Georgia State University
ScholarWorks @ Georgia State University

AYSPS Dissertations | Andrew Young School of Policy Studies

Summer 8-1-2022

Essays on Environmental Economics

Xin Zhang

Follow this and additional works at: https://scholarworks.gsu.edu/aysps_dissertations

Recommended Citation
Zhang, Xin, "Essays on Environmental Economics." Dissertation, Georgia State University, 2022.
doi: https://doi.org/10.57709/30562154

This Dissertation is brought to you for free and open access by the Andrew Young School of Policy Studies at ScholarWorks @ Georgia State University. It has been accepted for inclusion in AYSPS Dissertations by an authorized administrator of ScholarWorks @ Georgia State University. For more information, please contact scholarworks@gsu.edu.

ABSTRACT

ESSAYS ON ENVIRONMENTAL ECONOMICS

By

XIN ZHANG

August 2022

Committee Chair: Dr. Garth Heutel

Major Department: Economics

This dissertation comprises three essays on environmental economics. The first chapter studies the influence of media, both traditional TV news and emerging internet news, on U.S. foreign disaster aid. The Office of U.S. Foreign Disasters responds to an average of 65 disasters every year, spending 2.8 billion dollars. Due to the high stakes, it is essential that relief expenditure is determined by need rather than other factors. The results show a weak crowding out effect in TV news coverage of disasters and other breaking news. However, contrary to a previous study, OFDA relief during 2000-2019 is affected by the severity of the disasters but not by the attention they receive online or in TV news or the intensity of other contemporaneous breaking news.

In the second chapter, I study rational inattention in an overwhelming information environment, one of the main explanations for the existence of the energy efficiency gap. I conducted an incentivized laboratory experiment simulating a car purchase decision using complex fuel efficiency information. I evaluated the effectiveness of the EPA's information provision effort and used an inventive-compatible mechanism to elicit subjects' true willingness to pay for fuel economy labels, a fuel cost calculator and knowledge of their financially optimal car. When presented with the fuel economy information in basic text format, around half of the

subjects chose suboptimal options. Fuel economy labels do not improve subjects' decisions, but the fuel cost calculator significantly reduces their misoptimization by 62%.

The third chapter, coauthored with Dr. Garth Heutel, studies the incidence of pollution taxes and their impact on unemployment in an analytical general equilibrium efficiency wage model. We find closed-form solutions for the effect of a pollution tax on unemployment, factor prices, and output prices, and we identify and isolate different channels through which these general equilibrium effects arise. An effect arising from the efficiency wage specification depends on the form of the workers' effort function. Numerical simulations further illustrate our results and show that this efficiency wage effect can fully offset the sources-side incidence results found in models that omit it.

ESSAYS ON ENVIRONMENTAL ECONOMICS

BY

XIN ZHANG

A Dissertation Submitted in Partial Fulfillment
of the Requirements for the Degree
of
Doctor of Philosophy
in the
Andrew Young School of Policy Studies
of
Georgia State University

GEORGIA STATE UNIVERSITY
2022

Copyright by
Xin Zhang
2022

ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

Dissertation Chair:	Dr. Garth Heutel
Committee:	Dr. Stefano Carattini Dr. James C. Cox Dr. Toby W. Bolsen

Electronic Version Approved:

Dr. Sally Wallace, Dean
Andrew Young School of Policy Studies
Georgia State University
August 2022

ACKNOWLEDGEMENTS

This dissertation would not have been possible without the funding provided by GSU Provost's Dissertation Fellowship and GSU Dissertation Grant, as well as the support of many people.

First and foremost, I am extremely grateful for my advisor and committee chair, Dr. Garth Heutel for his invaluable guidance and tremendous patience. He was always there for me whenever I needed constructive advice and feedback. His continuous support has encouraged me throughout my academic life. I could not have imagined having a better mentor for my PhD study. I also would like to express my sincere gratitude to my committee members, Dr. Stefano Carattini, Dr. James Cox, and Dr. Toby Bolsen for their immense knowledge, insightful comments and thoughtful encouragement.

I would also like to thank faculty members of my department for their help and advice during my PhD study. I thank Mr. Kevin Ackaramongkolrotn for his technical assistance in the lab, as well as my colleagues and friends Sharad KC, Xiangyu Meng and Kukhee Han for their generous help and companionship.

My deepest gratitude goes out to my beloved family – my husband, two sets of parents and brother-in-law, as well as my dog Marty and my cat Mei-Mei. They have given me unconditional love, support, and encouragement, and always believed in me even when I was doubtful.

I would like to dedicate this work to my husband, Ryan McManus, who has been a source of strength, support and motivation for me. Thank you for your selfless love. I am forever grateful.

Table of Contents

List of Tables

List of Figures

Chapter 1

Media and U.S. Foreign Disaster Relief

1.1 Introduction

Natural disasters, such as hurricanes, floods, wildfires and extreme temperatures, are likely becoming more frequent due to climate change. They not only create humanitarian crises, but also have longer-term environmental impact. The Office of U.S. Foreign Disasters (OFDA) spends 2.8 billion dollars on emergency responses to an average of 65 natural disasters in about 50 countries every year. Their disaster responses help those suffering through some of the worst crises around the world, and it is essential that relief expenditure is not affected by factors unrelated to the need for relief.

However, there is evidence showing that news coverage of disasters influences these U.S. relief decisions. Eisensee and Strömberg (2007) find that more media coverage of a foreign natural disaster in US evening news leads to higher probability that the OFDA issues relief to that foreign country between 1968 to 2002. The main mechanism for such media influence is that more informed voters incentivize authorities to be more responsive to events in exchange for publicity or voters' support. Two comparable disasters could end up getting different relief responses because one gets less attention in the US than the other. Especially when there is domestic breaking news happening, (which I call "distraction news"), such as a presidential impeachment or domestic hurricanes, a foreign disaster is unlikely to make it into the major news coverage in the US.

In addition to traditional TV news, Internet has become another major source for news in recent decades. A 2020 survey shows that more than 86% U.S. adults say they get their news from a smartphone, computer, or tablet "often" or "sometimes", and about two-thirds of U.S.

adults say they get news at least sometimes from news websites or apps (68%) or search engines like Google (65%)[1]. In contrast to traditional TV broadcasts with a fixed time frame for news every day, internet provides a nearly unlimited pool of new information, thus the resource driving scarcity is no longer time limits for news sessions but rather people's attention.

This paper studies the influence of media on the U. S. government response to natural disasters overseas. It seeks to quantify to what extent Americans' public attention, reflected by TV news coverage and Google Search, influences policy decisions on foreign disaster aid.

There are two main challenges in answering this question. First, news coverage of a disaster correlates to the emergency response regardless of whether news coverage affects the emergency response directly. News coverage depends on the unobserved issues of salience and political agendas, both of which directly affect policy. I will address this endogeneity problem by using the availability of distraction news as an instrument for whether the disaster was covered by US media. I will examine whether a natural disaster is less likely to receive relief because news about this disaster was crowded out by other news stories. In this paper I will examine two types of media, traditional TV news and online news. I largely follow Eisensee and Strömberg (2007)'s method to construct the instrument variable for TV news coverage as a measurement of the breaking news distraction, but focus on natural disasters between 2000 and 2019, when people's media consumption habits might have changed. Secondly, for online news, since there is no fixed amount of time for news as on evening TV, I address the challenge of collecting meaningful Internet data to construct a valid measurement of the distraction. I utilize Google Trends, the top search keywords in Google News, to quantify the level of distraction and see how

[1] According to a Pew Research Survey in 2020. https://www.pewresearch.org/fact-tank/2021/01/12/more-than-eight-in-ten-americans-get-news-from-digital-devices/

that crowds out people's searches for the disaster and whether that in turn affects OFDA's relief decisions, as Eisensee and Strömberg (2007) have found for television news.

Specifically, I first examine how the level of breaking news distraction affects news coverage of, and relief to, disasters using linear probability OLS regression. Then, to consistently estimate the causal effect of disaster news on relief decisions, I run Two Stage Least Squares (2SLS) regression using distraction news measurements as instrument variables.

The results show that there is a weak crowding out effect in TV news coverage of disasters and other breaking news. An extra 3.8 minutes spent on the top three news segments of TV networks results in, on average, a 5% lower probability of a disaster being covered in TV news. The OFDA relief, during the sample period 2000-2019, is affected by the severity of the disasters but not the disasters' level of TV news coverage or the intensity of other breaking news happening at the same time. There is no detected crowding out effect on Internet searches. The search volumes for top trending keywords are hundreds- if not thousands- of times the search volumes for foreign disaster keywords. As long as the disasters are not close to U.S. territory, American Internet users barely pay any attention to foreign natural disasters. OFDA relief decisions are not affected by the Internet attention received in the United States, or the intensity of other trending searches happening at the same time as the foreign disaster.

The rest of the paper is organized in the following manner: Section 1.2 provides a literature review; Section 1.3 introduces the background and selection of data sources; Section 1.4 specifies the empirical strategy; Section 1.5 presents the results; Section 1.6 concludes.

1.2 Literature Review

This paper is closely related to Eisensee and Strömberg (2007), which studies the influence of TV news coverage of disasters on U.S. foreign aid in response to natural disasters. I adopt a similar empirical strategy using the presence of distraction in the form of other breaking news as an instrument variable but with updated TV news data and a focus on Internet news.

Many papers study the role of media in shaping economic and political outcomes generally. Biased media can have a persuasive effect on people's political opinions and thereby vote shares of political parties[2]. Besley and Prat (2006) develop a theoretical model showing the ability of government to exercise media capture and hence to influence political outcomes, which could explain why some media exhibit an agenda-setting role in a democratic system. DellaVigna and Gentzkow (2010) provide a survey of the effects of persuasive communication directed at consumers, voters, donors, and investors generally.

Even when media do not necessarily attempt to persuade readers or audience towards certain direction, they can still affect voters' behaviors. For example, researchers find voter turnout and political participation are impacted by the entries and exits of newspapers in the U.S. (Gentzkow et al., 2011), Italy (Drago et al., 2014) and France (Cagé, 2020). Gentzkow (2006) finds negative effects of television access on voter turnout during the diffusion of television in the 1950s. The entry of television in a market coincided with sharp drops in consumption of newspapers and radio and in political knowledge. Interestingly, Falck et al. (2014) find that,

[2] Some empirical evidence: biased television news increases the presidential vote share of Republicans in the US (DellaVigna and Kaplan, 2007; Martin and Yurukoglu, 2017). Other studies on biased TV news' political influence include Barone et al. (2015), Durante et al. (2017) and Enikolopov et al. (2011). Chiang and Knight (2011) studies the political influence of newspaper endorsements. Yanagizawa-Drott (2014) estimates the political impact of a popular radio station during Rwandan genocide.

decades later, internet availability also decreases the voter turnout, which can only be explained by a crowding-out of TV consumption and increased entertainment consumption.

Munger (2020) elaborates on the change in the news media environment as the Internet and social media become integral to daily life. Cheaper entry into the information market, lower costs of online news production, and widely varying levels of consumers' technical sophistication all together enable a "clickbait media" environment, in which each news story competes for attention with others on the internet. Gentzkow and Shapiro (2008) explore how more competition in the media market may limit bias or distortion, at least on the supply side. There is also empirical evidence for social media's important role in mobilizing protesters (Acemoglu et al. 2015, Eniklopov et al. 2020) and counteracting corruption (Enikolopov et al. 2018, Qin et al. 2017), since they enable the public to create, spread and receive information on a massive scale with extremely low cost[3].

News media's specific influence on environmental issues, especially on climate change, has gained attention from researchers in various social science fields as well. Bolsen and Shapiro (2018) review how the U.S. news media have framed climate change over time, which has contributed to the polarization of public opinions. Boykoff and Boykoff (2004) shows that US prestige-press coverage of global warming from 1988 to 2002 has contributed to a significant divergence of popular discourse from scientific discourse. Millner and Ollivier (2016) review the literature on social beliefs and political economy of environmental policy, specifically discussing three factors that determine the public's beliefs: individual inference, social learning, and the media.

