct. 2016. Web. (p.5) http://carbon.yale.edu/sites/default/files/files/Carbon_Charge_Pilot_Report_20161010.pdf

[6] Nordhaus, William. (2016). (p.25)

Air Travel Carbon Tax

Since 1992, aviation has accounted for 3.5% of the total greenhouse gas emissions from all human activity.[7] Aviation traffic has grown at approximately 9% per year since the 1960s and the number of kilometers flown is projected to keep on growing at an annual 5% rate.[8] The high projected rate of growth coupled with the carbon heavy output of aviation traffic has raised concerns on its impact in global warming.

Economists from University of Waterloo and University of British Columbia have studied the efficacy of an air travel passengers tax in offsetting carbon emissions. They developed a model to measure a passenger's willingness to pay, using variables such as: continent of origin, flight distance, awareness of climate change, disposable income, ticket price, etc. They concluded that traveler awareness of the impacts flying has on the environment, not disposable income or flying frequency, was the key driver of an individual's willingness to pay.[9] Additionally, they found the passengers were willing to average additional charge of 25 euros per purchase (chosen from a range of 5-100 euros); participants overwhelmingly did not select the lowest cost option (5 euros). Observing actual choices, instead of self-stated preferences, is better for uncovering willingness to pay because ones' responses may not reveal their true preferences. It is possible that the survey respondents stated a higher tax preference than their true willingness to pay to seem more environmentally conscious, thereby introducing measurement error. Observing actual choices avoids this issue of dishonestly.

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[7] Brouwer, R., Brander, L. & Van Beukering, P. Climatic Change (2008) 90: 299. doi:10.1007/s10584-008-9414-0 (p.4) https://link.springer.com/article/10.1007%2Fs10584-008-9414-0?LI=true
[8] Brouwer, R., et al. (2008). (p.6)
[9] Brouwer, R., et al. (2008). (p.12)

Applications of Behavioral Economics

Theories of behavioral economics are borrowed to complement traditional mechanisms for altering economic incentives, i.e. taxation. Behavioral economics detours from neoclassical thought to entertain the possibility that consumers are not strictly rational. Bounded rationality suggests economic agents deviate from rationality due to cognitive barriers in processing information. The theory of information saliency suggests that presentation may be more impactful than the accuracy and relevance of information.[10] Providing accurate and informative information may be pointless if concern is not taken for presentation. Any internal carbon tax initiative would include methods of increasing awareness of usage and emissions through information provision. Applying insights regarding salient information can increase the power of information provision on carbon emitting behavior.

Price Elasticity of Demand for Air Travel

An estimate of the price elasticity of demand for air travel, henceforth referred to simply as "elasticity", is necessary to evaluate the effects a given tax will have on university travel behavior, budget, and emissions.

Price elasticity of demand for air travel is influenced by four levels of substitution:

Level one: Non-travel substitution

- To travel or not to travel?

Level two: Destination substitution

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[10] Pollitt, M. G., & Shaorshadze, I. (2011). The Role of Behavioural Economics and Climate Policy. University of Cambridge: Electricity Policy Research Group. Department of Applied Economics. (p.5) https://doi.org/10.17863/CAM.1140

- To travel to destination A or destination B?

Level three: Mode Substitution

- To travel to the chosen destination by car or by airplane?

Level four: Intra-mode substitution

- To travel through Airline X or Airline Y?

Levels of substitution complicate the process of determining a price elasticity of demand, especially due to the lack of information available on nonprice factors such as geographic data, travel motives, service quality, and demographic information.[11]

Since travel motive is typically unobserved, many studies use flight class as a proxy. Those flying "business class" are assumed to be traveling for business purposes, and all other passengers are considered leisure travelers. These two types of travelers are expected to behave differently. Leisure travelers are expected to be utility maximizing; their demand is determined by travel costs, vacation experience, and consumption opportunities. In contrast, business travelers assumed to be cost minimizing; their behavior is influenced by travel costs, the relative price of complementary inputs of production, and the associated firm's output level.[12] Based on these differences, the elasticities of each group are typically modeled separately.

Martijn and colleagues performed a meta-analysis estimates a price elasticity of demand for air travel by utilizing a compilation of leading estimates from the literature. They evaluated both the combined and separated estimates of price elasticities of demand for leisure and business travelers. The mean price elasticity for overall travelers was found to be -1.46, implying that changes to price result in a larger than proportional change in demand. Findings did support the

[11] Martijn Brons, et al (2002). *Price elasticities of demand for passenger air travel: a meta-analysis.* Journal of Air Transport Management. Volume 8, Issue 3: 165-175. Elsevier. (p. 166) http://dx.doi.org/10.1016/S0969-6997(01)00050-3
[12] Martijn Brons, et al (2002). (p.168)

notion that elasticities vary across the two travel subgroups. On average, price elasticities of demand are of greater magnitude for leisure travelers than business travelers, implying that business demand is less sensitive to price changes.

University of Oregon air travel does not clearly fit into either the business or leisure group. While some travel is paid in full by the university, faculty and staff often pay a portion of travel costs with some form of disposable income (be that savings, grants, or research funding allowances). In comparison, business travel is fully reimbursed with funds that the traveler themselves cannot use for other purposes. To account for the universities hybrid form of travelers, it is best to estimate a university elasticity instead of using those provided in literature. To our knowledge our paper is the first attempt to do so, and therefore this research has implications beyond carbon reduction. Introducing this third type of travel may prove useful in future research seeking to estimate a price elasticity of demand for air travel.

Methodology

Travel Data

Data was supplied by UO Business Affairs and consists of 2004-2016 air travel reimbursement data recorded with the following information:

- Invoice
- Transaction Date of the Reimbursement
- Departure Date
- Arrival Date
- Departure City
- Arrival City
- Department Code
- Fund
- Fund Description
- Department Code
- Name of the Department

Through preliminary exploration we discovered that the dataset lacked full Athletic Department travel expenses. Our data only includes recruiting travel and coaching personnel travel for the Athletic Department. It did not contain any team travel, which makes up the bulk of the Athletic department's expenses. The athletic department has their own travel coordinator who keeps all travel data, which we were unable to obtain. Thus, the athletic department travel expenses in our data do not represent an accurate picture of the Athletics Department travel spending. In addition to lacking full Athletic Department travel, our data is fully based on travel reimbursements that have been submitted to departments. This limits our observations to only travel for which there is an air travel reimbursement request submitted and approved.

Department Surveys

University of Oregon lacks a uniform process for making travel expenditure decisions. Instead, protocol for travel expenditure are segmented across departments and decisions are made by a wide variety of titles. We administered a survey to the UO Travel Coordinators to better understand how department level decisions are made. Survey results serve an implementation purpose rather than an analytical one. Specifics about survey questions and results are discussed later.

Regression Analysis

Regression analysis is performed to obtain estimates of university price elasticity of demand for air travel. While the depth of data obtained is limited, determinants such as: trip month, trip year, unit, and department type are available and relevant for elasticity estimation. Distance, availability of substitutes, travel motive, and the mental cost associated with the department approval process are omitted and likely influence elasticity.

Sensitivity Analysis Model

In addition to regression analysis, sensitivity analysis will be used to test a range of carbon tax rates and elasticities to predict how a given tax would affect miles, expenditure, and emissions.

Procedure

Data Validation

Miles flown and airfare spent are the key variables needed to calculate price elasticities of demand with regression analysis. Total miles flown for each individual department was needed for the dependent variable and airfare expenditure per department was necessary for the key independent variable. Several steps, however, came before the data was ready for regression analysis. Due to variations in spelling of city name (Eugene, OR, Eugene, Oregon, EUG, OR etc.) we cleaned the data to fit a single structure. Domestic locations were cleaned and denoted as, city name and state abbreviation. International locations are denoted, city name and country name. For example, "Boston, Massachusetts" became "Boston, MA" and "Beijing, Chn" became "Beijing, China". Departure city and arrival city were combined to form a city pair for each observation, calling this new variable *City Pair*. For example, the flight Eugene, OR to Boston, MA is now "Eugene OR Boston MA".

For each city pair, linear distance was calculated between the departure and arrival city using a flight distance calculator.[13] Due to the time consuming and manual nature of this process, and the fact that the original dataset contained 4,000 unique city pairs, linear distance was calculated for only the top 70 city pairs which account for 40% of observations. Although the top 70 city pairs represent less than half of the data, the cutoff is reasonable because most remaining city pairs had a frequency of one. One airport was chosen for each departure and arrival city. Specific departure and arrival airport was unknown. Using a consistent but arbitrary airport for each given city allowed consistency without harm to accuracy, since miles between airports

[13] Webflyer. *Mileage Calculator*. Web. April 2017 . http://www.webflyer.com/travel/mileage_calculator/

within the same city are negligible. For example, we used John F. Kennedy airport for all city pairs with an arrival or departure from New York City, NY.

For a more accurate representation of department spending, departments were segmented to create the variable, *Units*. *Units* are categorized by the overarching academic or administrative body. For example, CAS, due to its sheer size, was segmented into three distinct academic disciplines (Humanities, Natural Sciences, and Social Sciences). Each major department within CAS was assigned to their respective academic discipline. For example, the psychology and economics departments are in Social Sciences. In addition, we created a dummy variable differentiating administrative and non-administrative departments. Anything related to the dean, provost, president, HR and admin were categorized as administrative. Data was merged to create one mater dataset that contained invoice and mileage data on only the top 70 *City Pair*s. Department type and unit data were merged by department code[14] and then collapsed upon: month and year of trip, department, and unit.

Survey

With the help of the UO Travel Program Manager we created a six- question survey to distribute to the travel coordinator of each department. The six questions are listed as follows:

- Does your department typically pay the full cost of travel, or are travelers responsible for all or some fraction of expenses?

- Is reimbursement paid for from an individual account or department account?

[14] A six-digit identifier unique to each department or office

- What percentage of travel is funded by external grants?
- How many guest speakers or visitors does your department invite each year?
- Are guest speakers/visitors travel expenses typically paid through a department account, or through the hosting professor's account?
- Please provide the title and department of the individual responsible for approving travel reimbursements? (Title, Department)

Survey data results are used for qualitative as opposed to quantitative analysis. Surveys were distributed via e-mail to various UO Travel Coordinators and a total of eighty-seven surveys were completed. Several travel coordinators contacted us concerned that the black and white nature of the questions may not reflect the true behavior of their respective departments. Travel Coordinator concerns, combined with actual survey results, allowed greater understanding of the university travel process. These insights prove beneficial, both when analyzing elasticity estimates and when evaluating the implications of a potential internal carbon tax.

Elasticity Estimation

Data Summary

Table 1

Variable Name	Value label **Observations: 2,073** **Variables: 43**
TRIP_MY	Month and year of trip in format (YYYY_MM)
DEPARTMENT	University Department
Unit	Overarching unit
ADMIN	Dummy variable =1 for administrative departments =0 otherwise
TRIP_YR	Year of trip in format (YYYY)
TRIP_MONTH	Month of trip in format (MM)
Price per Mile	Cost per one mile of air travel
Miles	Sum of miles flown by TRIP_MY DEPARTMENT and Unit
logprice	Log (Price per Mile)
logqty	Log (Miles)
LAW	Dummy variable =1 if Unit=Law School and 0 otherwise
SOC	Dummy variable =1 if Unit=Social Sciences and 0 otherwise
NATSCI	Dummy variable =1 if Unit=Natural Sciences and 0 otherwise
AAA	Dummy variable =1 if Unit=Allied Arts & Architecture and 0 otherwise
SOJC	Dummy variable =1 if Unit=School of Journalism & Communication and 0 otherwise
HUM	Dummy variable =1 if Unit=Humanities and 0 otherwise
LCB	Dummy variable =1 if Unit=Lundquist College of Business and 0 otherwise
Year.DUM	Dummy Variable =1 if TRIP_YR= relevant year (2008-2016) and 0 otherwise
Month.DUM	Dummy Variable =1 if TRIP_MONTH= relevant month (Feb-Dec) and 0 otherwise

Travel distance and price per mile are recreated in logarithmic form so the coefficient on *Price per Mile* can be interpreted as an elasticity. Fiscal years[15] 2004-2006 and 2017 were dropped as we lacked a full fiscal years' worth of data, leaving calendar years 2007-2016 in the sample. Month dummy variables were created to account for seasonality. Unit dummy variables are created for Humanities (*HUM*), Social Sciences (*SOC*), Natural Sciences (*NATSCI*), Journalism School (*SOJC*), Law School (*LAW*) and Business School (*LCB*) to calculate individual elasticities of major unit travelers.