[3] However, researchers such as Allcott and Gentzkow (2016) raise valid concerns that the internet and social media could incubate "fake news" – content produced by users with no track record or reputation and relayed without fact checking – as well as form "echo chambers" for like-minded citizens where they are insulated from contrary perspectives.

Public attention becomes an increasingly scarce resource in today's information environment, but humans' limited attention has always been a factor in their belief formation and decision making. People ignore some news due to distraction or the high cost of information acquisition. For example, studies have found investors under-react to earnings news when releases take place on Friday (DellaVigna and Pollet, 2009)- when the coming weekend is a source of distraction- as well as on days with a higher number of earnings announcements (Hirschleifer et al. 2009) competing for limited attention.

Given varying public attention, governments, politicians, or policymakers have valid incentives to respond to more media coverage, because their performance has a higher probability of "being seen" by the public. Johnson, Brace and Arceneaux (2005) investigate causal processes linking public opinions and state environmental policies in the US. Besley and Burgess (2002) discuss how more newspaper circulation, and thus a more informed and politically active electorate, correlates with greater public food distribution and calamity relief expenditure in India. Strömberg (2004) shows that U.S. counties with more radio listeners received more funds from the New Deal relief program. Lim et al. (2015) study the effect of newspaper coverage on the behavior of US state court judges. They find that newspaper coverage increases the length of sentences handed down by nonpartisan elected judges for violent crimes but has no significant effects on partisan elected and appointed judges. Snyder and Strömberg (2010) find that voters are less familiar with their representatives, federal spending is lower, and congressmen work less for their constituents in areas where the local U.S. House Representative receives less press coverage for exogenous reasons.

This paper is also related to literature on foreign disaster aid policies. Strömberg (2007) surveys studies on natural disasters, economic development and humanitarian aid. He summarizes the determinants and motives of international disaster relief, including political, cultural, and geographical relationships between the donor and recipient, the effect of media, and domestic factors other than the actual need of the recipient countries. Annen and Strickland (2017) find a large causal effect by the donor country's election cycle on humanitarian aid from the Office of Development Assistance (ODA) of the OECD. On average, humanitarian aid increases by 19% in the year before elections. Researchers in the fields of political science and international relations have conducted more extensive studies on this. Drury et al. (2005) analyze U.S. foreign disaster assistance during 1964–1995 and find that the initial decision of whether or not to grant aid is strongly political, but the subsequent decision of how much aid to grant is less so. Foreign policy and domestic factors are the overriding determinants of the decision. Nevertheless, they also find a "powerful impact of a disaster's media salience", with one New York Times article being worth more disaster aid dollars than 1,500 fatalities.

One valid question regarding this dynamic is why the Office of Foreign Disaster Assistance (OFDA) would respond to the media, considering the generally low political and public attention to foreign disaster aid and the bureaucratic nature of the policy decisions. Political scientists, such as Van Belle (2003) and Joly (2014), argue that bureaucracies like OFDA are essentially agents hired by elected officials such as Congress or the President. If an unsatisfactory policy decision made by a bureaucracy is brought to the attention of elected officials, they can complain, alert the bureaucracy, or threaten to either cut the budget of the bureaucracy or fire upper-level officials. The principal-agent model is a well-established framework in studies of interaction between elected politicians and bureaucracy (see Gailmard and Patty, 2012; Maggetti and Papadopoulos, 2016). The role of news media in this relationship is to provide a common referent for both principals and agents to judge the current or expected demands from the domestic political arena. “Bureaucracies should try to avoid the harsh negative sanctions that could be turned against them by adjusting their actions in accordance with the same domestic political cues they expect their potential punishers, elected officials, to use.” (Van Belle, 2003)

Across the fields of social science, there is plenty of literature addressing the wider political influence of mass media, but relatively little measuring the causal effect of news on foreign disaster aid policy during the information explosion of the present Internet era. This paper contributes by revisiting the question posed by Eisensee and Strömberg (2007) with updated data and an additional quantitative measurement of public attention using online search keyword data.

1.3 Background and Data

This section provides background and presents the data on natural disasters, OFDA disaster relief, TV news, and Google Trends.

I study the disaster responses by the Office of U.S. Foreign Disaster Assistance (OFDA), an office within the U.S. Agency for International Development (USAID). The OFDA was responsible for leading and coordinating the U.S. government’s response to disasters overseas. It had flexible authority to respond quickly to disaster-hit countries and regions, and the OFDA disaster declaration also triggered follow-up disaster assistance from other U.S. agencies with larger amounts of reliefs. Therefore, an OFDA response to a foreign natural disaster was a crucial step for the victims to get any disaster aid from the U.S. government. In 2020, the OFDA was combined with Food for Peace (FFP) and became the Bureau for Humanitarian Assistance.

Next, I present the disaster data for TV news analysis and Google Trends analysis parallelly, because data availability limits the two analyses to different time periods. I focus on the natural disasters from 2000 to 2019 for TV news analysis, and ones from 2017 to 2019 for Google Trends analysis. Table 1.1 presents the summary statistics for the main variables used in TV news analysis. Table 1.2 presents the summary statistics for the main variables used in Google Trends analysis.

Table 1.1 Summary Statistics for TV News Analysis

Variables	Obs	Mean	Std. Dev.	Min	Max
Total Deaths	5,042	252.5	4,806	1	222,570
Total Affected	5,694	581,116	6,228,000	1	330,000,000
Total Damages ('000 US$)	2,010	712,392	5,437,000	2	210,000,000
Relief	6,809	0.0753	0.264	0	1
Relevant Broadcasts	6,809	1.162	5.985	0	281
News	6,809	0.226	0.419	0	1
News Pressure	6,809	182.4	114.5	0	650.7

Notes: Data of *total deaths, total affected, total damages, relief* of disasters are from Emergency Disaster Database (EM-DAT). The variable *relevant broadcasts, news,* and *news pressure* are calculated based on data in Vanderbilt TV News Archive. *Relevant broadcasts* are the number of TV news segments that are associated with each disaster. *News* is a binary variable indicating whether the disaster was covered in TV news. *News pressure* represents the average duration (seconds) of the daily top three news segments of each TV network during the time period of each disaster, which measures the level of breaking news distraction for each disaster.

Table 1.2 Summary Statistics for Google Trends Analysis

Variables	Obs	Mean	Std. Dev.	Min	Max
Total Deaths	286	87.23	366.2	1	4,140
Total Affected	320	296,530	1,035,000	1	10,000,000
Total Damages ('000 US$)	106	840,472	2,479,000	175	17,000,000
Relief	368	0.109	0.312	0	1
Weekly News Pressure	368	441,300	493,088	56,796	3,534,000
Disaster Week Trend Index	368	710.7	9,737	0	183,213

Notes: Data of *total deaths, total affected, total damages, relief* of disasters are from Emergency Disaster Database (EM-DAT). The variables *weekly news pressure* and *disaster week trend index* are calculated using Google Trends data for the week in which a given disaster started. *Weekly news pressure* is the sum of the scaled Google Trends indices of the seven top trending keywords for that week, while *disaster week trend index* is the scaled Google Trends index of the disaster's keywords for that week.

1.3.1 Natural Disasters

I use natural disaster data from the Emergency Disaster Database (EM-DAT)[4] provided by the Center for Research on the Epidemiology of Disasters (CRED). The database records natural disasters around the world that meet at least one of the following criteria: (1) 10 or more people killed; (2) 100 or more people affected/injured/homeless; (3) declaration by the country of a state of emergency and/or an appeal for international assistance. The database is compiled from various sources including the UN, governmental and non-governmental agencies, insurance companies, research institutes and press agencies. I use three measurements of the severity of a disaster from the database, *totaldeaths*, *totalaffected* and *totaldamages.* The *totaldeaths* includes number of people killed or missing. The *totalaffected* includes the number of people injured, homeless or requiring immediate assistance during a period of emergency. The *totaldamages* measures the economic loss caused by a disaster. EM-DAT also documents whether a disaster received OFDA relief.

[4] https://www.emdat.be/

I only keep disasters for countries that had more than one disaster and received OFDA relief at least once during the time period of my analyses, such that I can include country fixed effects in my specifications. I also dropped disasters with missing data for start or end month[5].

1.3.1.1 Natural Disaster Data Used in TV News Analysis. For TV news analysis, I focus on natural disasters from 2000 to 2019. After the aforementioned steps of data selection, there are 6809 natural disasters left in my sample, occurring in 135 countries. On average, each disaster takes 253 lives and affects 581,116 people, with damages over 700 million USD. The majority of natural disasters are floods (42.74%) and storms (21.71%). The deadliest disaster type is droughts, with an average of 2265 killed per disaster, and they also affect the most people per disaster.

Out of the 6809 disasters, OFDA responded to 7.53% of them according to EM-DAT[6]. Disaster types that are most likely to receive OFDA relief are insect infestation (25%), wildfires (13.29%), earthquakes (12.36%) and volcanic activities (12.24%), while extreme temperature - such as heat wave or cold wave- has the lowest percentage (2.85%) of receiving reliefs. The summary statistics by disaster types for TV news analysis are in Table 1.3.

---

[5] If a disaster has start and end month data but misses the exact start/end day, I fill it out with the first/last day of the month, respectively.
6 OFDA annual reports (https://www.usaid.gov/what-we-do/working-crises-and-conflict/crisis-response/resources/annual-reports); Financial Tracking System (FTS) of the UN Office for the Coordination of Humanitarian Affairs (https://fts.unocha.org/).

Table 1.3 Summary Statistics by Disaster Types (TV)

Disaster Type	# of disasters	Share of disasters (%)	Deaths per disaster	Affected per disaster	Average damages ('000 USD)	Avg # of relevant broadcasts	Share covered in news (%)	Share receiving relief (%)
Drought	170	2.50	2,265	6,546,699	1,078,685	0.16	6.47	6.47
Earthquake	526	7.73	2,043	232,501	2,383,702	3.92	38.40	12.36
Epidemic	770	11.31	159	11,774	.	0.36	8.70	3.77
Extreme temperature	316	4.64	426	752,511	1,133,617	0.19	9.81	2.85
Flood	2910	42.74	47	626,806	500,931	0.88	19.86	8.32
Insect infestation	20	0.29	.	2,300,000	120,000	0.15	15.00	25.00
Landslide	378	5.55	49	19,864	86,844	0.18	12.17	3.17
Storm	1478	21.71	172	525,349	467,895	1.55	33.36	7.37
Volcanic activity	98	1.44	94	55,670	102,602	2.56	47.96	12.24
Wildfire	143	2.10	17	22,259	367,656	2.15	44.76	13.29
Total	6809	100	252	581,116	712,392	1.16	22.65	7.53

Notes: "." indicates missing data.

1.3.1.2 Natural Disaster Data Used in Google Trends Analysis. For the Google Trends analysis, I restrict the scope to the natural disasters between March 19, 2017, to December 31, 2019, due to the limited availability of Google Trends data. The subsample left includes 368 natural disasters. On average, each disaster takes 87 lives and affects 296,530 people, with damages over 840 million USD. The majority of natural disasters in this sample are floods (42.39%) and storms (23.91%). The deadliest disaster type is volcanic activity, with an average of 457 killed per disaster, while droughts affect the most people per disaster.

Out of the 368 disasters in my sample for Google Trends analysis, OFDA responded to 10.87% of them according to EM-DAT[7]. Disaster types that are most likely to receive OFDA relief are wildfire (44.44%), and volcanic activities (25%), while extreme temperature - such as heat wave or cold wave- and insect infestation has the lowest percentage (0%) of receiving reliefs. The summary statistics by disaster types for Google Trends analysis are in Table 1.4.

Table 1.4 Summary Statistics by Disaster Types (Google Trends)

Disaster Type	# of disasters	Share of disasters (%)	Deaths per disaster	Affected per disaster	Average damages ('000 USD)	Share receiving relief (%)	Average Weekly News Pressure	Average Disaster Week Trend Index
Drought	12	3.26	77	1,540,024	44,669	41.67	231612	0
Earthquake	32	8.70	224	194,251	1,019,575	12.50	654014	651.5
Epidemic	29	7.88	371	21,151	.	3.45	285939	2
Extreme temperature	9	2.45	85	19,362	.	0.00	332023	0.7
Flood	156	42.39	29	196,806	482,930	7.05	402236	1.1
Insect infestation	1	0.27	.	.	.	0.00	294974	12
Landslide	24	6.52	95	12,913	34,200	8.33	317799	6.1
Storm	88	23.91	43	452,634	1,166,152	12.50	578059	2730.3
Volcanic activity	8	2.17	457	256,392	126,782	25.00	502234	0
Wildfire	9	2.45	55	1,261,555	366,000	44.44	205810	1.2
Total	368	100	87	296,530	840,473	10.87	441300	710.7

Notes: "." indicates missing data.

7 See the following sources: OFDA annual reports (https://www.usaid.gov/what-we-do/working-crises-and-conflict/crisis-response/resources/annual-reports); Financial Tracking System (FTS) of the UN Office for the Coordination of Humanitarian Affairs (https://fts.unocha.org/).

1.3.2 Television News

1.3.2.1 Television News Coverage of Disasters. I first use television news coverage of disasters as a measure of public attention. I use the Vanderbilt TV News Abstracts in the Harvard Dataverse. It contains the broadcast title, abstracts, duration and broadcast time of the evening news segments of the major US TV networks. I restrict my attention to the evening news coverage of ABC, NBC, CNN, CBS, and FNC.

For each disaster documented in EM-DAT, it is considered covered by TV news if its relevant key words (e.g., “India” AND “earthquake”) appear in the broadcast title or abstract of a news segment. I use a time span from 2 days before the disaster start day to 40 days following the disaster end day as the interval to check for news coverage. In Table 1.1, *Relevant broadcasts* shows the number of TV news segments that are associated with each disaster. *News* is a binary variable indicating whether the disaster was covered in TV news.

Table 1.3 presents the summary statistics of disaster news coverage by disaster types. Out of the 6809 disasters, 22.65% are covered[8] by at least one of the five major news networks. The disaster types that are most likely to be covered by the US TV news are volcanic activities (47.96%) and wildfires (44.76%). Only 6.47% of droughts are covered in news, despite causing the most casualties. On average, each volcanic activity is covered by 2.56 news segments, highest among the disaster types, while an insect infestation is covered the least, by only 0.15 news segments per disaster.

8 Eisensee and Strömberg (2007) find that around 10% of the disasters during 1968 and 2002 are covered by the four major evening news (ABC, NBC, CNN, CBS). Fox News Channel (FNC) was founded in 1996, so it is not included. My coverage rate of foreign disasters is twice as high, possibly due to a different searching and matching process.

1.3.2.2 Other Television Breaking News. Following Eisensee and Strömberg (2007), the measurement of distraction is constructed by calculating the average "daily news pressure" over the 42-day time span of each disaster. When there is major breaking news happening, the evening network news tends to allocate longer segments to those events. Given a largely fixed duration of evening news, other less significant news stories including foreign disaster news are then likely crowded out. Thus, on a breaking news day, the total duration of the top three news segments of each program is likely to be longer. The "daily news pressure" is the median value of such top-three-news-duration across the five TV channels. It measures how large the "distraction" is from the breaking news of the day. For each disaster, I am then able to calculate the average "daily news pressure" during the 42-day time span, which I call news pressure. Table 1.1 presents news pressure measured in seconds.

1.3.3 Google Trends

To measure Americans' public attention to certain topics on Internet, one could use search volumes on search engines, numbers of posts on various social media websites (e.g., Twitter, Facebook), or viewership data on video websites (e.g., YouTube). In this paper, I use American netizens' Google search volume data captured by Google Trends to represent public attention. Google is by far the most visited website in the United States and worldwide in the past decade, followed by YouTube and Facebook, both of which have less than half of the traffic of Google since mid-2017[9]. Google has over 246 million unique US visitors, which is more than 75% of the US population[10]. Google's monopoly in the search engine market makes Google search data a great representation of U.S. public attention. In addition, users' activities on social

[9] https://statisticsanddata.org/data/most-popular-websites-in-the-world-1996-2021/
[10] https://review42.com/resources/google-statistics-and-facts/

media or video platforms are often largely affected by websites' recommendation algorithms and/or inorganic marketing efforts, which makes these alternatives less ideal for representing public attention.

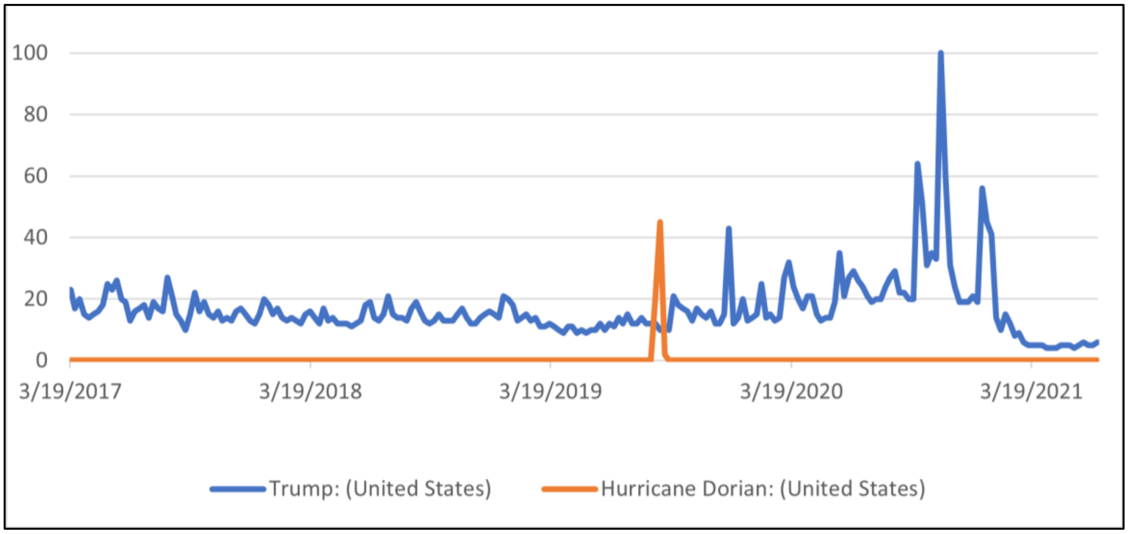
Google Trends[11] is a website by Google that analyzes the popularity of top search queries in Google Search across various regions and languages. It provides a time series index of the volume of queries users input into Google. The query index is based on query share: the total query volume for the search term in question within a particular geographic region divided by the total number of queries in that region during the time period being examined. Query indexes are rounded to the nearest integer and the maximum query share in the time period specified is normalized to be 100 (Choi and Varian, 2012). Google Trends query indices have been broadly used in research in epidemiology (Ginsberg et al. 2009) and finance (Da et al. 2011) to measure public attention (Ripberger, 2011).

Figure 1.1 illustrates the nature of Google Trends data using the example of the keywords "Trump" and "Hurricane Dorian" searched in the United States from March 2017 and June 2021. The search volume of the keyword "Trump", the last name of the former US President Donald Trump, is on average higher than the search volume of "Hurricane Dorian", and peaked at the week of Nov. 1-7, 2020, concurrent with the presidential election, resulting in a query index of 100. The search of "Hurricane Dorian" in Google peaked at the week of Sep 1-7, 2019, when the hurricane passed multiple states in the southeastern US, with a peak query index of 45. This means that between these two keywords, "Trump" has the largest weekly search volume in the given time period in US, and the maximum of the weekly search volume of "Hurricane Dorian" is about 45% of that of "Trump". Google Trends allows the comparison of up to five keywords at

[11] The website of Google Trends: https://trends.google.com/trends/?geo=US.

once, where the indices of the five keywords are consistent with each other and comparable. It provides the data at daily granularity for time periods under 90 days, and at weekly granularity for time periods between 3 months to 5 years.

Figure 1.1 Visualization of the Google Trends of "Trump" and "Hurricane Dorian"



Other than tracking internet users' interests over time, Google Trends also publishes Daily Search Trends, which highlights searches that "*jumped significantly in traffic*"[12] among all searches over the past 24 hours. The website Trend Calendar[13] archives the US Daily Search Trends in Google since March 17th, 2017.

In order to access the Google Trends data at a large scale, I make use of Pytrends[14], a third-party application programming interface (API) for Google Trends. For each keyword I am interested in, whether it is a foreign natural disaster like "Australia Wildfire", or a domestic

[12] Although Google is not clear about what "jumped significantly in traffic" means, daily trending keywords are not determined based on the absolute increase of the Google Trends index, but more likely the percentage increased or an equivalent algorithm.
[13] https://us.trend-calendar.com/
[14] https://pypi.org/project/pytrends/

breaking news keyword like "George Floyd", the top daily trending keyword on May 27th, 2020, I request its weekly query indices over time ("interest over time") from Google Trends, and then scale the indices of each keyword to be consistent and comparable between each other. For detail on the scaling process, please see Appendix A.

1.3.3.1 Top Daily Trending Keywords. In total, I collect 1016 daily top trending keywords15 between March 19th, 2017, and December 31st, 2019, and obtain the scaled "interest over time" of these keywords using the method described in Appendix A. These keywords are the words that jumped most significantly in traffic among all searches over the past 24 hours for each day, rather than the most-searched keyword of the day16. Table 1.5 lists the top 20 trending keywords ranked based on their index during their trending week.

The *Index of the Trending Week* measures the query volume of the keyword for the *week*, during which the keyword jumped most significantly in traffic on one day[17]. The indices in this table are all very large numbers due to being scaled to be comparable to the indices for foreign disaster keywords that have significantly smaller query volumes. Column "Max" shows the maximum indices of the keywords between Mar. 19th, 2017, and Dec. 31st, 2019. Column "Mean" presents the average Google index of the keywords over time between March 19th, 2017, and Dec. 31st, 2019. This represents the average overall search intensity of each keyword over time. Column "Std. dev" presents the standard deviation of the keyword's search index over

[15] There are 1016 days, thus 1016 daily top trending keywords during this time. I dropped "Google", which was the top trending keyword on Sep 27th and 28th of 2019, Google's anniversary. I also dropped keywords that are numbers, of which the returned "interest over time" would not be meaningful, including "2.0" (a movie's name trending on Nov 29th, 2018), "420" and "123".

[16] The most-searched keyword on Google are usually names of major websites, such as "Google", "Facebook", "YouTube", "Amazon", etc. The high search volume does not necessarily make a keyword the top trending search of the day, if the keyword is constantly searched in large amount around that time without a significant spike in traffic in the past 24 hours.

[17] Weekly data is the smallest granularity Google Trends allow for the time range of my interest.

time. Using the mean and standard deviation, I then calculate the Z-score ($Z = \frac{Index-Mean}{Std.dev}$) of the index of the trending week for each keyword. This measures the deviation of the index of the trending week from the mean.

The top of the list is the keyword "Thanksgiving", the top trending search on Nov. 23rd, 2017, and Nov. 22nd, 2018, both with a scaled Google search index 1,101,112 during the week of Thanksgiving of each year. This shows that, although "Thanksgiving" has percentagewise the most significant jump in traffic on Nov. 23rd, 2017, and Nov. 22nd, 2018, compared to other keywords, it reaches its absolute highest search volume on some other day. This can be illustrated again by the next keyword on the list, "Halloween", which was trending on Oct. 30th, 2020, Oct 31st, 2018, and Oct. 19th, 2019. "Halloween" has the most significant jump in traffic on these three days. Following the two traditional holidays is the keyword "Houston" trending on Aug. 28th, 2017, when Houston experience catastrophic flooding under the influence of Hurricane Harvey. The 7th on the list is "NFL" trending on Sep. 9th, 2018, the start of the season, followed by "Powerball" on two days of the 8/20/2017 week, when someone won the $758.7 million Powerball jackpot. Other than football and lotteries, celebrity names were often trending, such as "Tom Petty", "Kate Spade", "Mac Miller", "Cameron Boyce", "Nipsey Hussle" and "Anthony Bourdain" when they passed away. The 16th keyword in the table, "earthquake" was trending when the 2019 Ridgecrest earthquake occurred in California, causing 1 death, 25 injured and $5.3 billion total damage[18], followed by another natural disaster "Hurricane Michael" causing 74 fatalities and $25.5 billion damage[19]. "Nike" was trending on Sep. 4th, 2018, when the

[18] https://en.wikipedia.org/wiki/2019_Ridgecrest_earthquakes
[19] https://en.wikipedia.org/wiki/Hurricane_Michael

brand featured Colin Kaepernick, the football player who sparked controversy by kneeling during the national anthem to protest racial injustice, in their ad campaign.