[15] Fiscal year is defined as the University of Oregon's academic calendar therefore it is from June 30th to June 29th. Therefore, a departure date of 7/4/2009 would belong to the year 2010 instead of 2009.

Model Specification

An estimate of university price elasticity of demand for air travel, referred to simply as "elasticity", is needed to evaluate the effect a given tax would have on university air travel behavior and university carbon emissions.

Regression analysis is conducted for the sole purpose of producing an elasticity estimate, therefore, each regression features *Miles,* in logarithmic form, as the dependent variable and *Price per Mile, in logarithmic form,* as an independent variable. Transforming both the dependent and independent variable of interest to logarithmic form allows the coefficient on *Price per Mile* to be easily interpreted as an elasticity.[16]

(1) $\log(\textit{Miles}) = \beta 0 + \beta 1 \log(\textit{Price per Mile}) + u_i$

(2) $\log(\textit{Miles}) = \beta 0 + \beta 1 \log(\textit{Price per Mile}) + \beta 2\ \textit{Year.DUM}$[17] $+ u_i$

(3) $\log(\textit{Miles}) = \beta 0 + \beta 1 \log(\textit{Price per Mile}) + \beta 2\ \textit{Year.DUM} + \beta 3\ \textit{Month.DUM}$[18] $+ u_i$

(4) $\log(\textit{Miles}) = \beta 0 + \beta 1 \log(\textit{Price per Mile}) + \beta 2\ \textit{Year}.\mathrm{DUM} + \beta 3\ \textit{Month.DUM} + \beta 4\ \textit{Administrative} + u_i$

Regression (1) is the simplest model for forming an elasticity estimate, quite probably too simple. Regression (2) includes yearly dummies to account for the probability of a time trend. While variation may occur annually, it also may occur seasonally. Regression (3) includes monthly dummies to account for seasonality in behavior and pricing. Regression (4) introduces

[16] log-log allows elasticity interpretation: A 1%Δ in the independent variable corresponds with a β1%Δ in the dependent variable

[17] *Year.DUM* is a stand in for each annual dummy: one for each year 2008-2016 (2007 is the excluded)

[18] *Month.DUM* is a stand in for each monthly dummy: months Feb. through Dec. (Jan. is the excluded)

the *Administrative* dummy accounting for the possibility that administrative and non-administrative departments may behave differently.

Regressions (5) through (10) build off, what will be used as the base regression, regression (4). They contain all the variables in the base regression and introduce dummies to account for differences of academic units.

The College of Arts & Sciences (CAS) makes up the bulk of travel miles within the data, and therefore, is deemed interesting enough to explore through separate regressions. To explore the effects of varied CAS units, regressions (5) through (7) add a dummy variable for each singular unit and its associated interaction term. Regression (8) includes each of the unit dummy variables, and their interactions, to capture the entirety of CAS in one regression. CAS units include: Humanities (HUM), Social Sciences (SOC), and Natural Sciences (NATSCI).

(5) $\log(\textit{Miles}) = \beta0 + \beta1 \log(\textit{Price per Mile}) + \beta2\ \textit{Year}.\text{DUM} + \beta3\ \textit{Month}.\text{DUM} + \beta4\ \textit{Administration} + \beta5\ \textit{HUM} + \beta6\ (\textit{HUM} \cdot \textit{Price}) + u_i$

(6) $\log(\textit{Miles}) = \beta0 + \beta1 \log(\textit{Price per Mile}) + \beta2\ \textit{Year}.\text{DUM} + \beta3\ \textit{Month}.\text{DUM} + \beta4\ \textit{Administration} + \beta5\ \textit{SOC} + \beta6\ (\textit{SOC} \cdot \textit{Price}) + u_i$

(7) $\log(\textit{Miles}) = \beta0 + \beta1 \log(\textit{Price per Mile}) + \beta2\ \textit{Year}.\text{DUM} + \beta3\ \textit{Month}.\text{DUM} + \beta4\ \textit{ADMIN} + \beta5\ \textit{NATSCI} + \beta6\ (\textit{NATSCI} \cdot \textit{Price}) + u_i$

(8) $\log(\textit{Miles}) = \beta0 + \beta1 \log(\textit{Price per Mile}) + \beta2\ \textit{Year}.\text{DUM} + \beta3\ \textit{Month}.\text{DUM} + \beta4\ \textit{Administration} + \beta5\ \textit{NATSCI} + \beta6\ (\textit{NATSCI} \cdot \textit{Price}) + \beta5\ \textit{HUM} + \beta6\ (\textit{HUM} \cdot \textit{Price}) + \beta7\ \textit{SOC} + \beta8\ (\textit{SOC} \cdot \textit{Price}) + u_i$

In addition to evaluating the effects of CAS, it is also interesting to explore how independent "schools" behave with respect to air travel. Four independent "schools" are evaluated: Lundquist

College of Business (LCB), Allied Arts & Architecture, and the Law School. Regressions (9) through (12) again build off the base regression; one independent school dummy variable, and its interaction with price is introduced at each regression. Regression (13) is again identical to regression (4) but includes the dummy variable for each CAS unit and each independent school, along wither their relevant interaction terms to observe how estimates may change when all interactions are combined in one regression.

(9) log(*Miles)* = β0 + β1 log(*Price per Mile*) + β2 *Year*.DUM + β3 *Month*.DUM + β4 *Administration* + β5 *LCB* + β6 (*LCB ·Price*) + u_i

(10) log(*Miles)* = β0 + β1 log(*Price per Mile*) + β2 *Year*.DUM + β3 *Month*.DUM + β4 *Administration* + β5 *AAA* + β6 (*AAA · Price*) + u_i

(11) log(*Miles)* = β0 + β1 log(*Price per Mile*) + β2 *Year*.DUM + β3 *Month*.DUM + β4 *Administration* + β5 *SOJC* + β6 (*SOJC ·Price*) + u_i

(12) log(*Miles)* = β0 + β1 log(*Price per Mile*) + β2 *Year*.DUM + β3 *Month*.DUM + β4 *Administration* + β5 *LAW* + β6 (*LAW ·Price*) + u_i

(13) log(*Miles)* = β0 + β1 log(*Price per Mile*) + β2 *Year*.DUM + β3 *Month*.DUM + β4 *Administration* + β5 *LCB* + β6 (*LCB ·Price*) + β7 *AAA* + β8 (*AAA ·Price*) + β9 *SOJC* + β10 (*SOJC ·Price*) + β11 *LAW* + β12 (*LAW ·Price*) + β13 *SOC* + β14 (*SOC ·Price*) + β15 *NATSCI* + β16 (*NATSCI ·Price*) + u_i

All regressions are run with heteroskedastic robust standards errors. This decision was supported by both the White Test and the Breusch-Pagan, which revealed heteroskedasticity. In interest of airing on the conservative side regarding coefficient significance, heteroskedastic robust standard errors were chosen.[19]

Results

This section displays results for regressions (1) through (13) outlined in '*Model Specification'*.

[19] Results of the White Test and the Breusch-Pagan Test can be found in the Appendix.

<u>Table 2</u>

Collapse by Trip Date: *Variable Summary*					
Variable	*Obs.*	*Mean*	*Std. Dev.*	*Min*	*Max*
Miles	2,073	3356.782	3946.346	234	32674*
Price Per Mile	2,073	.667872	.6292819	.013882	3.959098
ADMIN	2,073	-	.2699792	0	1
AAA	2,073	-	.26617977	0	1
SOJC	2,073	-	.1251923	0	1
LCB	2,073	-	.2372041	0	1
LAW	2,073	-	.2468023	0	1
HUM	2,073	-	.230825	0	1
SOC	2,073	-	.283767	0	1
NATSCI	2,073	-	.2298952	0	1
Trip Month	2,073	6.285094	3.334367	1	12
Calendar Year	2,073	5.443319	2.586868	2007	2016

Table 2 displays summary statistics for each variable involved in analysis <u>before</u> logarithmic transformation. *Price per mile* is the only variable of interest in Table 2. The average price per mile paid over the sample period is ~ $0.0667872 per mile. The price variation is large: the lowest price per mile paid by any given department of any given department of any year is ~ $0.014 per mile, while the maximum price per mile paid by any given department of any given year is ~ $3.60. This variation will allow an estimate of elasticity to be obtained.

Dummy variable means have been removed as they fail to deliver any useful information. Statistics on *Miles* are misleading, they are calculated as the mean miles traveled, the minimum miles traveled, and the maximum by a given unit within a singular department over the <u>entire</u> sample period. This explains why the maximum of 32,674 is more miles than needed to travel around the globe. This number is not the maximum miles of an individual trip, but rather the maximum miles traveled by a given department within a given unit within a given month and year.

Table 3

Simple Regressions

Variables[1]	(1) Miles	(2) Miles	(3) Miles	(4) Miles
Price Per Mile	-0.595***	-0.593***	-0.589***	-0.588***
	(-0.0184)	(-0.0185)	(-0.0185)	(-0.0185)
Administration				-0.257***
				(-0.0490)
2008		0.111	0.0994	0.0963
		(-0.0942)	(-0.0966)	(-0.0961)
2009		0.116	0.127	0.133
		(-0.0957)	(-0.0963)	(-0.0959)
2010		0.166*	0.155	0.161
		(-0.0975)	(-0.0985)	(-0.0981)
2011		0.0854	0.0874	0.09
		(-0.0945)	(-0.0951)	(-0.0946)
2012		-0.00918	-0.0183	-0.0116
		(-0.0927)	(-0.0938)	(-0.0933)
2013		0.00777	0.0103	0.0128
		(-0.0909)	(-0.0921)	(-0.0916)
2014		0.13	0.125	0.122
		(-0.0938)	(-0.0953)	(-0.0948)
2015		0.103	0.1	0.0963
		(-0.0985)	(-0.1010)	(-0.1000)
2016		0.165	0.156	0.155
		(-0.1240)	(-0.1280)	(-0.1280)
4-Feb			-0.236**	-0.232**
			(-0.1030)	(-0.1030)
March			-0.0376	-0.03
			(-0.0996)	(-0.0996)
April			-0.133	-0.14
			(-0.0948)	(-0.0949)
May			-0.187*	-0.187*
			(-0.1010)	(-0.1010)
June			-0.0418	-0.0407
			(-0.0969)	(-0.0971)
July			-0.116	-0.121
			(-0.1020)	(-0.1020)
August			0.0302	0.0372
			(-0.1130)	(-0.1130)
September			-0.286***	-0.290***
			(-0.1030)	(-0.1030)
October			-0.166	-0.165
			(-0.1020)	(-0.1020)
November			-0.138	-0.135
			(-0.0975)	(-0.0976)

December			-0.146	-0.14
			(-0.1080)	(-0.1080)
Constant	7.115***	7.034***	7.158***	7.176***
	(-0.0271)	(-0.0793)	(-0.1130)	(-0.1130)
Observations	2,073	2,073	2,073	2,073
R-squared	0.318	0.321	0.328	0.332

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

1 The independent variable of interest (Price Per Mile) and the dependent variable (Miles) are in log form

Table 3 displays output for the four basic models. For each regression, the coefficient on *Price Per Mile* is interpreted as the overall university elasticity. The regression (1) coefficient estimate of -0.595 suggests a 1% increase in the price per mile of air travel corresponds with a 0.595% decrease in miles traveled.

Yearly dummies are introduced in regression (2) to absorb time trend from the residual. While none of the year coefficients are significant, their introduction slightly increases the elasticity suggesting that the regression (1) coefficient on *Price Per Mile* may biased downward[20].

Monthly dummies are introduced in regression (3) to account for potential seasonality in the data. While most of the monthly dummies are insignificant, the ones that *are* significant are significant in each regression model. February is significant at the 5% level and September at the at the 1% level for both regressions in which they appear; implying that those months correspond with less miles traveled than January.[21]

[20] Biased Downward implies the omitted variables are correlated positively with x and negatively with y or negatively with y or correlated negatively with x or positively with y.

[21] January is the excluded dummy variable to which the included are compared

Introducing monthly dummies in regression (3) affects the *Price Per Mile* coefficient, driving it more negative than it was in regression (2), suggesting that the regression (2) coefficient on *Price Per Mile* was likely biased upwards[22]

The dummy variable, *Administrative,* is introduced in regression (4) to allow for administrative and academic department to respond differently to price changes. The *Administrative* coefficient is significant at the 1% level and implies that being an "administrative" department corresponds with 26% less miles traveled[23]. Introducing *Administrative* affects the *Price Per Mile* coefficient, making it less negative.