Table 1.5 Top Trending Keywords Based on Weekly Search Index

Rank	Keyword	Trending Date	Week	Index of the Trending Week	Max	Mean	Std. Dev.	Z-score
1	Thanksgiving	23-Nov-17	11/19/2017	1,101,112	1,223,86 5	53,822	169,693	6.17
1	Thanksgiving	22-Nov-18	11/18/2018	1,101,112	1,223,86 5	53,822	169,693	6.17
3	Halloween	31-Oct-18	10/28/2018	927,060	927,060	88,946	177,839	4.71
5	Halloween	31-Oct-19	10/27/2019	897,745	927,060	88,946	177,839	4.55
6	Houston	28-Aug-17	8/27/2017	743,846	743,846	212,390	50,300	10.57
7	NFL	9-Sep-18	9/9/2018	643,079	873,928	304,724	244,598	1.38
8	Powerball	20-Aug-17	8/20/2017	652,240	652,240	57,323	73,404	8.10
8	Powerball	24-Aug-17	8/20/2017	652,240	652,240	57,323	73,404	8.10
10	NFL	7-Jan-18	1/7/2018	643,079	873,928	304,724	244,598	1.38
11	Tom Petty	3-Oct-17	10/1/2017	630,254	630,254	7,278	52,123	11.95
12	Kate Spade	6-Jun-18	6/3/2018	621,093	621,093	16,841	50,686	11.92
13	Mac Miller	8-Sep-18	9/2/2018	611,933	611,933	9,663	52,229	11.53
14	Cameron Boyce	7-Jul-19	7/7/2019	595,443	595,443	5,195	49,313	11.97
14	Cameron Boyce	8-Jul-19	7/7/2019	595,443	595,443	5,195	49,313	11.97
16	Earthquake	5-Jul-19	6/30/2019	531,319	531,319	25,688	48,772	10.37
17	Hurricane Michael	8-Oct-18	10/7/2018	522,158	522,158	4,091	43,297	11.97
18	Nike	4-Sep-18	9/2/2018	507,501	507,501	132,704	37,295	10.05
19	Nipsey Hussle	1-Apr-19	3/31/2019	489,180	489,180	6,852	43,013	11.21
20	Anthony Bourdain	8-Jun-18	6/3/2018	459,866	459,866	5,936	39,630	11.45

For any given week, there are seven top trending keywords, each of which has a Google Trends index for that week. By adding up the seven indices, I obtain a measurement for the intensity of breaking news happening during that week, which I call *weekly news pressure*. For each disaster, *weekly news pressure* is the sum of the scaled Google Trends indices of the seven top trending keywords for the week during which the disaster started. Table 1.2 shows the summary statistics for this variable.

1.3.3.2 Google Trends of Natural Disasters. Other than domestic top trending keywords, I also scraped the Google Trends weekly query index of foreign natural disaster keywords. I use "country name" + "disaster type" (e.g., India earthquake) as the keywords representing each disaster, except hurricanes, for which I use hurricane names (e.g. Hurricane Dorian) as the keywords. Table 1.6 lists the top 20 disaster keywords based on their maximum weekly search indices in the United States between March 19th, 2017, and December 31st, 2019. The top four mostly searched disasters are all hurricanes that affected the U.S. territory, and the maximum search indexes differ drastically even among the top 20 keywords.

For each disaster, the variable *disaster week trend index* captures the scaled Google Trends index of the disaster's keywords for the week when the disaster started. Table 1.2 summarizes the statistics of this variable. The average of *disaster week trend index* is 710.1, the maximum is 183,213 for Hurricane Irma, and the minimum is 0 – some disasters getting no attention at all in Google Search. Table 1.4 presents the average *disaster week trend index* by disaster type, which shows that storms and earthquakes gains significant attention on Internet compared to other disaster types. For simplicity, the rest of the paper refers to *disaster week trend index* as *disaster index.*

Table 1.6 Top Disaster Keywords Based on Maximum Search Index

Rank	Disaster keywords	Max search index	Peak week
1	Hurricane Irma	183,213	9/3/2017
2	Hurricane Dorian	75,117	9/1/2019
3	Hurricane Michael	49,468	10/7/2018
4	Hurricane Maria	27,482	9/17/2017
5	Mexico Earthquake	9,161	9/17/2017
6	Hurricane Nate	5,496	10/1/2017
7	Indonesia Tsunami	4,892	12/23/2018
8	Hurricane Katia	3,664	9/3/2017
9	Hurricane Willa	1,832	10/21/2018
10	Japan Earthquake	1,791	9/17/2017
11	Haiti Earthquake	1,451	10/7/2018
12	Japan Typhoon	1,329	10/6/2019
13	Philippines Earthquake	1,200	4/21/2019
14	Iran Earthquake	1,114	11/12/2017
15	Taiwan Earthquake	1,088	2/4/2018
16	Hurricane Beryl	1,068	7/1/2018
17	Indonesia Earthquake	910	9/30/2018
18	Philippines Typhoon	815	9/9/2018
19	Cuba Tornado	786	1/27/2019
20	Peru Earthquake	761	5/26/2019

1.4 Identification Strategy and Econometric Methods

1.4.1 TV News

First, I restrict my attention to television news. The econometric specification follows a similar approach to Eisensee and Strömberg (2007). For disaster i, the latent variable $relief_i^*$ represents the relief worthiness from the OFDA's perspective.

$$relief_i^* = \alpha_1 news_i + \alpha' \theta_i + \epsilon_i$$

where $news_i$ is a binary variable indicating whether the disaster was covered in TV news. The vector θ_i contains disaster-specific variables *Total Deaths, Total Affected, Total Damages* and fixed effects for disaster type, country, year, etc. Relief is provided if $relief_i^*$ is above a threshold value,

$$relief_i = \begin{cases} 1 & if\ relief_i^* > 0 \\ 0 & if\ relief_i^* \leq 0 \end{cases}$$

where $relief_i$ is the binary variable indicating whether OFDA provided disaster relief to disaster i. I will test the hypothesis that $\alpha_1 > 0$, which means the news coverage of a disaster has a positive effect on the reception of relief from OFDA. Similarly, the latent variable $news_i^*$ represents the news worthiness of disaster i from TV networks' perspective.

$$news_i^* = \beta_1 newspressure_i + \beta' \theta_i + \omega_i$$

$$news_i = \begin{cases} 1 & if\ news_i^* > 0 \\ 0 & if\ news_i^* \leq 0 \end{cases}$$

The hypothesis is that disasters are less likely to be covered when there is a high level of breaking news distraction, as measured by *newspressure*, therefore, $\beta_1 < 0$. To identify the causal effect of news on relief, I use the instrumental variable *newspressure*. Assuming a linear probability model and that news pressure is uncorrelated with the unobserved ϵ_i and ω_i, conditional on variables in θ_i, the parameters may be consistently estimated using Two Stage Least Squares (2SLS).

1.4.2 Google Trends

Following a similar specification but using Google Trends instead of TV news, we have

$$relief_i^* = \alpha_1 disasterindex_i + \alpha' \theta_i + \epsilon_i$$

where $disasterindex_i$ is the scaled Google Trends index of the disaster keyword of the week when the disaster *i* starts. The vector θ_i contains the same set of disaster-specific variables as in the TV news analysis, including *Total Deaths, Total Affected, Total Damages* and fixed effects for disaster type, country, year, etc. Binary variable $relief_i$ is the same as in the TV news specification. I will test the hypothesis that $\alpha_1 > 0$, which means public attention to a disaster on internet has a positive effect on the reception of relief from OFDA. From internet users' perspective,

$$disasterindex_i = \beta_1 weeklynewspressure_i + \beta'\theta_i + \omega_i$$

where $weeklynewspressure_i$ is the sum of the scaled Google Trends index of the top trending keyword of each day in the week when the disaster *i* starts. The hypothesis is that disasters keywords (country name + disaster type, e.g. Australia Wildfire) are searched less when there are other major news trending as a distraction, measured by *weeklynewspressure*, therefore, $\beta_1 < 0$. To identify the causal effect of news on relief, I use the instrumental variable *weeklynewspressure*. Assuming a linear probability model and that news pressure is uncorrelated with the unobserved ϵ_i and ω_i, conditional on variables in θ_i, the parameters may be consistently estimated using Two Stage Least Squares (2SLS).

1.5 Results

This section presents the empirical results. All the regressions include disaster type, country, year, and month fixed effects.

1.5.1 TV News Results

Table 1.7 presents the results for how the availability of other breaking news affects news coverage of, and OFDA relief to, disasters. Disasters with missing values for *total deaths, total affected* and *total damages* are dropped, resulting in 1520 observations remaining. Columns (1) and (5) are the baseline specification where the dependent variables are *news* and *relief*, respectively. Column (3) replaces the binary variable *news* with *relevant broadcasts*, the number of TV news segments that cover the disaster. Columns (2) (4) and (6) control for the log value of *total deaths*, *total affected* and *total damages*.

The first stage results show that higher *news pressure* reduces both the probability of a disaster being covered by news networks and its number of relevant broadcasts. For example, the parameter in Column (1) implies that 1 extra second spent on the first three news segments decreases the probability that a disaster is covered in the news by 0.0319%. In other words, an extra 3.8 minutes (2 standard deviations) spent on the top three breaking news stories on average results in a 7.3% lower probability of a disaster being covered. Similarly, Column (3) implies that an extra 3.8 minutes spent on the top three news segments reduces the number of relevant broadcasts to a disaster by 0.72. However, the result is not statistically significant, which implies that the crowding-out effect does not present within my sample period. Both the probability of a disaster being covered by networks and its number of relevant broadcasts are significantly affected by the severity of the disaster. The reduced form regression shows that the probability that the disaster receives relief is significantly affected by the severity of the disaster but not the news pressure.

Because missing data shrinks the sample size significantly, which reduces the precision of the estimation, I impute the missing values of *total deaths*, *total affected* and *total damages* to the average for each type of disaster, resulting in a sample size of 6019. Table 1.8 presents the linear probability OLS regression results of how the availability of other breaking news affects news coverage and OFDA relief of disasters with imputed missing data. Column (1) to (4) are the first stage results. Higher *news pressure* decreases the probability of a disaster being covered in TV news. Column (1)'s estimation shows that 1 extra second spent on the first three news segments decreases the probability that a disaster is covered in the news by 0.0219%. In other words, an extra 3.8 minutes (2 standard deviations) spent on the top three breaking news on average results in a 5% lower probability of a disaster being covered in TV news. Controlled for the log value of the imputed *total death*, *total affected*, and *total damages*, the estimate does not change much; an extra 3.8 minutes (2 standard deviation) spent on the top three breaking news on average results in a 5.3% lower probability of a disaster being covered in TV news. These two estimates are statistically significant at 5 percent level, which implies that there is a crowding-out effect to some extent.

The result of other columns in Table 1.8 are similar to those of Table 1.7. The probability that the disaster receives relief is significantly affected by the severity of the disaster, but not the *news pressure*, which is not consistent with Eisensee and Strömberg (2007). One possible interpretation of this result is that as time passes by OFDA disaster relief is no longer affected by *news pressure*, since the sample period of this paper, 2000-2019, barely overlaps with Eisensee and Strömberg (2007)'s sample period, 1968-2002.

Table 1.9 presents the result of 2SLS regression estimating the effect of news coverage and relevant broadcasts of a disaster on relief. This effect is likely to be heterogeneous, being greater for medium disasters that are marginal both in news coverage decisions and relief decisions. Thus, 2SLS estimates the average effect for the subgroup of disasters that are covered in the news if and only if there are few other newsworthy stories at the same time. The effect of news on relief is not statistically significant. An additional statistical test[20] on the first stage confirms that the instrument variables *news pressure* is not sufficiently correlated with the endogenous regressors *news* and *relevant broadcasts*.

[20] F statistic is not significant and much lower than 10.

Table 1.7 Effects of News Pressure on Disaster News and Relief (TV News)

	(1)	(2)	(3)	(4)	(5)	(6)
	First Stage		**First Stage**		**Reduced Form**	
Variables	News	News	Relevant Broadcasts	Relevant Broadcasts	Relief	Relief
News Pressure	-0.000319	-0.000299	-0.00315	-0.00327	0.0000702	0.000097
	(0.000257)	(0.000248)	(0.00306)	(0.00535)	(0.000167)	(0.000166)
Total Deaths	0.00213*		0.824***		0.00145	
('000)	(0.00111)		(0.185)		(0.00161)	
Total Affected	0.00712***		-0.00561		0.00273*	
('000000)	(0.00141)		(0.0384)		(0.00149)	
Total Damages	0.00366*		0.0659***		0.00666**	
('000000 USD)	(0.00197)		(0.0151)		(0.00269)	
Log Deaths		0.0528***		2.639***		0.0461***
		(0.00797)		(0.653)		(0.00699)
Log Affected		0.00881		-0.146		0.0141***
		(0.00551)		(0.121)		(0.00349)
Log Damages		0.0203***		0.291***		0.0252***
		(0.00621)		(0.108)		(0.00473)
Constant	0.329**	-0.231*	-0.446	-15.11***	0.700*	0.0205
	(0.130)	(0.140)	(2.600)	(5.097)	(0.407)	(0.430)
Observations	1,520	1,520	1,520	1,520	1,520	1,520
R-squared	0.372	0.416	0.707	0.321	0.328	0.426

Linear probability OLS regression. All regressions include year, month, country and disaster type fixed effects.
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 1.8 Effects of News Pressure on Disaster News and Relief with Missing Data Imputed (TV News)

	(1)	(2)	(3)	(4)	(5)	(6)
	First Stage		**First Stage**		**Reduced Form**	
Variables	News	News	Relevant Broadcasts	Relevant Broadcasts	Relief	Relief
News Pressure	-0.000219**	-0.000231**	-0.000503	-0.000326	-0.0000717	-0.0000846
	(0.000111)	(0.000110)	(0.000978)	(0.00126)	(0.0000642)	(0.0000643)
Total Deaths Imputed	0.00428***		0.845***		0.00378***	
('000)	(0.0012)		(0.201)		(0.00142)	
Total Affected Imputed	0.0032		-0.000393		0.00177	
('000000)	(0.00203)		(0.0165)		(0.00109)	
Total Damages Imputed	0.0049**		0.65***		0.00646***	
('000000 USD)	(0.00236)		(0.153)		(0.0021)	
Log Deaths Imputed		0.0161***		0.593***		0.0165***
		(0.00318)		(0.164)		(0.00228)
Log Affected Imputed		0.0142***		0.223***		0.0148***
		(0.00176)		(0.0357)		(0.00108)
Log Damages Imputed		0.00599**		0.231***		-0.000299
		(0.00279)		(0.0624)		(0.00194)
Constant	0.123**	-0.235***	-2.488***	-10.59***	0.0153	-0.280***
	(0.0505)	(0.0700)	(0.533)	(2.221)	(0.0323)	(0.0488)
Observations	6,019	6,019	6,019	6,019	6,019	6,019
R-squared	0.289	0.297	0.583	0.127	0.128	0.152

Linear probability OLS regression. All regressions include year, month, country and disaster type fixed effects.
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 1.9 2SLS Regression Results (TV News)

Variables	(1) IV	(2) IV	(3) IV	(4) IV
News	-0.220	-0.325		
	(0.550)	(0.606)		
Relevant Broadcasts			-0.0223	-0.0297
			(0.0570)	(0.0694)
Total Deaths	0.00192		0.0198	
('000)	(0.00208)		(0.0474)	
Total Affected	0.00430		0.00261*	
('000000)	(0.00425)		(0.00145)	
Total Damages	0.00747**		0.0214	
('000000 USD)	(0.0359)		(0.0376)	
Log Deaths		0.0633*		0.124
		(0.0329)		(0.182)
Log Affected		0.0170***		0.00980
		(0.00655)		(0.0111)
Log Damages		0.0318**		0.0339
		(0.0135)		(0.0214)
Constant	0.772*	-0.0544	0.690*	-0.428
	(0.437)	(0.444)	(0.416)	(1.183)
Observations	1,520	1,520	1,520	1,520
R-squared	0.218	0.295	0.120	

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

Table 1.10 shows the 2SLS regression results with imputed data. The effect of news on relief is positive, but still not statistically significant. An F statistic test on the first stage confirms that the instrument variables *news pressure* is not sufficiently correlated with the endogenous regressors *news* and *relevant broadcasts*. The result with imputed data suggests that even though there is a weak crowding out effect of news, the correlation between disaster news and other breaking news is not strong enough for *news pressure* to be a valid instrument.

Table 1.10 2SLS Regression Results with Missing Data Imputed (TV News)

Variables	(1) IV	(2) IV	(3) IV	(4) IV
News	0.328	0.366		
	(0.317)	(0.310)		
Relevant Broadcasts			0.143	0.260
			(0.278)	(0.974)
Total Deaths Imputed	0.00238		-0.117	
('000)	(0.00187)		(0.233)	
Total Affected Imputed	0.000718		0.00183	
('000000)	(0.00119)		(0.00245)	
Total Damages Imputed	0.00485**		-0.0861	
('000000 USD)	(0.00209)		(0.182)	
Log Deaths Imputed		0.0106*		-0.137
		(0.00549)		(0.575)
Log Affected Imputed		0.00960**		-0.0430
		(0.00454)		(0.216)
Log Damages Imputed		-0.00249		-0.0604
		(0.00274)		(0.226)
Constant	-0.0249	-0.194**	0.370	2.471
	(0.0449)	(0.0943)	(0.708)	(10.35)
Observations	6,019	6,019	6,019	6,019
R-squared	0.039	0.014		

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

1.5.2 Google Trends Results

Table 1.11 presents the first stage result showing how the public attention to the top trending news on the Internet affects the attention to foreign natural disasters and whether disasters receive OFDA relief. If I dropped disasters with missing *total deaths*, *total affected* or *total damages*, there would be only 90 disasters left in the sample. Therefore, I impute the missing values of *total deaths*, *total affected* and *total damages* to the average for each type of disaster, resulting in a sample size of 329. Columns (1) and (3) are the baseline specification where the dependent variables are *disaster index* and *relief*, respectively. Columns (2) and (4) control for the log value of imputed *total deaths, total affected and total damages*.

The first stage result in Column (1) shows that *weekly news pressure* does not significantly affect *disaster index*, although the negative sign of the estimate is as expected – higher weekly news pressure distracts people from searching for foreign disasters. After controlling for the log values of the disaster severity variables, *disaster index* is affected by the number of people affected and economics value of damages positively at a 10% significance level.

Table 1.11 Effects of News Pressure on Disaster Index and Relief (Google Trends)

	(1)	(2)	(3)	(4)
	First Stage		**Reduced Form**	
Variables	Disaster Index	Disaster Index	Relief	Relief
Weekly News Pressure	-30.21	-56.3	0.036	0.0227
('000000)	(74.6)	(75.8)	(0.0259)	(0.0296)
Total Deaths Imputed	797		0.963***	
('000)	(925)		(0.242)	
Total Affected Imputed	16.2		0.0957***	
('000000)	(28.7)		(0.0307)	
Total Damages Imputed	120		0.00752	
('000000 USD)	(87.8)		(0.0128)	
Log Deaths Imputed		40.02		0.0405***
		(41.12)		(0.0156)
Log Affected Imputed		36.88*		0.0287***
		(19.04)		(0.00733)
Log Damages Imputed		60.13*		0.00114
		(32.83)		(0.0103)
Constant	183,021***	182,032***	0.950***	0.565***
	(189.9)	(660.4)	(0.103)	(0.175)
Observations	329	329	329	329
R-squared	0.997	0.997	0.479	0.412

Linear Probability OLS regression. All regressions include year, month, country and disaster type fixed effects. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Columns (3) and (4) show that the probability that a disaster receives OFDA relief is very responsive to the severity of the disasters, measured by the number of deaths, affected and damages. However, the *weekly news pressure* at the time when the disaster happened does not affect OFDA's relief decision significantly.

Table 1.12 presents the preliminary result of 2SLS regression estimating the effect of Google Trends index on disasters on OFDA relief. The effect of *disaster index* on *relief* is not significant. Based on the first stage result and the F statistic test, there is no crowding out effect presented on Google Trends.

Table 1.12 2SLS Regression Results (Google Trends)

Variables	(1) IV	(2) IV
Disaster Week Trend Index	-0.00112	-0.000403
	(0.00245)	(0.000680)
Total Deaths Imputed ('000)	1.86	
	(1.98)	
Total Affected Imputed ('000000)	0.114*	
	(0.0603)	
Total Damages Imputed ('000000 USD)	0.142	
	(0.277)	
Log Deaths Imputed		0.0566*
		(0.0307)
Log Affected Imputed		0.0435*
		(0.0241)
Log Damages Imputed		0.0254
		(0.0365)
Constant	206.1	73.95
	(447.8)	(123.9)
Observations	329	329

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

I also explore using an alternative measurement of news pressure with Google Trends data. Instead of constructing *weekly news pressure* with daily "top trending" keywords, I use

Google's "Year in Search" keywords that represent more significant events or news of each year. Please see details in Appendix A.

1.6 Conclusion

This paper explores the relationship between foreign natural disasters, the attention they receive from TV news media and Internet queries as captured by Google Trends, and the OFDA's relief decisions. A previous study found that other breaking news can crowd out news coverage of a foreign natural disaster and thus reduces the probability that the disaster receives the OFDA relief. I revisit this question with more recent data after almost two decades during which people's news consumption habit has changed following the rapid development of Internet technology. I analyze whether the crowding out effect still exists in TV news coverage and Google searches, as well as the effect of media and public attention on OFDA relief.

The results show that there is a weak crowding out effect in TV news coverage of disasters and other breaking news. An extra 3.8 minutes spent on the top three news segments of TV networks on average results in a 5% lower probability of a disaster being covered in TV news. OFDA relief, during the sample period 2000-2019, is affected by the severity of the disasters but not the disaster's TV news coverage or the intensity of other contemporaneous breaking news. There is no detected crowding out effect for Internet searches. The search volumes for top trending keywords are hundreds, if not thousands, of times the search volumes for foreign disaster keywords. American Internet users barely pay any attention to foreign natural disasters, provided the disasters are not close to U.S. territory. OFDA relief decisions are not affected by online attention from the United States, or the intensity of other trending searches happening at the same time as the foreign disaster.

Chapter 2

Costly Attention and Energy Efficiency Gap: An Experiment

2.1 Introduction

The energy efficiency gap refers to the difference between the cost-minimizing level of energy efficiency and the level of energy efficiency realized by households and businesses in practice. Environmental economic studies propose different explanations for this gap, including behavioral bias in energy consumption and market failure because of asymmetric information. However, this so-called behavioral bias might not be purely irrational, as consumers may ignore the energy efficiency information due to its overwhelming complexity. Deciphering and breaking down energy efficiency information increases the attention cost and cognitive effort on the consumer's part. In other words, people's attention is costly. Thus, government-funded information services seek to lower the attention cost for each individual consumer, which minimizes the social cost of effort, improves energy efficiency, and facilitates the adoption of energy-saving technologies.