For each model, elasticity estimates are consistently significant at the 1% level. R^2 is highest for regression (4), however, the improvement is minimal compared to the other regressions and may reflect addition of regressors as opposed to fit. Nevertheless, regression (4) extracts the most explanatory power from the data at hand and will be used as the base regression model that all others will be built upon.

[22] Biased Upwards implies that the omitted variables are correlated negatively with both x and y or correlated positively with box x and y

[23] log-level coefficient interpretation are as follows: a 1 unit Δ in X corresponds with a $100 \cdot \beta 4$ % Δ change in Y

Table 4

CAS Regressions+

Variables[1]	(5) Miles	(6) Miles	(7) Miles	(8) Miles
Price Per Mile	-0.588***	-0.600***	-0.622***	-0.638***
	(-0.0183)	(-0.0182)	(-0.0175)	(-0.0162)
Administration	-0.205***	-0.186***	-0.162***	0.00204
	(-0.0489)	(-0.0490)	(-0.0483)	(-0.0476)
HUM	1.106***			1.349***
	(-0.1800)			(-0.1790)
(I*) HUM	0.243**			0.287**
	(-0.1150)			(-0.1140)
SOC		0.890***		1.109***
		(-0.1210)		(-0.1190)
(i*) SOC		0.204**		0.241***
		(-0.0933)		(-0.0926)
NATSCI			1.606***	1.790***
			(-0.1340)	(-0.1340)
(i*) NATSCI			0.18	0.206
			(-0.1760)	(-0.1760)
2008	0.0884	0.106	0.118	0.122
	(-0.0934)	(-0.0936)	(-0.0869)	(-0.0777)
2009	0.136	0.128	0.137	0.135*
	(-0.0936)	(-0.0934)	(-0.0878)	(-0.0797)
2010	0.160*	0.155	0.163*	0.153*
	(-0.0951)	(-0.0955)	(-0.0896)	(-0.0801)
2011	0.0734	0.0929	0.111	0.0963
	(-0.0922)	(-0.0922)	(-0.0853)	(-0.0769)
2012	-0.00993	-0.0105	0.0117	0.0174
	(-0.0917)	(-0.0901)	(-0.0848)	(-0.0766)
2013	0.0098	0.0329	0.0451	0.0697
	(-0.0896)	(-0.0892)	(-0.0832)	(-0.0755)
2014	0.115	0.132	0.138	0.142*
	(-0.0927)	(-0.0924)	(-0.0874)	(-0.0797)
2015	0.0926	0.0979	0.111	0.109
	(-0.0971)	(-0.0979)	(-0.0893)	(-0.0794)
2016	0.13	0.115	0.158	0.0771
	(-0.1210)	(-0.1260)	(-0.1150)	(-0.0981)
February	-0.215**	-0.223**	-0.207**	-0.173**
	(-0.1040)	(-0.0996)	(-0.0885)	(-0.0835)
March	-0.00768	-0.014	0.00627	0.0585
	(-0.0987)	(-0.0935)	(-0.0906)	(-0.0790)
April	-0.112	-0.118	-0.091	-0.0244
	(-0.0952)	(-0.0895)	(-0.0860)	(-0.0770)
May	-0.176*	-0.176*	-0.169*	-0.140*
	(-0.1020)	(-0.0969)	(-0.0893)	(-0.0824)

June	-0.0207	-0.00979	-0.0143	0.0521
	(-0.0977)	(-0.0926)	(-0.0883)	(-0.0812)
July	-0.0965	-0.108	-0.105	-0.0582
	(-0.1020)	(-0.0981)	(-0.0912)	(-0.0824)
August	0.0502	0.0469	0.0344	0.0616
	(-0.1150)	(-0.1090)	(-0.0994)	(-0.0945)
September	-0.287***	-0.261***	-0.303***	-0.265***
	(-0.1050)	(-0.0992)	(-0.0991)	(-0.0951)
October	-0.158	-0.154	-0.132	-0.107
	(-0.1010)	(-0.0975)	(-0.0906)	(-0.0819)
November	-0.129	-0.12	-0.113	-0.0831
	(-0.0979)	(-0.0925)	(-0.0894)	(-0.0809)
December	-0.137	-0.126	-0.186*	-0.169*
	(-0.1070)	(-0.1040)	(-0.0968)	(-0.0878)
Constant	7.115***	7.079***	7.022***	6.809***
	(-0.1130)	(-0.1090)	(-0.1020)	(-0.0930)
Observations	2,073	2,073	2,073	2,073
R-squared	0.37	0.373	0.444	0.555

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

+ (i*) indicates the coefficient should be interpreted as an interaction term between the given variable and *Price per Mile*.
1 The independent variable of interest (Price Per Mile) and the dependent variable (Miles) are in log form

Table 4 illustrates output for the four regressions focusing on the three distinct CAS units. Regression (5) contains the same variables as base regression (4) but adds the dummy variable *HUM* and its interaction with *Price per Mile*. The *Price per Mile* coefficient is less negative in regression (5) than regression (4) suggesting that the base regressions elasticity estimate was likely biased downwards.

Regression (6) replaces the *HUM* dummy, and its interaction term, with the *SOC* dummy and its relevant interaction with *Price per Mile.* Interestingly, the coefficient estimate on *Price per Mile* is unchanged relative to regression (5).

Regression (7) replaces the *HUM* dummy, and its interaction term, with the *NATSCI* dummy and its relevant interaction with *Price per Mile*. The coefficient estimate on *Price per Mile* is more negative than in regressions (5) and (6) indicating that the previous regressions may be biased upwards.

Regression (8) consists of all parameters in base regression (4) and includes all CAS units and their interaction terms. The coefficient on *Price per Mile* becomes more negative than in any of the previous regressions at -0.638.

The coefficients on each dummy interaction term[24] indicate the difference between the respective unit elasticity and the university elasticity. Interaction terms for HUM and SOC are significant at least at the 5% level in their individual regressions, (5) and (6) respectively, as well as the CAS inclusive regression (8). The NATSCI interaction term is not significant at any reasonable significance level in its individual regression or regression (8)

[24] The elasticity for each unit is given by the sum of the coefficient on its respective interaction term and the coefficient on the *Price per Mile* regressor in the respective model

Table 5

School Regressions+

Variables[1]	(9) Miles	(10) Miles	(11) Miles	(12) Miles	(13) Miles
Price Per Mile	-0.591***	-0.581***	-0.587***	-0.589***	-0.642***
	(-0.0189)	(-0.0196)	(-0.0186)	(-0.0195)	(-0.0182)
Administration	-0.245***	-0.247***	-0.258***	-0.256***	0.0295
	(-0.0493)	(-0.0497)	(-0.0491)	(-0.0491)	(-0.0482)
LCB	0.240*				0.601***
	(-0.1240)				(-0.1240)
(i*) LCB	0.0659				0.133
	(-0.0857)				(-0.0860)
AAA		-0.374***			-0.0392
		(-0.0724)			(-0.0689)
(i*) AAA		-0.117**			-0.0558
		(-0.0488)			(-0.0472)
SOJC			-0.0616		0.0808
			(-0.1800)		(-0.1770)
(i*) SOJC			-0.0813		-0.0449
			(-0.1590)		(-0.1500)
LAW				-0.238***	0.105
				(-0.0728)	(-0.0719)
(i*) LAW				-0.00727	0.0416
				(-0.0477)	(-0.0473)
SOC					1.162***
					(-0.1200)
(i*) SOC					0.245***
					(-0.0931)
NATSCI					1.845***
					(-0.1350)
(i*) NATSCI					0.213
					(-0.1760)
HUM					1.400***
					(-0.1790)
(i*) HUM					0.289**
					(-0.1140)
2008	0.0982	0.0863	0.0957	0.0869	0.126*
	(-0.0959)	(-0.0954)	(-0.0964)	(-0.0966)	(-0.0761)
2009	0.132	0.135	0.132	0.126	0.133*
	(-0.0956)	(-0.0947)	(-0.0959)	(-0.0964)	(-0.0779)
2010	0.156	0.156	0.16	0.149	0.140*
	(-0.0980)	(-0.0972)	(-0.0982)	(-0.0986)	(-0.0786)
2011	0.0895	0.0808	0.0896	0.0855	0.0946
	(-0.0945)	(-0.0936)	(-0.0946)	(-0.0949)	(-0.0756)
2012	-0.0151	-0.0207	-0.0126	-0.0132	0.00739

	(-0.0932)	(-0.0927)	(-0.0934)	(-0.0936)	(-0.0751)
2013	0.0136	0.0161	0.0116	-0.00104	0.0725
	(-0.0913)	(-0.0906)	(-0.0918)	(-0.0921)	(-0.0736)
2014	0.122	0.118	0.121	0.11	0.142*
	(-0.0946)	(-0.0943)	(-0.0950)	(-0.0953)	(-0.0780)
2015	0.0937	0.0998	0.0955	0.0839	0.105
	(-0.0998)	(-0.0993)	(-0.1010)	(-0.1010)	(-0.0769)
2016	0.15	0.136	0.156	0.134	0.0645
	(-0.1270)	(-0.1270)	(-0.1280)	(-0.1280)	(-0.0949)
4-Feb	-0.225**	-0.237**	-0.231**	-0.254**	-0.150*
	(-0.1030)	(-0.1030)	(-0.1030)	(-0.1030)	(-0.0812)
March	-0.0177	-0.0199	-0.0295	-0.0521	0.101
	(-0.0997)	(-0.0996)	(-0.0996)	(-0.0995)	(-0.0771)
April	-0.13	-0.139	-0.139	-0.158*	0.00938
	(-0.0948)	(-0.0949)	(-0.0950)	(-0.0949)	(-0.0748)
May	-0.184*	-0.191*	-0.187*	-0.206**	-0.122
	(-0.1010)	(-0.1010)	(-0.1010)	(-0.1010)	(-0.0797)
June	-0.0362	-0.044	-0.0402	-0.0622	0.0734
	(-0.0969)	(-0.0972)	(-0.0972)	(-0.0972)	(-0.0787)
July	-0.118	-0.119	-0.121	-0.145	-0.041
	(-0.1020)	(-0.1030)	(-0.1030)	(-0.1030)	(-0.0798)
August	0.0338	0.0344	0.0344	0.00705	0.0571
	(-0.1120)	(-0.1120)	(-0.1130)	(-0.1130)	(-0.0902)
September	-0.286***	-0.290***	-0.289***	-0.313***	-0.245***
	(-0.1030)	(-0.1040)	(-0.1030)	(-0.1030)	(-0.0943)
October	-0.166	-0.16	-0.165	-0.180*	-0.104
	(-0.1010)	(-0.1020)	(-0.1020)	(-0.1020)	(-0.0786)
November	-0.137	-0.137	-0.137	-0.161*	-0.0804
	(-0.0969)	(-0.0977)	(-0.0980)	(-0.0977)	(-0.0779)
December	-0.142	-0.15	-0.14	-0.162	-0.165*
	(-0.1080)	(-0.1080)	(-0.1080)	(-0.1080)	(-0.0868)
Constant	7.160***	7.206***	7.178***	7.220***	6.744***
	(-0.1130)	(-0.1130)	(-0.1130)	(-0.1150)	(-0.0897)
Observations	2,073	2,073	2,073	2,073	2,073
R-squared	0.334	0.338	0.332	0.335	0.568

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

+ (i*) indicates the coefficient should be interpreted as an interaction term between the given variable and *Price per Mile*.
1 The independent variable of interest (Price Per Mile) and the dependent variable (Miles) are in log form

Regressions (9) through (10) are base regression (4) including a dummy variable for one of the following independent schools and their associated interaction term with *Price per Mile*: *LCB*, *AAA*, *SOJC*, and *LAW*. In individualized regressions (9) through (10) *AAA* is the only significant interaction term with significance at the 5% level.

Regression (11) is a catch all regression in which each CAS and school dummy variable, as well as their associated interaction terms, are added to base regression (4) to create one all-encompassing regression. This catch all regression delivers a high R^2 relative to previous regressions. This suggests superior fit; however, several variables lack the significance they once had. The *HUM* and the *SOC* interaction terms are the only significant interactions in the catch all regression with significance at the 5% level. *Administration* is also insignificant for the first time. Previously significant coefficients losing their significance in the catch all model may be a multicollinearity issue introduced when all variables are present within one model.