Sallee (2014) elevates consideration of rational inattention in the study of energy economics and demonstrates with data on automobiles that consumers only experience minor welfare losses when choosing cars without detailed information. Rational inattention, or costly attention, to energy efficiency shifts the focus of policy design away from corrective taxation and toward information provision that reduces attention costs. Mandatory information disclosure like government fuel economy labels has been widely studied (Larrick and Soll 2008; Allcott 2013; Newell and Siikamki 2013). However, literature rarely discusses information services that lower the cognitive effort of processing energy cost information, although they directly affect most consumers' decision-making.

This paper uses an economic experiment to test if consumers misoptimize in car purchasing decisions involving complex fuel economy information and whether calculation tools provided by a government website (https://www.fueleconomy.gov/) effectively address the energy efficiency gap. In addition, this paper also attempts to measure the attention cost quantitatively to guide the optimal policy design for information provision of energy costs.

The experiment simulates the overwhelming information environment of the automobile purchasing process. Subjects face an experiment task to choose a car from a list of hypothetical options that have identical features outside of fuel economy. Each subject enters the experiment with an endowment of experiment currency as their budget. Upon starting the task, the treatment groups are offered various information tools, such as fuel economy labels, a fuel cost calculator, or even their optimal choice, after which the subjects are briefly exposed to the information that the task requires them to process. Then they proceed at their natural pace to figure out which car they want to pick with or without the tools, depending on whether their willingness to pay (WTP) for the service offered is higher than the service's randomly generated threshold price. After they finish the task, they pay the MSRP, energy cost and other relevant expenditures associated with the car they pick. The remaining experiment currency from their original budget determines their payoff. I use an incentive compatible mechanism to elicit subjects' true willingness to pay (WTP) for the additional offer. The difference between the average WTP for the treatment group that offers their best choice directly and the expected misoptimization size for the subjects who didn't get access to any tool should represent a measurement of the average effort cost.

Subjects' performance in the experiment verified the existence of an energy efficiency gap. Around half of the subjects chose suboptimal options when having the fuel economy information presented to them in basic text format. Subjects with the fuel economy labels on average misoptimized even more, although the difference in the mean misoptimization is not statistically significant. The replica of the fuel cost calculator on EPA's website significantly improved subjects' performance, with 65% of them choosing the optimal car and the remaining 35% choosing the second-best option. This yielded a mean misoptimization about 62% lower than subjects without it. This result indicates that fuel economy labels are not effective as a tool reducing energy efficiency gap, but that the fuel cost calculator is highly effective. The results also show that subjects are willing to pay $1.50, $2.42, and $5.51 US dollars on average, which are roughly 3%, 5%, and up to 11% of their budget, for having access to the fuel economy labels, fuel cost calculator and the service telling them their optimal car, respectively. The average effort cost of processing the fuel cost information of the eight cars is estimated to be EC$ 2,517 Experiment Currency, which amounts to $2.51 US dollars.

This paper contributes in the following ways. Energy efficiency policies regarding information provisioning have been focusing on how to convey the quantitative value of energy efficiency to consumers more accurately. However, little literature covers the information processing cost of consumers even if they know an accurate figure or the corresponding methods to lower such a cost. In addition to literature that seeks to understand how corrective environmental policies should be designed in the presence of behavioral economic considerations (Allcott, Mullainathan, and Taubinsky 2014; Heutel 2011; Fischer, Harrington, and Parry 2007; Tsvetanov and Segerson 2013), this paper points to policies that lower barriers to information acquisition and processing. The notion of costly attention suggests that it is not necessarily welfare-improving to incentivize attention because real costs are involved. This is distinct from most cases of behavioral bias in that it rationalizes the “bias”.

The rest of the paper is structured as follows. Section 2.2 reviews literature. Section 2.3 lays out the theoretical framework. Section 2.4 presents the experiment design and its implementation. Section 2.5 presents the results. Section 2.6 concludes.

2.2 Literature Review

Numerous studies have shown the existence of the energy efficiency gap and estimated its magnitude[21]. The main explanations of the phenomenon, especially in the automobile market, are consumers being either imperfectly informed, inattentive, myopic, or struggling cognitively to understand fuel economy. Greene (2010) reviews 25 studies estimating behavioral bias in automobile purchases, and more recently there are several papers measuring consumers' valuation of fuel economy, including Allcott (2013), Busse, Knittel, and Zettelmeyer (2013), Allcott and Wozny (2014), Grigolon, Reynaert and verboven (2015), and Sallee, West and Fan (2016). However, there is still no clear agreement whether consumers undervalue or overvalue fuel economy, or whether there is any systematic bias.

Most of this empirical literature tends to focus on revealed preference tests to see whether consumers appear to fully value energy efficiency, in other words whether consumers are indifferent between $1 in purchase price and $1 in present discounted lifetime fuel costs. Sallee (2014)'s rational inattention model breaks this logic. It argues that it might be rational for consumers to pay limited attention to energy efficiency, because making a proper valuation is costly in time and effort. Because of this, firms might only bring products whose technical innovations are salient enough to garner attention, and thus consumers rationally choose only

[21] Gillingham, Newell and Palmer (2009) summarize the literature on this. Klemick and Wolverton (2013) summarize explanations that have found support in the empirical economics literature for an observed energy efficiency gap in diverse sectors.

among the products on offer. The idea of costly attention reconciles two of the main potential explanations for the energy efficiency gap, imperfect information and behavioral failures. It addresses the energy paradox in such a way that demand-side failures affect producers through markets and thus cause overall inefficiency in the adoption and diffusion of new green products. Some other research about energy efficiency adopts a similar idea to Sallee (2014), such as Howarth and Andersson (1993). Their model differs in that it allows consumers' choices to be discrete and consumers' preferences to be heterogeneous. Houde (2014) captures a similar insight by modeling the costly search for energy efficiency information about refrigerators, concluding that in equilibrium many consumers choose to forgo searching and appear insensitive to energy information.

Some evidence indicates that consumers can make systematic mistakes when evaluating if products are sufficient[22]. One example related to energy efficiency in the automobile market is the "MPG illusion", a systematic misperception of fuel economy that conceives an automobile's gas consumption as a linear function of its MPG (Larrick and Soll, 2008). More generally, when consumers buy a vehicle, they do not have all the basic building blocks of knowledge assumed by the model of economically rational decision-making, and they make large errors estimating gasoline costs and savings over time (Turrentine and Kurani, 2007).

Among experimental literature studying the rational inattention theory, Gabaix et al. (2006) test the directed cognition model using two experiments in which the information acquisition is costly because of an explicit financial cost and scarce time, respectively. The directed cognition model, which assumes agents use partially myopic option-value calculations to select their next cognitive operation, predicts the laboratory data better than the fully rational

[22] For example, Abaluck and Gruber (2011), Bollinger et al. (2011), Barber et al. (2005); Grubb (2009); Handel and Kolstad (2015), Hossain and Morgan (2006), Jensen (2010), Kling et al. (2012).

model. Caplin et al. (2015) develop a revealed preference test that characterizes all patterns of choice "mistakes" consistent with a general model of optimal costly information acquisition. Some other papers testing the rational inattention theory include Cheremukhin et al. (2011), Martin (2016), Dean and Neligh (2017), and Goecke et al. (2013).

Imperfect information and inattention have become a crucial justification for energy efficiency policies. An emerging body of literature has sought to provide optimal energy policies and welfare analysis in the presence of inattention, biased perception, and other behavioral economic considerations[23]. The three main categories of policies are economics incentives, energy efficiency standards[24] and information strategies. The idea of rational inattention to energy efficiency shifts the focus of policy design toward the third category, namely information provision to reduce attention costs. Gillingham and Palmer (2013) summarize information strategies intending to improve energy efficiency. For the automobile market, there is mandatory information disclosure- like fuel economy labels for new cars- that has been studied with consideration to the "MPG illusion" (Larrick and Soll, 2008; Allcott, 2013). Newell and Siikamki (2013) study the impacts of alternative labels and find that simple information on the economic value of saving energy was the most important element guiding more cost-efficient investments in energy efficiency. This paper contributes to the literature by guiding the optimal strategy for information provision with consideration of attention cost.

[23] Many experimental papers also address policies in other fields such as student loan enrollment (e.g., Cox, Kreisman, and Dynarsky, 2020) and healthcare plan choices (e.g., Kling, Mullainathan, Shafir, Vermeulen, Wrobel, 2012).

[24] Some examples of the first two types of policies are as follow. Allcott, Mullainathan, and Taubinsky (2014) develops a general model for optimal combination of energy tax and product subsidy in presence of both externalities and internalities caused by different psychological biases. Fischer, Harrington, and Parry (2007) develop models concerning consumers' valuation of fuel economy to explain and estimate the welfare effects of raising CAFE standards for new passenger vehicles. Allcott and Taubinsky(2015) use a theoretical model and two randomized experiments to evaluate imperfect information and inattention as potential motivations for energy efficiency standards and subsidies in light bulb market. Tsvetanov and Segerson(2013) and Heutel(2015) discuss energy policies when consumers have temptation, self-control problem or present bias.

With respect to information policy, this paper is also related to experimental research measuring the effects of energy cost information for durable goods, including Allcott and Sweeney (2017), Davis and Metchalf (2016), Dolan and Metcalfe (2013), and Jessoe and Rapson (2015). For example, Davis and Metcalf (2016) conduct an online stated-choice experiment to measure the potential welfare benefits from energy labels tailored to each household's state of residence and find better information leads to better choices. Dranove and Jin (2010) provide a review for quality disclosure and certification.

2.3 Theoretical Model

I consider a simple theoretical model to design the experiment. A subject maximizes the following payoff function:

$$\max_{j} U(j) = X - P_j - e_j - C$$

where U is the payoff and X is the monetary endowment. A subject chooses car j with an upfront price P_j and fuel costs e_j realized later depending on the usage to maximize payoff U. The last term C is the cost of processing information related to the decision measured in monetary units.

In standard economic theory, $C = 0$, because consumers are assumed to be able to optimize their payoff without any friction. Let $j^o = argmaxU$, which is the real optimal option. The maximized payoff is $U(j^o) = X - P_{j^o} - e_{j^o}$. In real life, consumers might end up choosing $j^* \neq j^o$ without thorough research and calculation before making the decision. The corresponding suboptimal payoff is $U(j^*) = X - P_{j^*} - e_{j^*}$. The misoptimization size is $\mathrm{D}_{j^*,j^o} = U(j^o) - U(j^*) > 0$. I assume the effort cost C is negatively related to the expected misoptimization size D. Their relation can be represented by $D(C)$, and $D(\cdot)$ varies depending on the presentation of information. Generally, the greater C is, the more probable that j^* is closer to j^o.

Thus, before the consumer decides which durable goods to purchase, they first implicitly decide how much effort cost to spend on making that decision:

$$\max_C U = U(j^o) - D(C) - C$$

Let the optimal effort cost be $\bar{C}$. A consumer being "rationally inattentive" should be indifferent between the following two packages: (1) exert effort cost $\bar{C}$ and tolerate the expected size of misoptimization $D(\bar{C})$; (2) a service saving all the information processing effort (i.e. directly tell them what their best choice is) that costs $\bar{C} + D(\bar{C})$ monetary units with no misoptimization ($D = 0$). Package 2 gives the consumer their privately optimal option directly and charges their $\bar{C} + \mathrm{D}(\bar{C})$ for this information provision service. In other words, the consumer's willingness to pay (WTP) for such service is supposed to equal $\bar{C} + D(\bar{C})$.

$$WTP = \bar{C} + D(\bar{C})$$

Thus, when such an information service is not offered, the expected size of misoptimization $D(\bar{C})$ is observable; when such information service is offered, the consumer's WTP for this service gives the measurement of $\bar{C} + D(\bar{C})$. The difference of the two would be $\bar{C}$, the effort cost of information processing. The experiment elicits subjects' willingness to pay and observes subjects' misoptimization in their car decision, thus allowing me to estimate subjects' effort cost of quantitatively processing information.