Table 6

Elasticity	**Min**	**Mean**	**Max**
University	-0.642	-0.600	-0.581
Humanities	-0.353	-0.350	-0.335
Social Sciences	-0.397	-0.381	-0.351
Natural Sciences	-0.432	-0.434	-0.429
Business School	-0.525	-0.517	-0.509
AAA	-0.698	-0.698	-0.698
Journalism	-0.687	-0.678	-0.668
Law School	-0.600	-0.598	-0.596

The range above will be used in sensitivity analysis to observe the effects, and specify a fitting internal tax on carbon emission for the university.

Carbon Emissions Sensitivity

Sensitivity Analysis

Sensitivity analysis tests the effect of a range of internal carbon tax on each department using their respective air travel elasticities. Individual elasticity estimates are used for major units: The Journalism School, Law School, Business School, and the College of Arts and Sciences (broken into their respective disciplines). Their individual elasticities will be calculated in the **Results** section later in this paper. We assume a university wide air travel elasticity for the rest of the departments as there is not enough travel data for each department to calculate each individual elasticity.

Air Travel Elasticities

Based on results from regression analysis we obtained the minimum, mean and maximum air travel price elasticities for each unit. The seven units that travel significantly more relative to other units will have unique elasticities:

- Allied Arts and Architecture (*AAA*)
- Lundquist School of Business (*LCB*)
- School of Journalism and Communications (*SOJC*)
- Law School (*LAW*)
- Humanities (*HUM*)
- Natural Sciences (*NATSCI*)
- Social Sciences (*SOC*)

The university wide elasticity will be assumed for all other units. Respective elasticities are shown below. Unique elasticities are bolded. At a brief glance, the elasticities shown below are less than unitary elastic meaning a 1% change in price has less than a 1% response change in miles flown.

<u>Table 7</u>

Unit	Min Elasticity	Mean Elasticity	Max Elasticity
AAA	**-0.698%**	**-0.698%**	**-0.698%**
ACAD	-0.642%	-0.595%	-0.581%
ADMIN	-0.642%	-0.595%	-0.581%
AE	-0.642%	-0.595%	-0.581%
ATHLETICS	-0.642%	-0.595%	-0.581%
BUSINESS AFFAIRS	-0.642%	-0.595%	-0.581%
CACATR	-0.642%	-0.595%	-0.581%
CE	-0.642%	-0.595%	-0.581%
HONORS COLLEGE	-0.642%	-0.595%	-0.581%
CLUB SPORTS	-0.642%	-0.595%	-0.581%
CPFM	-0.642%	-0.595%	-0.581%
CRES	-0.642%	-0.595%	-0.581%
DEV	-0.642%	-0.595%	-0.581%
ED	-0.642%	-0.595%	-0.581%
EL	-0.642%	-0.595%	-0.581%
EM	-0.642%	-0.595%	-0.581%
EMU	-0.642%	-0.595%	-0.581%
HLC	-0.642%	-0.595%	-0.581%
HR	-0.642%	-0.595%	-0.581%
HUMANITIES	**-0.642%**	**-0.370%**	**-0.581%**
IS	-0.642%	-0.595%	-0.581%
LAW SCHOOL	**-0.353%**	**-0.598%**	**-0.335%**
BUSINESS SCHOOL	**-0.642%**	**-0.517%**	**-0.581%**
LIBRARY	-0.642%	-0.595%	-0.581%
NATURAL SCIENCES	**-0.525%**	**-0.422%**	**-0.509%**
OIA	-0.600%	-0.595%	-0.596%
PD	-0.642%	-0.595%	-0.581%
PER	-0.416%	-0.595%	-0.429%
PT	-0.642%	-0.595%	-0.581%
RESEARCH	-0.642%	-0.595%	-0.581%
SOCIAL SCIENCES	**-0.642%**	**-0.370%**	**-0.581%**
JOURNALISM SCHOOL	**-0.642%**	**-0.678%**	**-0.581%**
MUSIC SCHOOL	-0.642%	-0.595%	-0.581%
SRS	-0.397%	-0.595%	-0.335%
UNKNOWN	-0.687%	-0.595%	-0.668%
UA	-0.642%	-0.595%	-0.581%
UC	-0.642%	-0.595%	-0.581%
UGS	-0.642%	-0.595%	-0.581%
UH	-0.642%	-0.595%	-0.581%
HEALTH CENTER	-0.642%	-0.595%	-0.581%
UO	-0.642%	-0.595%	-0.581%
VPSL	-0.642%	-0.595%	-0.581%

Table 7 above shows the minimum, mean and maximum air travel elasticity for each individual unit. The seven units of interest are bolded

Carbon Output Analysis

Using the social cost of carbon, calculated by the Environmental Protection Agency (EPA), we tested a range of taxes to find the optimal internal carbon tax. The social cost of carbon, SCC, in the United States is \$39 per ton of CO_2 . [25] We tested tax rates at intervals of 20%, and with the last one at 10%, of the SCC. Thus, the taxes we tested were \$39, \$31.2, \$23.4, \$15.6, \$7.8, \$3.9

[25] "Q&A: The Social Cost of Carbon." Carbon Brief. N.p., 03 Mar. 2017. Web. https://www.carbonbrief.org/qa-social-cost-carbon

per ton of CO_2. We will focus on the tax rate results using the mean elasticity estimate featured in Table 6. Analysis using the minimum and maximum elasticities are featured in the appendix.

<u>Figure 1</u>

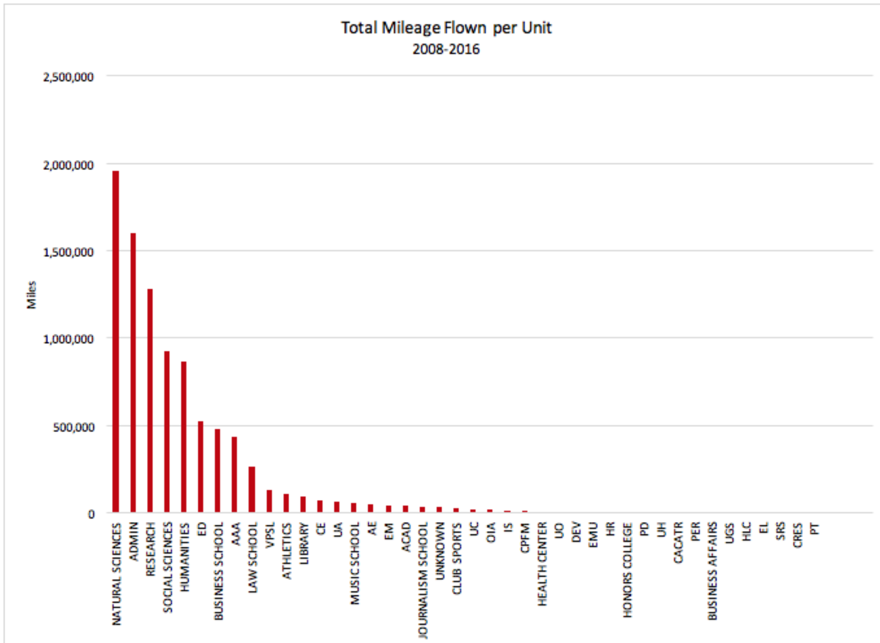


Figure 1 above shows the total mileage flown by each unit over the period from 2008-2016

<u>Figure 2</u>

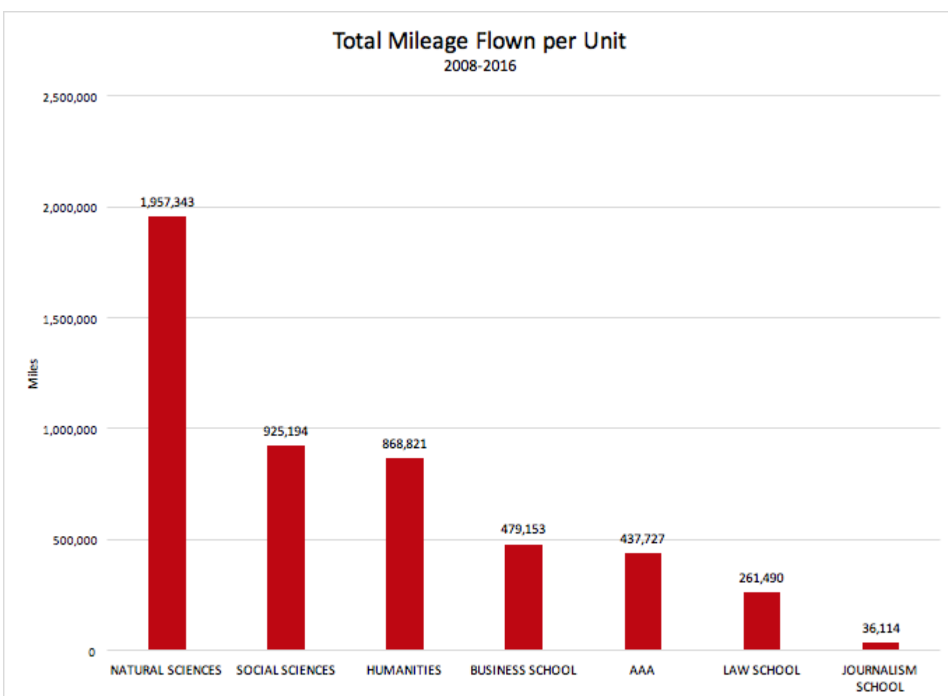


Figure 1 represents the total mileage flown by each unit from 2008-2016 without the presence of a carbon tax. Figure 2 shows the seven units of interest with their total mileage flown labeled above their respective bar. Natural Sciences lead all units in miles flown at 1,957,343 miles.

Next we graphed each unit's carbon dioxide emissions measured in tons. We calculated their carbon emissions using quantity of carbon emitted per mile flown, measured at .199 kg per passenger mile. Therefore, .000199 tons of CO_2 per passenger mile.[26] We used passenger mile to measure the carbon output emitted per mile for an individual flier. Natural Sciences flew the most miles over the sample period at 1,957,343 and emitted the most carbon at 389.6 tons as shown in figure 3.

[26] "Emission Factors for Greenhouse Gas Inventories." *2015 ASABE International* Meeting(2015): n. pag. Epa.gov. EPA, 19 Nov. 2015. Web. https://www.epa.gov/sites/production/files/2015-12/documents/emission-factors_nov_2015.pdf

Figure 3

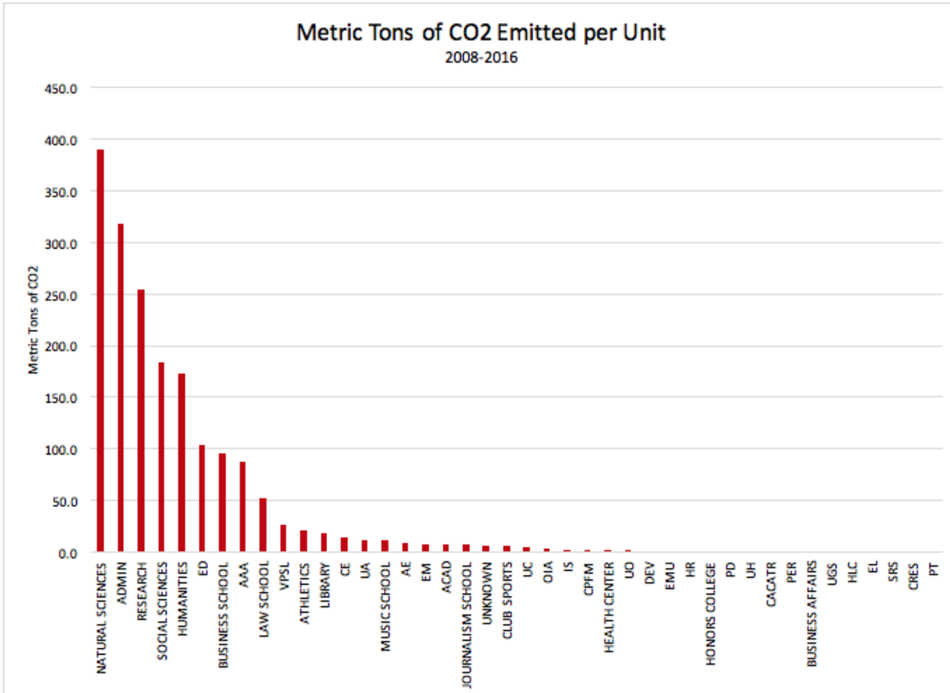
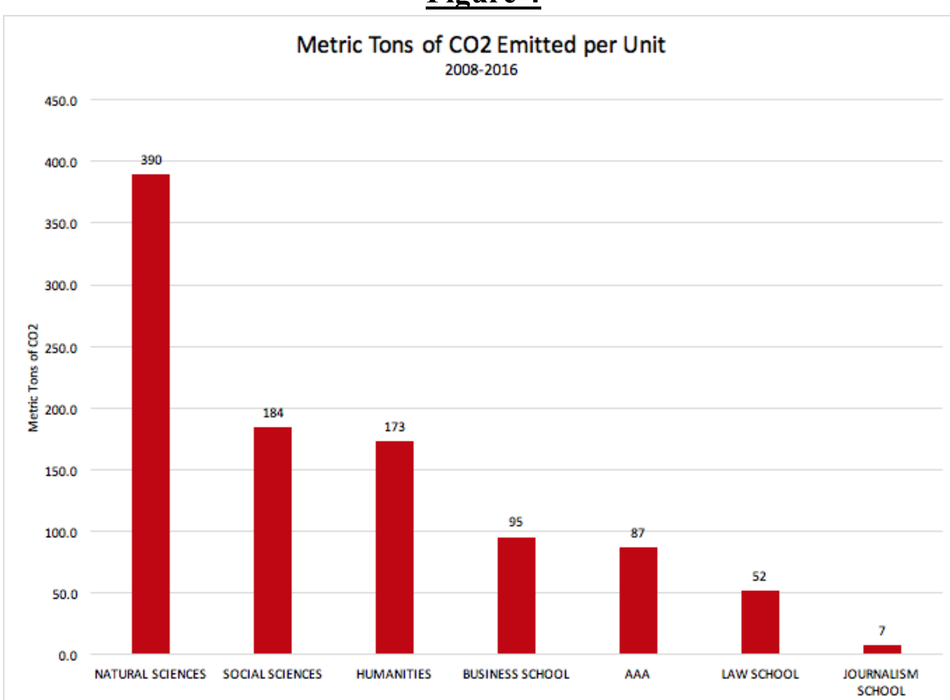


Figure 3 above shows the tons of carbon dioxide emitted by each unit over the time period 2008-2016

Figure 4



Six different tax rates were applied at varied levels of the SSC, to calculate tax penalty measured in tons of carbon emitted by each unit over the sample period. As a reminder, the SCC is $39 per ton and we tested it at 100%, 80%, 60%, 40%, 20% and 10% of the SCC as shown in figure 5 below. At 100% of the SCC ($39 per ton), the biggest flier, Natural Sciences, faces a tax penalty of $15,190.94 for their total air travel carbon emissions over the eight year span.

<u>Figure 5</u>

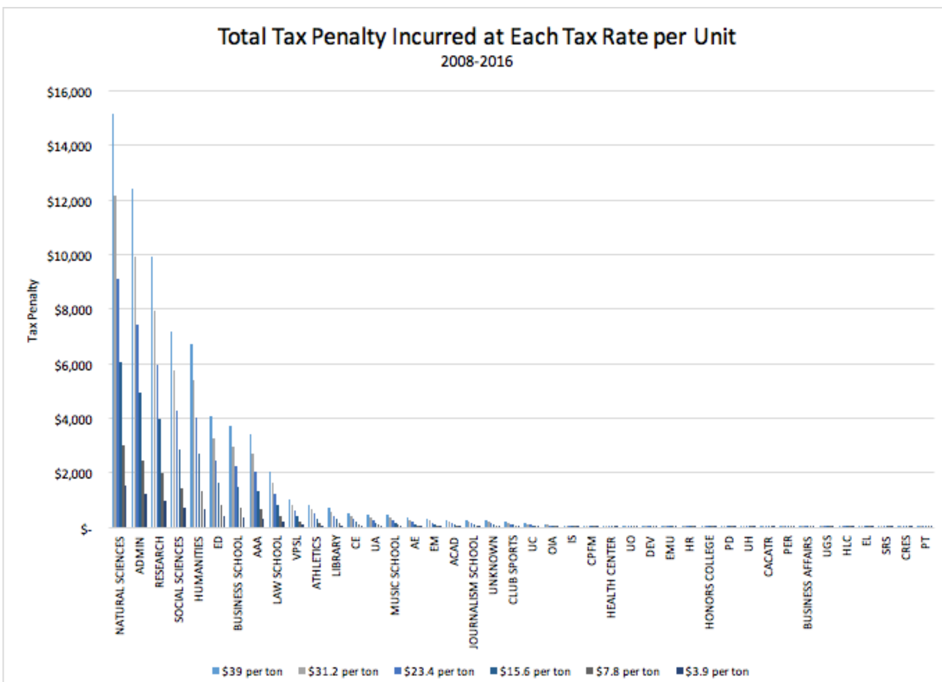


Figure 5 above shows the total tax penalty for each unit at different tax rates over the time period 2008-2016

Figure 7 represents only the tax penalty for the seven units of interest. Figure 8 shows the average tax penalty incurred by each unit per tax rate. Per figure 6, the seven units incur tax penalties significantly higher than the average penalties shown in figure 7.

Figure 6

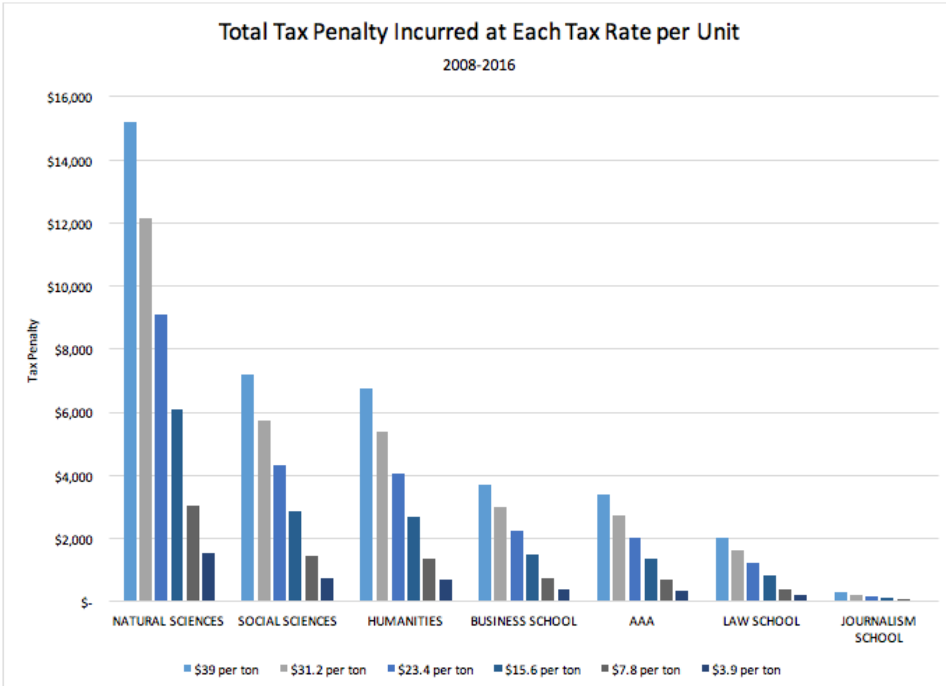


Figure 7

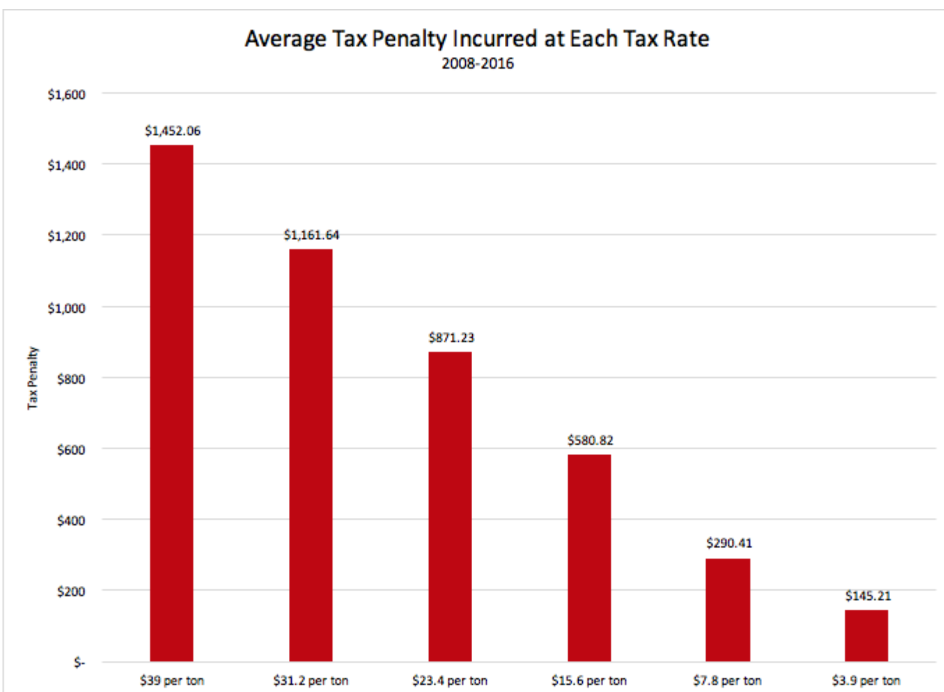


Figure 7 above shows the average tax penalty for each unit per tax rate over the time period 2008-2016

Using the hypothetical tax penalties each unit would absorb into their budget, we then calculate the new price per mile flown, PPM, to see how these different tax rates would affect their air travel in terms of total mileage. The PPM without the presence of a tax was measured at $.667 per mile. Table 7 below shows the new price per mile at each tax rate as well as the change in price at each tax rate. At the highest tax rate of $39 per ton of CO_2, the price changes by only $.008.

Table 8

	PPM ($39)	PPM ($31.2)	PPM ($23.4)	PPM ($15.6)	PPM ($7.8)	PPM ($3.9)
	$ 0.675	$ 0.673	$ 0.672	$ 0.670	$ 0.669	$ 0.6678
Change in Price	$ 0.008	$ 0.006	$ 0.005	$ 0.003	$ 0.002	$ 0.0008

Table 8 shows the PPM at each different tax rate and the change in price from the original $.667 price per mile

Using the new PPM's above, with mean elasticities, we calculated the difference in mileage flown in the presence of a tax. Figure 8 below indicates the difference in mileage flown when there is a carbon tax applied keeping ceteris paribus. As seen in figure 8, even when the full SCC tax is levied onto the units, only changes total miles flown by less than five miles except for the few significant fliers. Figure 9 shows the mileage difference only for the seven units of interest.

Figure 8

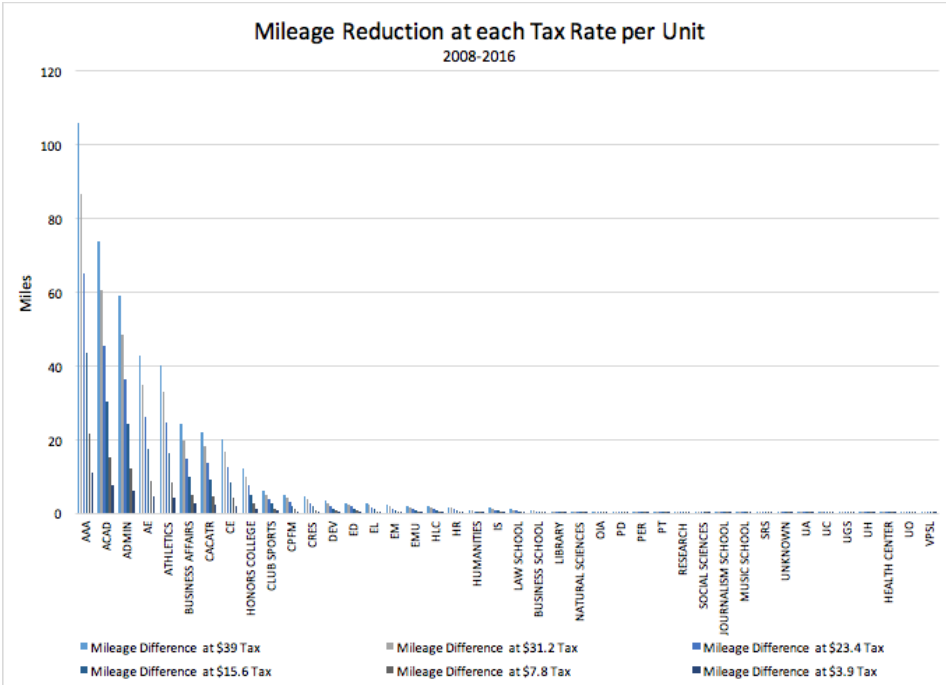
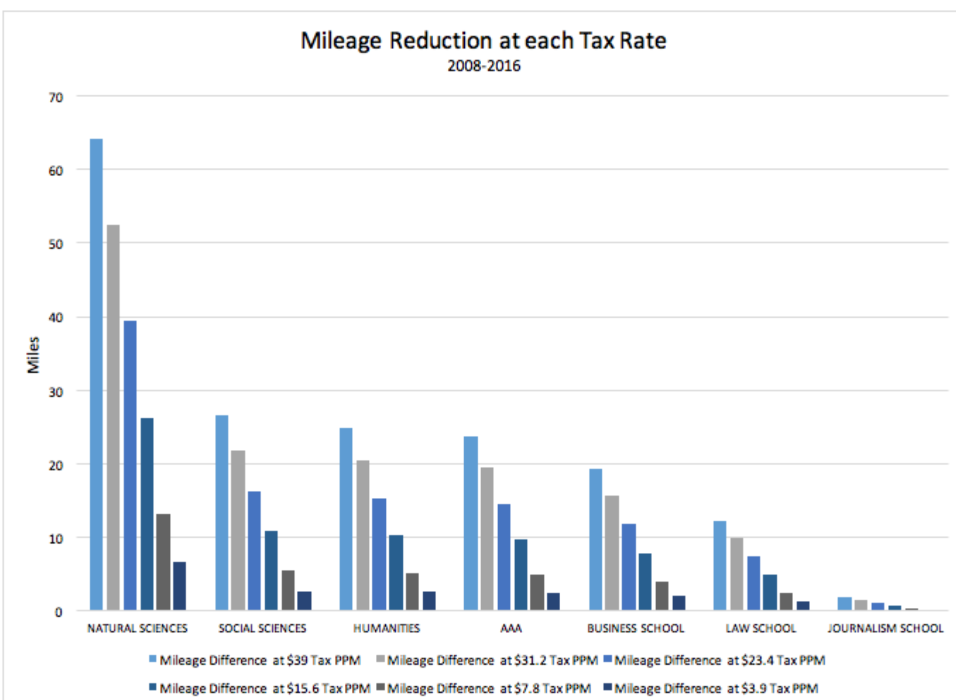