It is worth mentioning here that the subjects' expectation of the misoptimization size D plays an important role in determining how much effort cost C they want to exert. People who have strong confidence in their decision-making ability or underestimate the complexity of the problem might expect D to be extremely small, while people who have no confidence or overestimate the complexity of the problem might expect D to be large. However, it is the real cognitive and calculation ability of subjects that brings the uncertainty into the problem. People with higher cognitive ability are less likely to deviate from j^o, i.e. with a smaller variance. The deviation of subjective expectation of uncertainty (confidence) from the objective heterogeneous uncertainty (cognitive ability) complicates the characterization of risk attitude in this problem. Due to the individual difference in information processing skills, the risk they are facing varies. The same behavior of different individuals might suggest totally different risk attitudes. Thus, it is hard to characterize the risk attitude based on this implicit heterogeneous risk. In the experiment, I use a simple risk attitude test and survey questions to get a sense of subjects' risk preference, their expectation of task complexity, confidence in their cognitive ability and so on.

2.4 Experimental Environment

2.4.1 Experiment Design

This experiment focuses on discrete choice decisions in a car purchasing context. To create an information environment that has realistic complexity, I use information provided by the EPA and select 8 car models that satisfy the following criteria: (1) mid-size sedan or hatchback; (2) MSRP between $25000 to $45000; (3) automatic transmission, (4) fuel type is gasoline, electricity or a combination of the two; (5) vehicle type is conventional gasoline, hybrid, plug-in hybrid or electric; and (6) 2020 - 2022 models. From the car models captured with these filters, I choose car makes that have relatively more complete product lines and comparable models. When I present these car options to the subjects, I hide features other than their fuel economy so that they do not affect subjects' decisions.

Participants are endowed with $50,000 Experiment Currency (EC$). They are asked to choose a car from 8 options, each with an upfront cost (MSRP price P_j) and potentially also tax credit incentives. Subjects are informed of their driving patterns, from which they could calculate their annual mileage and the proportion of city/highway driving. They are also provided the fuel type of the cars (electric, plug-in hybrid, hybrid, and conventional gasoline), each model's fuel economy, energy prices (regular/premium gasoline and electricity), and the charging options for an electric vehicle (EV) or plug-in hybrid electric vehicle (PHEV). The information displayed is collected from mainstream sources, such as the official websites of the EPA, Georgia Power and major car manufacturers. Appendix B presents the list of the car makes and models, their corresponding fuel economy and price information, as well as the driving patterns and fuel price information given to the subjects.

Before subjects proceed to make decisions in the experiment, the instruction makes it clear that they do not need to consider the brand, design, performance or other features of the hypothetical vehicles; the environmental impact of their choice; or how that is perceived by others. Rather, they simply wish to choose the least costly car that satisfies their designated driving needs. Other potentially relevant factors, such as maintenance costs, resale value of the vehicles, and any difference in the value of Experiment Currency over time, are all clarified to be excluded from subjects' consideration.

Subjects then proceed to read through the task introduction and preview examples of car information so that they can have a sense of how much information they will be processing and how the information will be presented. Then they are randomly assigned to one of the three treatment groups of the experiment, which determines the subsequent procedure as summarized in Table 2.1.

Table 2.1 Summary of the Experiment Procedure for Treatment Groups

Groups	Before the Task	Information Service	Task	After the Task
Treatment 1	Elicit their WTP for the following information service using incentive compatible mechanism	If WTP ≥ TP, fuel economy labels	Choose the car with the help of the labels	Risk attitude test; cognitive ability test; demographic survey
		If WTP < TP, none	Choose the car based on their calculation	
Treatment 2		If WTP ≥ TP, labels + webpage fuel cost calculator	Choose the car with the help of the labels and the fuel cost calculator	
		If WTP < TP, none	Choose the car based on their calculation	
Treatment 3		If WTP ≥ TP, directly tell them the best option	Immediately finish the task	
		If WTP < TP, none	Choose the car based on their calculation	

Before proceeding to the task, the three treatment groups are offered the option to "pay" for an information service that will help them with making their decision out of their EC$ 50,000 Experiment Currency budget. The offer is framed in the following way:

"Now we can offer you [information service of the treatment]. *This offer has a fixed "threshold price" TP. If the price you are willing to pay (WTP) is greater than or equal to TP, then you will have access to this* [information service of the treatment], *and you will pay TP for*

it, which means your final payoff will be the highest payoff subtracted by TP. If the price you are willing to pay (WTP) is lower than TP, then you do not get the offer. You must make the decision by yourself. If you are not willing to spend any token for such an offer, please put 0 as your WTP.

It is in your best interest to state your true WTP, not a smaller amount. If, instead, you were to strategically state an amount Y that is less than your true WTP then you will regret doing this if it turns out that the fixed number TP is between your true WTP and the smaller amount you stated. In such a case you would not be given the access to [information service of the treatment].

How much are you willing to pay for [information service of the treatment]*?*

WTP =_____. (Please enter a whole dollar amount)"

An illustrating example is given to help subjects understand that it is in their best interest to state their true WTP. The "threshold price" (TP) is randomly generated for each participant. The purpose of the random TP is to elicit their real WTP without potential risk of cross-session contamination.

The information service provided varies across treatment groups. Subjects in Treatment 1 are offered the fuel economy labels of each car including additional information like EPA estimated annual fuel cost and how much they can save in fuel costs over five years based on the average driving patterns of the U.S. population. Labels for plug-in hybrid vehicles also include the axis illustration of the driving range for electricity and gasoline. Examples of the fuel economy labels are shown in Appendix B.

Subjects in Treatment 2 are offered the same fuel economy labels as well as a web browser-based fuel cost calculator similar to the one provided by the U.S. Department of Energy and Environmental Protection Agency at fueleconomy.gov[25]. The fuel cost calculator allows subjects to input their "personalized" fuel prices and driving habits, which they were assigned at the beginning of the experiment, and have the fuel costs of the selected vehicle displayed to them. A screenshot of the fuel cost calculator is shown in Appendix B.

Subjects in Treatment 3 are offered their personal best option directly.

For those who obtain access to the service, the subjects' reward is the payoff their choice yields minus the randomly generated threshold price. Those who do not obtain access to the service make their decision based on their own calculations and get the payoff that their choice yields. Subjects may proceed at their natural pace with no explicit time constraint. After they confirm their choice, the payoff is realized and shown to the subjects.

2.4.2 Risk Attitude, Cognitive Ability and Demographic Questions

After completing the main task of choosing a car, subjects are asked to pick a gamble to play that will give them a bonus reward. Following the Eckel and Grossman method as in Dave et. al (2010), participants are presented with 6 gambles, each has a 50/50 chance of getting a low/high payoff, from which they must choose the one that they wish to play. The instructions for the gamble task are presented in Appendix B.

Table 2.2 summarizes the 6 gambles with their payoffs and the implied risk attitude. Note that Gamble 6 has the same expected payoff as Gamble 5 but with a higher standard deviation. Risk-averse subjects should choose those with a lower standard deviation (Gambles 1–4), risk-neutral subjects should choose a gamble with a higher expected payoff (Gamble 5), and risk-seeking subjects should choose Gamble 6. Under the assumption of constant relative risk

[25] https://www.fueleconomy.gov/feg/savemoney.jsp

aversion (CRRA), subjects' utility can be represented by the function $u(x) = x^{1-r}$, with r being the coefficient of relative risk aversion. Individuals with $r > 0$ are risk averse, with $r < 0$ are risk seeking, and with $r = 0$ are risk neutral. Subjects' choice of gamble implies an interval for the coefficient r, as presented in the rightmost column of Table 2.2.

Table 2.2 Flip-the-Coin Risk Attitude Test

Choice	Low Payoff	High Payoff	Expected Return	Standard Deviation	Implied CRRA Range
Gamble 1	560	560	560	0	Risk averse 3.46<r
Gamble 2	480	720	600	120	Risk averse 1.16<r<3.46
Gamble 3	400	880	640	240	Risk averse 0.71<r<1.16
Gamble 4	320	1040	680	360	Risk averse 0.5<r<0.71
Gamble 5	240	1200	720	480	Risk neutral 0<r<0.5
Gamble 6	40	1400	720	680	Risk seeking

Following the risk preference test, I collect subjects' responses to demographic survey questions, including their first language, major, financial situation, academic performance, and mental health condition, as well as a series of questions about their real-life car purchasing experiences and awareness of fuel efficiency. Then I evaluate participants' cognitive ability through a set of tests used in Frederick (2005). The cognitive reflection test is composed of the following three questions: (i) A bat and a ball cost $1.10 in total. The bat costs $1.00 more than the ball. How much does the ball cost? (ii) If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets? (iii) In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half the lake? I recorded the total number of correct responses (i.e., 5 cents, 5 minutes, and 47 days) as the measure of cognitive ability.

From the results of this experiment, we shall obtain an answer the following questions: (1) Do subjects misoptimize in the selection of an energy-using durable good? If so, by how much? (2) How much are they willing to pay for the services that reduce their information processing cost? (3) How much is the average effort cost? (4) What is the relation of the above outcomes with their cognitive ability and other demographic characteristics?

2.4.3 Experiment Implementation

The experiment was built using Qualtrics and conducted in person at the lab of the GSU Experimental Economics Center in Spring 2022. The subjects were 100 undergraduate students at Georgia State University recruited through the EXCEN Experiment Recruiter. Each treatment group consisted of 33-34 subjects. Each subject was paid within a range of 5-25 US dollars depending on their decisions during the experiment. The payments to subjects were funded by a $2000 GSU Dissertation Grant.

Before running the experiment, I conducted a pilot study with 20 volunteers to elicit feedback on the experiment design, software interface, as well as the participants' experience. The longest reported duration for finishing the experiment in the pilot study was 50 minutes. To give subjects sufficient time when officially running the experiment, I set the maximum time for each session to be 1.5 hours. No subject needed extra time beyond this.

When recruiting subjects, students in the participant pool received an invitation email about an opportunity to participate in an experiment. Subjects did not know what the study was about prior to the day of the experiment. I ran four sessions in total, each of which had around 10 to 30 subjects, depending on the number of students who accepted the invitation for that day. Upon arrival, subjects were seated at lab computers with the experiment interface and a Windows calculator on the screen. They were also given pen and paper for taking notes or doing calculations. Subjects then proceeded to finish the experiment task independently without talking to each other or using any other tools. The detailed experiment consent and instructions are presented in Appendix B. After finishing the experiment, they were quietly guided by an experimenter outside of the lab to receive payment in cash based on their decisions in the experiment. The average payoff in US dollars was around $20.

Table 2.3 reports the characteristics of subjects who participated in the experiment. They are on average 21.3 years old, 62% female, 74% English native speakers and 82% self-reported mentally healthy; they are 53% black, 26% Asian, 13% white, and 6% Hispanic. Our subjects come from various fields of study, with 30% majoring in natural or formal science, 28% in social science and 26% in business.

Table 2.3 Summary Statistics of Subjects

Variable	Obs	Mean	Std. Dev.	Min	Max
Age	98	21.327	3.217	18	47
Female	100	0.62	0.488	0	1
Native Speaker	100	0.74	0.441	0	1
Mentally Healthy	100	0.82	0.386	0	1
Race					
White	100	0.13	0.338	0	1
Black	100	0.53	0.502	0	1
Asian	100	0.26	0.441	0	1
Hispanic	100	0.06	0.239	0	1
Major					
Business	100	0.26	0.441	0	1
Arts	100	0.07	0.256	0	1
Social Science	100	0.28	0.451	0	1
Natural/Formal Science	100	0.30	0.461	0	1
Health	100	0.10	0.302	0	1

Note: Table shows means, standard deviation, min and max for subjects in the experiment. All measures are self-reported.

2.5 Results

2.5.1 Willingness-To-Pay for Information Tools and Service

This section presents the results of the experiment. 100 subjects were randomly assigned to the three treatment groups offering access to cars' fuel economy labels, fuel economy labels and a fuel cost calculator, and the answer for their personal optimal car, respectively. This resulted in 33, 34 and 33 subjects in these three treatment groups. The first decision subjects made is how much Experiment Currency out of their EC$ 50,000 budget they would like to pay for the offer.