Figure 8 shows the total mileage reduced at each different tax rate over the time period 2008-2016

Figure 9



Summary

As seen in our findings above, taxing air travel at or below the social cost of carbon has a marginal effect on miles flown by each unit. Refer to Figure 9. At a tax rate of $39 per ton of CO_2, reduces miles traveled for Natural Sciences, the biggest flier, by only 64 miles and reduces the rest of the units an average of eight miles, over the span of eight years. Hence, a smaller tax rate than $39 would have even less of an effect on miles traveled. In total, a $39 per ton of carbon tax would reduce University of Oregon's total mileage flown from 2008-2016 by 368 miles. The 368 miles is equivalent to 73.22 kilograms of carbon.[27] Thus a lower tax rate would see even smaller differences in miles traveled and carbon (kg) reduced. The table below shows how many miles and kilograms of carbon are reduced at each tax rate.

Table 9

	$39/metric ton CO2	$31.2/metric ton CO3	$23.4/metric ton CO4	$15.6/metric ton CO5	$7.8/metric ton CO6	$3.9/metric ton CO7
Miles	368	301	226	151	75	38
Carbon (kg)	73.2	59.9	45.0	30.0	15.0	7.5

Table 9 shows the miles and the equivalent kilograms of carbon reduced at each tax rate

Given our results, we tested our data with another set of air travel elasticities acquired through our literature review. These elasticities were calculated by Martjin Brons, Eric Pels and Peter NijKamp from the University of Amsterdam. Compared to our price elasticities, which are unique to the University of Oregon, these new air travel price elasticities were obtained through meta-analysis of a sample of leading estimates of elasticity that are based only on business and leisure travelers (with hybrid university travelers not uniquely estimated). The literature review

[27] "Emission Factors for Greenhouse Gas Inventories." *2015 ASABE International Meeting* (2015): n. pag. *Epa.gov*. EPA, 19 Nov. 2015. Web.

elasticities are presented below in the same format as minimum, mean and maximum price elasticities in the table below.

Table 10

Air Travel Price Elasticities		
Minimum	Mean	Maximum
-3.2	-1.146	0.2

Table 10 above shows the air travel price elasticities calculated by the University of Amsterdam.

Just as we focused analysis on the mean elasticity when utilizing our own estimates, we will do the same with the mean estimate derived from literature in Table 10 above. University of Amsterdam's mean price elasticity exceeds unit elasticity; a one percent change in price has a change greater than one percent on miles traveled. Figure 10 below illustrates the miles reduced at each tax rate using the elasticity estimates from University of Amsterdam. Figure 11 illustrates the miles reduced only for the seven units of interest.

Figure 10

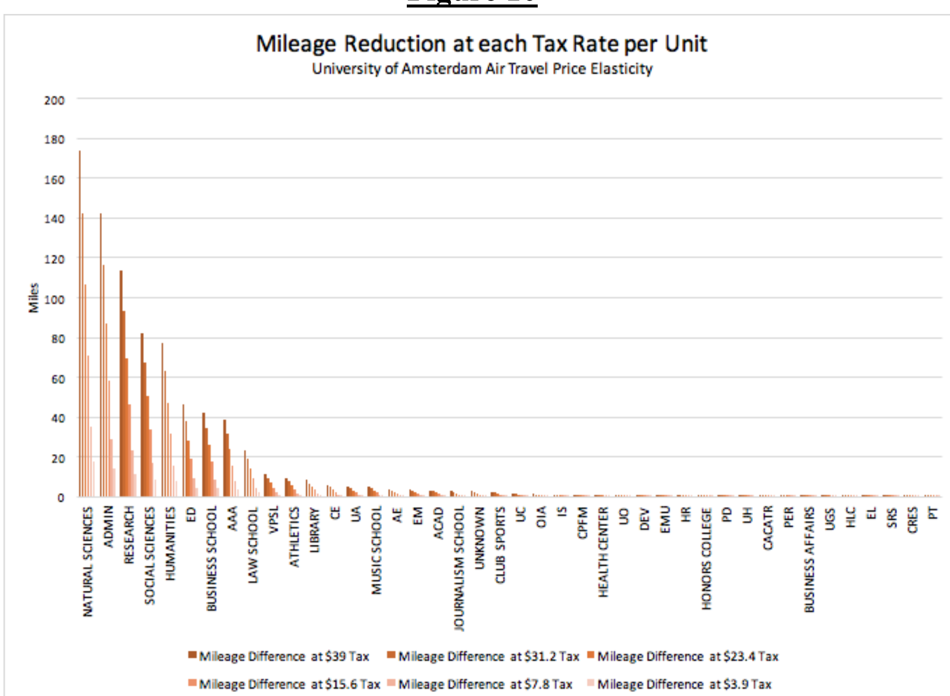


Figure 10 above shows the mileage reduction over the time period 2008-2016, at each tax rate, using the University of Amsterdam's mean price elasticity estimate.

Figure 11

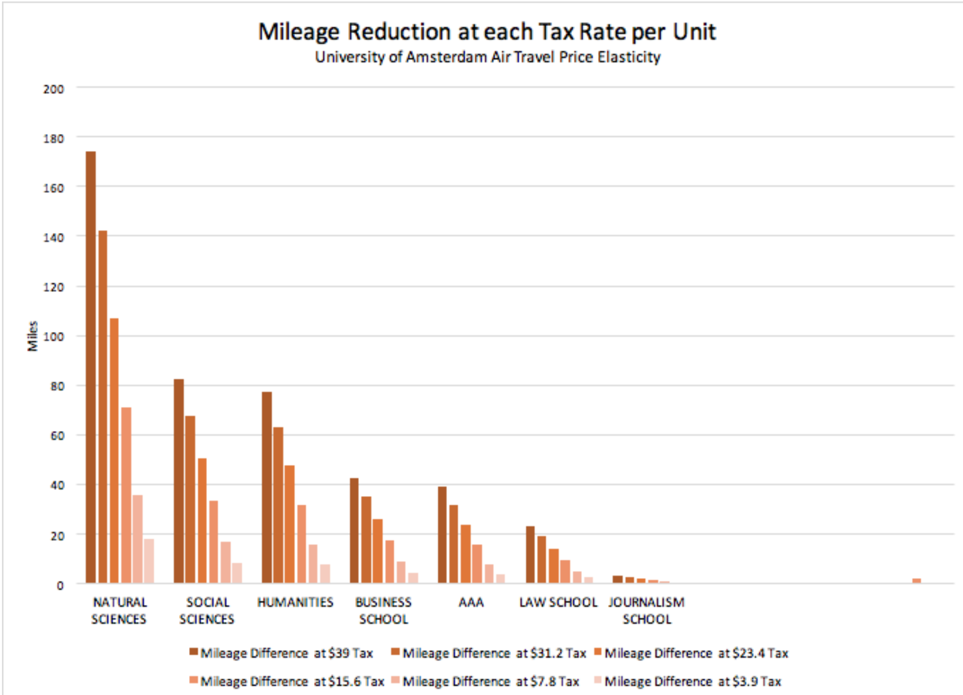


Figure 12

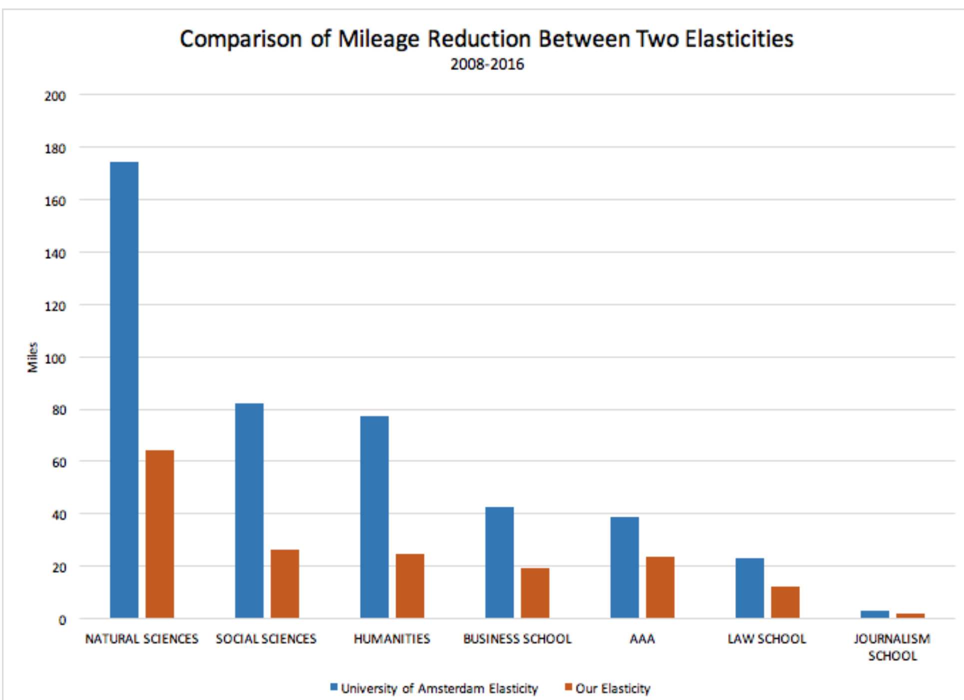


Figure 12 above compares the mileage reduction between the two elasticities applied to the seven units of interest

Table 11

Unit	University of Amsterdam Elasticity	Our Elasticity	Difference
NATURAL SCIENCES	174	64	110
SOCIAL SCIENCES	82	27	56
HUMANITIES	77	25	52
BUSINESS SCHOOL	43	19	23
AAA	39	24	15
LAW SCHOOL	23	12	11
JOURNALISM SCHOOL	3	2	1

Table 11 above shows the miles reduced using our elasticity and the University of Amsterdam's elasticity on the seven units of interest

Figure 12 and Table 11 above compare the difference in mileage reduction between our calculated price elasticity and the one sourced from our literature review respectively. We only compared the mileage reduced at the $39 per ton of CO_2 tax rate as it is the most impactful to reduce mileage and carbon emissions.

Using the University of Amsterdam's price elasticity, air travel miles are reduced by a total of 818 miles. The 818 miles reduced is equivalent to 162.8 kilograms of CO_2.[28] However, even with an increase in miles reduced, the reduction of total amount of carbon emitted is marginal at best because the 162.8 kilograms represents the carbon reduced over an eight-year, from 2008-2016.

[28] "Emission Factors for Greenhouse Gas Inventories." *2015 ASABE International Meeting* (2015): n. pag. *Epa.gov*. EPA, 19 Nov. 2015. Web.

Difficulties

As mentioned in the **Literature Review** section, estimates of the price elasticity of demand for air travel are notoriously difficult to estimate reliably. Two main reasons for such difficulty is limited price variation observed in air travel data due to government regulation and lack of specificity involved in data. Combined, these two issues, make for estimates plagued by both multicollinearity and omitted variable bias. It is unlikely that our estimates stray from this trend.

Sample data used in elasticity estimation was limited both in quantity and in depth. Though initially provided university air travel reimbursement data from 2004-2017, several years contained too few observations to be representative of an entire fiscal year. In response, fiscal years lacking decent representation throughout the entire period were dropped. Thus, the sample data used for regression analysis includes fiscal years 2008-2016[29].

Date of airfare purchase is excluded from the data, and therefore, all regressions are run based on the departure date of the trip. Departure date can capture the effect of certain times of the year being more expensive to travel than others. It will not, however, control for price variation due to purchase date. The price of an airline ticket will be more expensive if purchased the day before departure than if it were purchased ahead of time. Since this information is not included in the sample data, "early bird" effects are not controlled for in our regression models. This exclusion, in combination with other exclusions as well, likely result in biased coefficient estimates and perhaps endogeneity.

[29] Fiscal years 2008-2016 include trips over calendar years 2007-2017

There is room for categorical error in creation of the *Administrative* variable. The original provided data did not specify whether a given department was academic or administrative in nature. To create the *Administrative* dummy variable, we had to enlist some creative license in categorizing each department based on the department name. We likely under-classified departments as administrative, meaning there are likely administrative departments categorized as non-administrative departments (with a value of 0) in the *Administrative* dummy. Under-classification likely skews the coefficient estimates to appear that administrative departments travel far less than academic departments than they truly do, simply because there are so few of them.

The Athletic Department spends more on air travel than any other department[30], however, our data almost completely lacks Athletic Department data. Due to the exclusion of Athletic air travel, our analysis is simply not informative of their travel behavior.

Evidence of endogeneity was discovered within our model. The specific source of the issue is unknown but could be a result of measurement error, omitted variables, or a combination of the two. Variables such as source of funding, travel motive, and size of travel budget. Additionally, measurement error is likely present in the data. Travel re-imbursements are entered exactly as they are filled out on staff reimbursement slips, which leaves room for errors that may be correlated with other included variables. Additionally, measurement error may have occurred within our own specification of departments as administrative vs. non-administrative, as this process was discretionary.

[30] Sonya. Mital. (p. 15)

Opportunities for Further Research

Having team travel data from the athletic department would have improved our analysis significantly. Athletic date included in our analysis was limited to coaches and personnel expenses. Preliminary research showed that the athletic department is the main offender in carbon emissions and travels significantly more than the next highest offender. Conducting similar analysis with Athletic data would be interesting to because scheduled athletic events require them to travel. Due to this characteristic, they likely behave much differently than other units.

Another area of improvement for further research would be implementing survey results to get a qualitative perspective along with the quantitative data. Survey results are important because it allows you to get an in-depth analysis on department travel characteristics due to the non-binary nature of departmental travel policies. Thus, these answers from individuals can be used to form new variables to use in regression analysis for a better fit.

Furthermore, sensitivity results can be more accurate if all travel distances are used rather than just using a portion as a representation for all. For example, in our research, we only calculated the distance for the top 70 city pairs in frequency and used that data as the base for the rest of our calculations. This tedious task of finding the distance for each individual city pair would take significantly more time but this would give a more accurate representation of the miles flown for each department.

Conclusion

Elasticity estimates indicate that university travel demand is not very sensitive to price. Our analysis reveals that charging the social cost of carbon does not hinder department productivity, however, it also does not substantially reduce university emissions. Levying a tax consistent with the social cost of carbon, $39 per ton, has minimal effect on university carbon emissions. Based on our mean elasticity estimate, had a tax been in place over the period of 2008-2016, at the rate of the social cost per ton, the university would have consumed only 368 less miles and reduced carbon emissions by only 73.22 kilograms. Thus, a tax above the estimated social cost of carbon is needed to trigger substantial reduction to university emissions. Since the price elasticities of individual units are so low, and the amount of carbon per passenger on a commercial flight is much less than a ton, a tax on air travel based on a per ton of carbon tax would have to be significantly high to see emission reduction. For example, our highest tested tax rate of $39 per ton of carbon, increases the price per mile by $.008. A $390 per ton of carbon tax would still only increase the price per mile of air travel by $.05.

Given our mean estimate of university price elasticity of demand for air travel, a UO internal carbon tax would need to be set well above the social cost of carbon to prompt any substantial reduction in emissions. A flat tax per trip would be more feasible, and more effective at reducing emissions, if the rate was set based on an emissions target and the university elasticity. More extensive analysis should be conducted to obtain a more reliable estimate of university elasticity, and the elasticity of individual departments before an internal tax structure is seriously proposed. It is possible that omitted variables could be making the elasticity estimate less negative, therefore, making the university appear less sensitive to price than it truly is.

We stand by our assertion that an internal carbon tax would need to be revenue neutral at the department level by design. Departments are reluctant to agree to a tax in which some other body keeps the revenue. The Athletic Department is a political barrier to implementation as they fly most often, bring in the most money, and likely have the most inelastic demand for air travel. The most feasible next step in exploration of an internal carbon tax would be to perform more extensive and in depth research on university elasticity and use those findings to propose a pilot program.

Appendix

Summary Statistics by Department:

Variable	Sum(Miles)	Mean(CPM)
AAA		
0#	6599265	.66996757
1+	359344	.64264664
SOJC		
0	6871829	.66950076
1	86780	.56718775
LCB		
0	6462031	.67189607
1	496578	.60462348
LAW		
0	6665685	.66751125
1	292924	.6730515
HUM		
0	6035566	.67838392
1	923043	.49213517
SOC		
0	5860924	.67599627
1	1097685	.58396611
NATSCI		
0	5848353	.66573593
1	1110256	.70390977
ADMIN		
0	6599114	.66624909
1	359495	.68676361

0: if not classified within the relevant Unit or School
+ 1: if classified within the relevant Unit or School

Testing for Heteroskedasticity:

White's Test

H_0: homoskedasticity
H_1: unrestricted heteroskedasticity

$Chi^2(156) = 192.23$
Prob > Chi2 = 0.0257

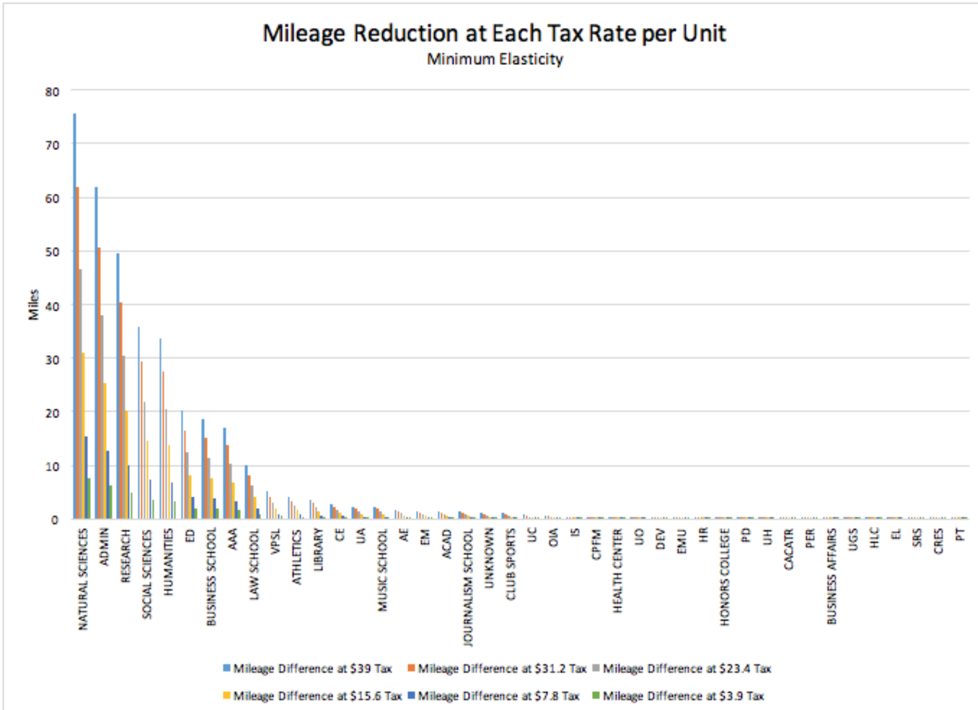
Source	chi^2	df	p
Heteroskedasticity	192.23	156	0.0257
Skewness	254.87	22	0.0000
Kurtosis	14.72	1	0.0001
Total	461.83	179	0.0000

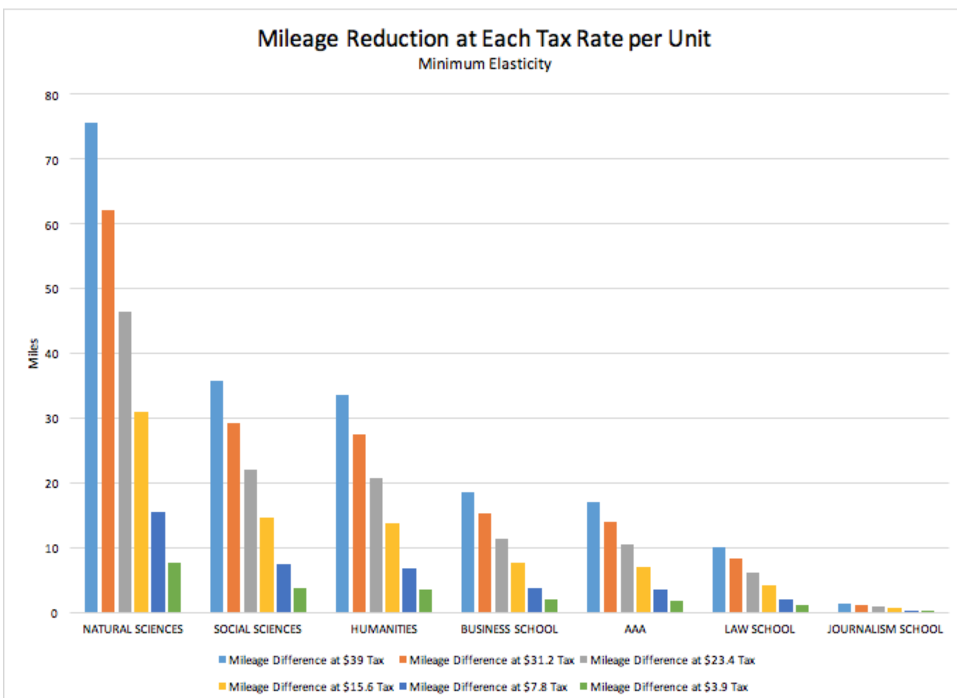
Breush-Pagan		
H0: Constant Variance **Variables:** *Price per Mile, Year.DUM, Month.DUM, Administration*		
chi2(22)	=	98.52
Prob > chi2	=	0.000

Testing Endogeneity with squared residuals:

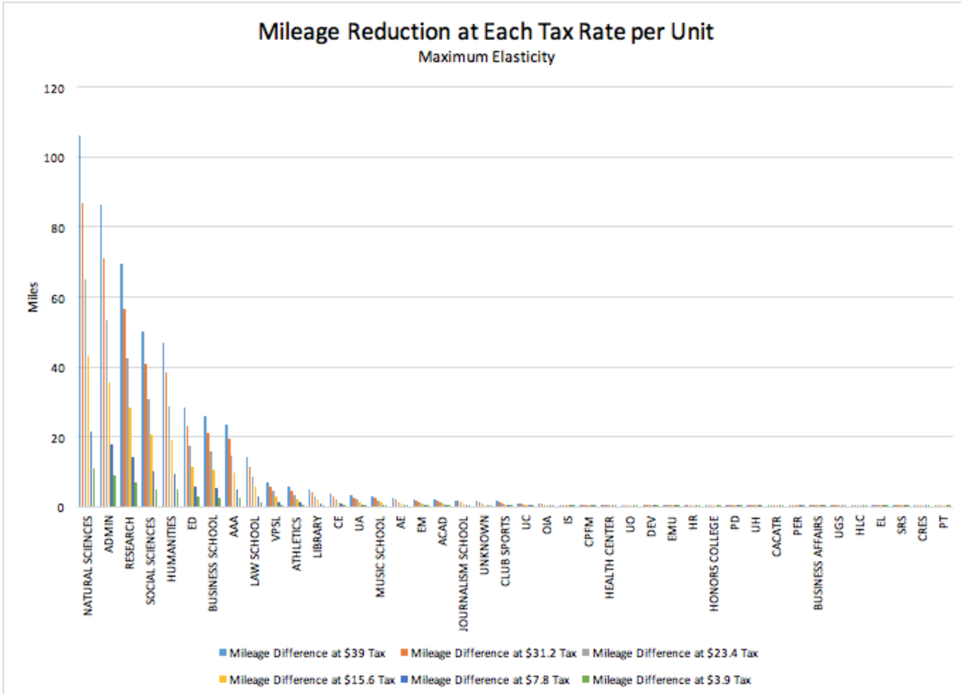
+Endogeneity Testing: $e^2 = \beta 0 + \beta 1$ *Price per Mile* $+ \beta 2$ *Year.DUM* $+ \beta 3$ *Month.DUM* $+ \beta 4$ *Administrative* + ui		
Variable	**e^2**	**P-Value**
Price Per Mile	0.190	7.65
Administration	-0.442	-4.97
2008	-0.027	-0.22
2009	-0.021	-0.17
2010	0.044	0.36
2011	-0.058	-0.47
2012	-0.086	-0.71
2013	-0.072	-0.61
2014	-0.101	-0.82
2015	0.064	0.51
2016	0.053	0.33
February	-0.190	-1.51
March	-0.031	-0.26
April	-0.153	-1.32
May	-0.141	-1.15
June	-0.065	-0.55
July	-0.130	-1.02
August	0.108	0.82
September	-0.267	-1.97
October	-0.041	-0.34
November	-0.222	-1.82
December	-0.187	-1.38
Constant	1.043	7.55

Testing Tax Rates based on the Minimum Elasticity:

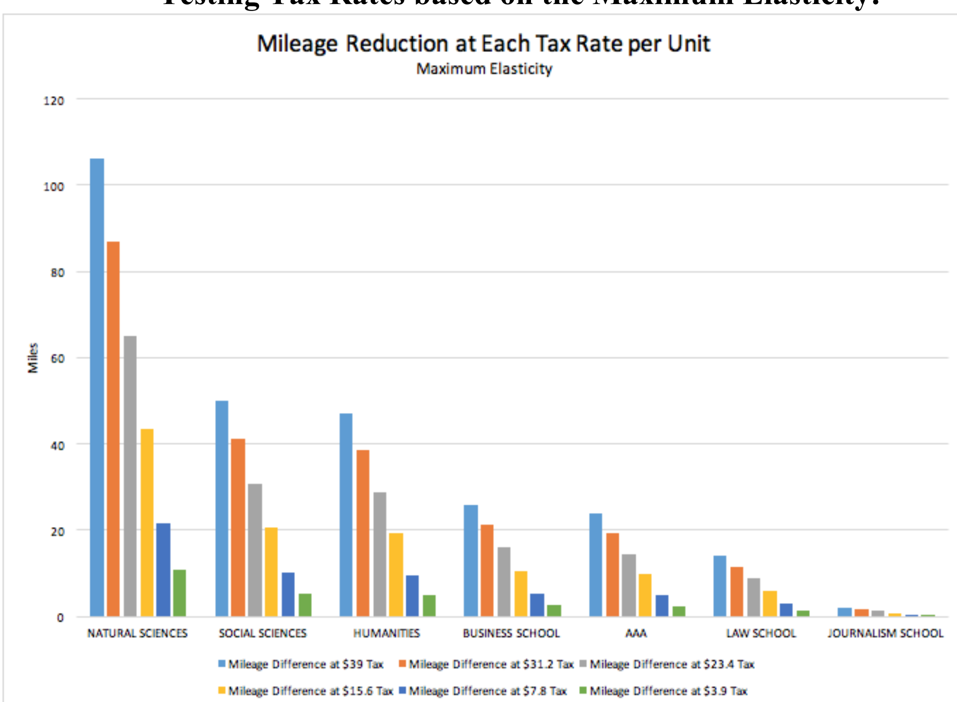




	Mileage Difference at $39 Tax	Mileage Difference at $31.2 Tax	Mileage Difference at $23.4 Tax	Mileage Difference at $15.6 Tax	Mileage Difference at $7.8 Tax	Mileage Difference at $3.9 Tax
Miles	355	291	218	146	73	36
Carbon (kg)	71	58	43	29	14	7



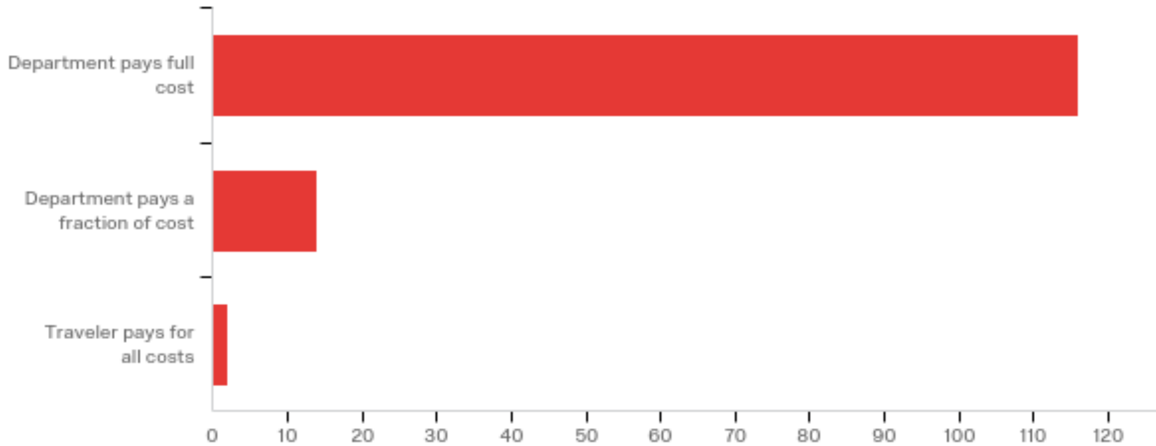
Testing Tax Rates based on the Maximum Elasticity:



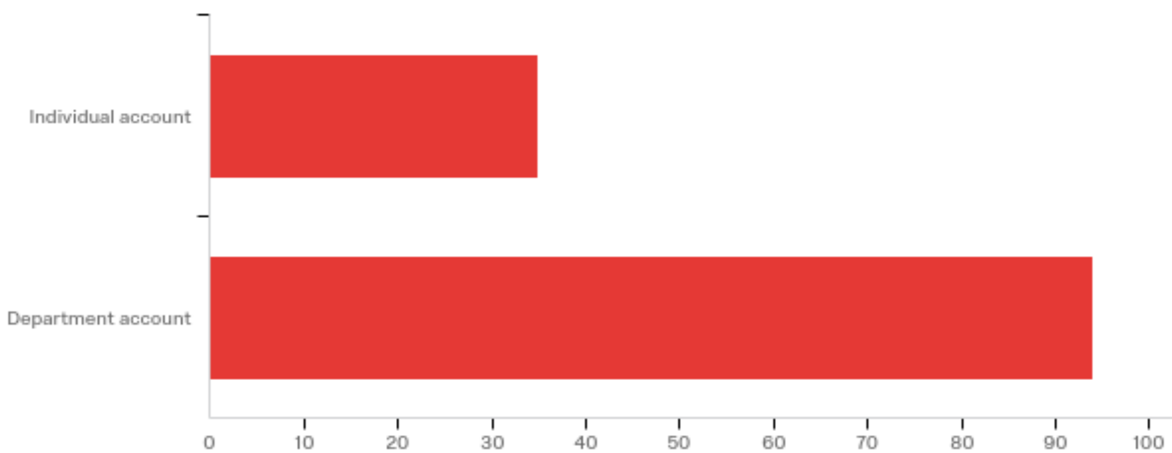
	Mileage Difference at $39 Tax	Mileage Difference at $31.2 Tax	Mileage Difference at $23.4 Tax	Mileage Difference at $15.6 Tax	Mileage Difference at $7.8 Tax	Mileage Difference at $3.9 Tax
Miles	498	408	306	204	102	51
Carbon (kg)	99	81	61	41	20	10

Survey Results:

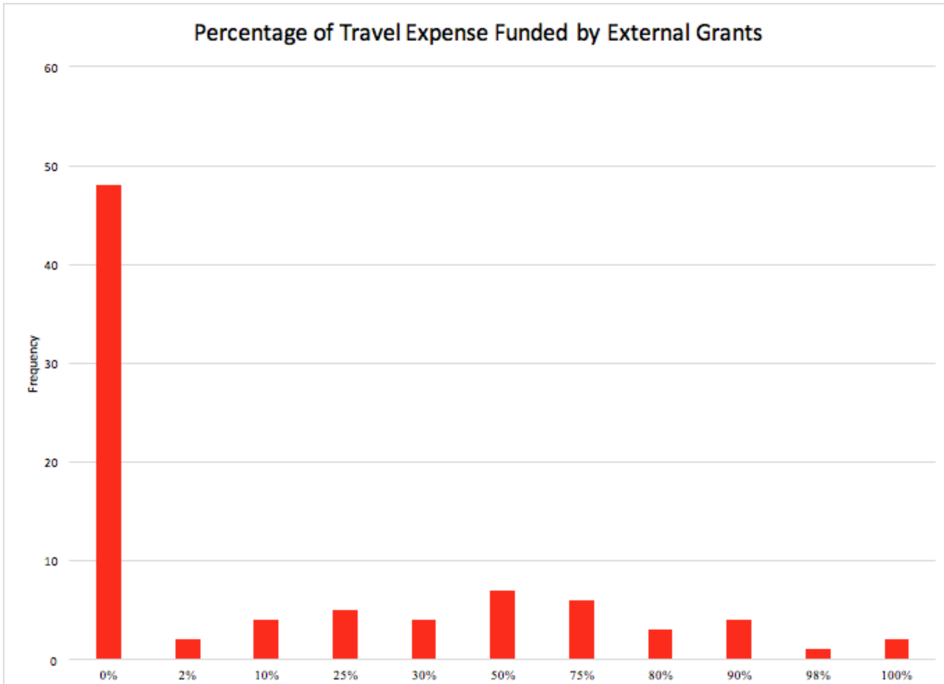
Q: Does your department typically pay the full cost of travel, or are travelers responsible for all or some fraction of expenses?



Q2 - Is reimbursement paid for from an individual account or department account? (For example, ASA would be considered an individual account, a separate departmental travel budget would be a department account.)



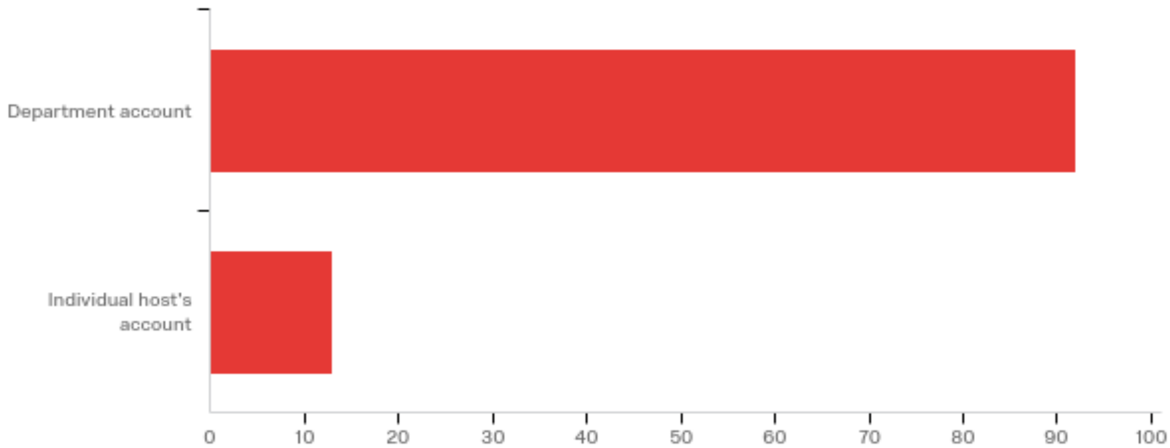
Q3 - What percentage of travel is funded by external grants?



Q4 - How many guest speakers or visitors does your department invite each year?

Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count
Visitors per year	0.00	30.00	11.40	10.51	110.48	101

Q5 - Are guest speaker / visitor travel expenses typically paid through a department account, or through the hosting professor's account?



Q6 - Please provide the title and department of the individual responsible for approving travel reimbursements? (Title, Department)

Responses for questions six are omitted due to the presence of individual names.