The average willingness-to-pay (WTP) for the fuel economy labels was EC$ 1,497.0, with a standard deviation of EC$ 2175.6, a minimum WTP of zero – some subjects were not willing to pay anything for it – and a maximum of EC$ 10,000. The average WTP for the access to fuel economy labels and the fuel cost calculator was higher at EC$ 2,417.4, with a larger standard deviation and a range from zero to EC$ 20,000. The average WTP for revealing the answer for personalized optimal car was the highest, EC$ 5,514.4, with also the largest standard deviation and range: from zero to EC$ 35,000. Table 2.4 presents these results in detail.

Table 2.4 Subjects' Willingness-to-Pay for Service Offered by Treatment Groups

	Subjects	**Willingness to Pay**				**Threshold Price**		**Subjects Purchased the Service**	
Treatment	Count	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Count	%
Group 1: label	33	1497.0	2175.6	0	10000	504.8	299.9	20	60.6%
Group 2: label + calculator	34	2417.4	4543.7	0	20000	562.2	277.0	20	58.8%
Group 3: answer	33	5514.4	10080.2	0	35000	451.6	319.7	19	57.6%
Total	100							59	59%

Note: Table summarizes the mean, standard deviation, min and max of subjects' WTP for information service in each treatment groups, the randomly generated threshold prices and the consequent counts of subjects who ended up getting the services.

To the extent that the experiment is a reproduction of the car purchase scenario, the willingness-to-pay for these information services is significant – subjects are willing to pay roughly 3%, 5%, and up to 11%, respectively, of their EC$50,000 budget for having access to these tools or services that save them the effort of processing fuel cost information. If they enter the task without the labels, fuel cost calculator or the answer, they should still be able to figure out their optimal car with all the information presented to them. In other words, these information services do not offer any new information but simply reduce their cognitive effort costs and save them time.

Some could argue that this simple experiment task lacks external validity in terms of representing the car purchasing decision process in real life, where a much larger financial stake exists. If we interpret subjects' WTP in terms of real US dollars, they are on average willing to pay \$1.50, \$2.42, and \$5.51 for having access to fuel economy labels, labels and fuel cost calculators, and the optimal answer, respectively, to save time and effort for the subsequent experiment task of comparing eight hypothetical car options. This is arguably a meaningful representation of how subjects perceive the values of these tools or services in helping them with the task. Although the experiment subjects might not be representative of the general population of US automobile consumers, the collective willingness-to-pay potentially scales up to a significant value. From a cost-benefit analysis perspective, this result supports the notion that fuel economy information provisioning can be a worthwhile investment, and further endeavors to develop, improve, and promote these tools or services are warranted.

After each subject typed in their WTP, the experiment randomly generated a threshold price between EC\$ 1 – EC\$ 1,000 for each subject, which determined whether they got the offer. The means and standard deviation of these threshold prices are reported in Table 2.4.

2.5.2 Car Selection Task

As a result of self-reported WTP and randomly generated threshold prices, 20 subjects (60.6%) of Treatment Group 1 got the offer of fuel economy labels, 20 subjects (58.5%) of Treatment Group 2 got the offer of labels and the fuel cost calculator, and 19 subjects (57.6%) of Treatment Group 3 got the offer revealing the name of their optimal car. The 41 subjects who didn’t end up getting the offer proceeded without any tools or service, only having the information of the cars presented in a basic text format. Therefore, subjects ended up being in 4 different information groups: 41 subjects with basic information, 20 subjects with basic information and fuel economy labels, 20 subjects with basic information, fuel economy labels and the fuel cost calculator, and 19 subjects with the knowledge of their personalized best car, i.e., the correct answer of the task. The 19 subjects with the answer then immediately finished the task with the best car selected.

Table 2.5 Car Selection Result by Information Groups

		Basic		Label		Label & Calculator	
Car Selected	Car Payoff ((EC$)	Freq.	Percent	Freq.	Percent	Freq.	Percent
Millennium EV	5000	1	2.44	1	5	0	0
Roamer Gas	7531	0	0	1	5	0	0
Evolution Hybrid	11438	4	9.76	1	5	0	0
Flux EV	12959	1	2.44	2	10	0	0
Aeon PHEV	13957	0	0	2	10	0	0
Twister Gas	16259	6	14.63	8	40	0	0
Serpent Hybrid	17572	10	24.39	5	25	7	35
Moonlight PHEV	20803	19	46.34	2	10	13	65
	Total	41	100	20	100	20	100

Note: Table reports the numbers and percentage of subjects choosing each car in the three information groups.

Table 2.5 presents the car selection results for the first three information groups. Based on the assigned driving habits and energy prices, the least costly car for subjects was the Moonlight PHEV with a maximum payoff of EC$ 20,803 after deducting the upfront MSRP and fuel costs (and considering tax break incentives) from their EC$ 50,000 initial budget. The second-best option was the Serpent Hybrid, which had an EC$ 17,572 payoff after accounting for all the costs associated with the car. They were followed by the Twister, Aeon PHEV, Flux EV, Evolution Hybrid, and Roamer, while the costliest car was the Millennium EV, which only yielded an EC$ 5,000 remaining in funds. Given that a rational subject with perfect perception and understanding of the given information should choose the Moonlight PHEV, choosing any other car is considered a misoptimization on their part.

Out of the 41 subjects with information presented to them in only basic text format, 19 subjects (46.34%) successfully selected the best car, 10 subjects (24.39%) chose the second-best option, 6 subjects (14.63%) chose the third best and the rest misoptimized significantly. Among the subjects with access to the fuel economy labels, only 2 subjects (10%) selected the best car, 5 subjects (25%) chose the second-best option, and 8 subjects (40%) chose the third-best option, Twister. The subjects with both fuel economy labels and the fuel cost calculator performed the best on average, with 13 subjects (65%) that chose the best car and 7 subjects (35%) that chose the second best. No subjects in this last group misoptimized by over EC$ 3,231.

Table 2.6 Car Selection and Misoptimization for Each Information Group

	Car Payoff (EC$)		Misoptimization (EC$)
Car Info	Mean	Standard deviation	Mean
Basic	17859.56	3657.664	2943.44
Label	16449.6	4310.87	4353.4
Label & Calculator	19672.15	1581.124	1130.85

Table 2.6 reports the means and standard deviation of the misoptimization in the car selection task by information groups. By comparing the means of subjects' payoffs and misoptimizations in Experiment Currency, I find that subjects with access to both fuel economy label and the fuel cost calculator had the highest payoff at EC$ 19,672.15, with only an average misoptimization of EC$ 1130.85. Surprisingly, subjects with access to fuel economy labels misoptimized more than subjects with only basic information. The average misoptimized amount

for the Label group was EC$ 4353.4 and for the Basic group it was EC$ 2943.44. The fuel economy labels did not seem to help improve subjects' processing of fuel efficiency information.

Welch's t-tests are performed to determine if there is a statistically significant difference in the misoptimization between information groups. The results show that- even though the average misoptimization of subjects with fuel economy labels was EC$ 1409.95 more than the subjects with only the basic information- the difference in misoptimization between these groups is not statistically significant ($t = -1.2583$, $p = 0.1084$). However, subjects with fuel economy labels and the fuel cost calculator on average misoptimized EC$1812.59 less than the subjects with only basic information, and a Welch's t-test shows that this difference is statistically significant ($t = 2.6981$, $p = 0.0045$). The 95% confidence interval for the true mean difference between the basic group and calculator group is found to be (468.8594, 3156.319).

This result implies that the fuel cost calculator significantly improved consumers' accuracy in processing the fuel cost information and reduced the chance and extent of misoptimization, while the fuel economy labels did not help with improving the decision-making involving fuel economy information and may have been more confusing and misleading than anything else.

Assuming consumers' WTP for a service informing them the personalized least costly car equals to the sum of expected size of misoptimization and the effort cost of information processing ($WTP = \bar{C} + D(\bar{C})$), the experiment result implies that the subjects' average effort cost of processing eight car's fuel economy information was 5514.4 - 2943.4 = EC$ 2,517, which amounts to 5%, a significant proportion, of their budget. Converting this to the US dollar paid to subjects, that is $2.50.

2.5.3 Car Relevant Experience, Cognitive Ability and Other Factors

Next, I explore what factors contribute to subjects' misoptimization in the car selection task. The first potential factor is subjects' experience with and knowledge about cars in real life. Experience might help them reach a conclusion quickly without having to calculate fuel cost explicitly. I use variable *Own Car* to represent whether they self-report owning or driving a car. *Attention to Gas Price* and *Attention to Fuel Economy* are categorical variables representing how much they claim to pay attention to gas prices and fuel economy of cars in real life, respectively. I also surveyed subjects about how many times they have purchased a car to measure their real-life experience in dealing with similar tasks. Lastly, I asked subjects whether they have a dream car and if so what the make and model is. The question is meant to reflect how much subjects care about cars and their preference in cars. 63% of subjects claim to have a dream car, and 15% of the subjects have a dream car that is an electric vehicle, such as Tesla. *Dream Car EV* is the dummy variable that captures if one has an EV as their dream car.

I ran an OLS regression of the size of misoptimization on all these variables mentioned above, as well as subjects' family income, with information group fixed effect, and the result is shown in Column (1) in Table 2.7.

The result shows that whether subjects own or drive a car, the times they have purchased cars and whether they pay attention to gas prices or fuel economy have no statistically significant effect on their performance in the experiment task. There's also little evidence suggesting income level is a significant factor. However, one significant characteristic that correlates with their experiment performance is whether they have an EV as a dream car. On average, subjects who have an EV as their dream car misoptimized EC$ 2,731 less than the subjects who don't at $p<0.01$ significance level.

Table 2.7 Effects of Car Relevant Experience and Other Factors on Misoptimization

Variables	(1) Misoptimization	(2) Misoptimization	(3) Misoptimization
Basic Group	2,934***	3,175***	3,076***
	(850.4)	(869.0)	(922.7)
Label + Calculator Group	1,105	1,309	893.8
	(1,007)	(1,031)	(1,168)
Label Group	4,093***	4,327***	3,703***
	(987.6)	(1,025)	(1,103)
Own Car	473.4	407.9	482.9
	(407.7)	(424.8)	(471.0)
Attention to Gas Price	-204.2	-21.01	151.5
	(466.9)	(520.1)	(544.4)
Attention to Fuel Economy	0.841	-95.05	-255.0
	(283.6)	(296.8)	(324.3)
Times Purchased Car	675.6	698.6	-537.0
	(516.7)	(526.3)	(730.7)
Has Dream Car	1,211*	1,552**	1,266
	(722.7)	(773.5)	(826.8)
Dream Car EV	-2,731***	-3,057***	-2,563**
	(932.2)	(995.5)	(1,094)
Income	25.83	31.87	-76.10
	(89.02)	(95.52)	(109.0)
Num Correct		428.5	312.8
		(348.4)	(387.2)
Mentally Healthy		808.1	-141.1
		(910.7)	(1,056)
Native Speaker		-403.9	345.8
		(758.2)	(912.2)
Risk Preference		-65.85	-70.63
		(206.8)	(219.0)
Demographics			x
Major			x
Observations	99	99	97

Note: Table reports the effects of cognitive ability, risk attitude and car related experience, knowledge and preference, and demographics on misoptimization in car choice task from an OLS regression. Standard error in parentheses.

The second category of potential factors are subjects' cognitive ability to understand and process complicated information. While I surveyed subjects' SAT scores, most subjects reported not remembering their scores, so I measure subjects' cognitive abilities using the number of correctly answered questions in Frederick (2005)'s cognitive reflection test. The variable *Num Correct* takes values from 0 to 3. Some other related variables include *Mentally Healthy* that is a dummy variable indicating whether subjects report having mental health concerns and *Native Speaker* that indicates whether there could be potentially a language barrier that might have affected their performance.

In case risk-tolerant subjects tried to guess the best answer as if it was a gamble without actually putting in the effort to finish the task, I also controlled for the risk attitude measured by their choice among the six gambles, with the variable *risk* taking a value from 1 to 6, which respectively correspond to the most risk averse and the most risk seeking. The OLS regression of misoptimization including all these potential factors shows that neither cognitive ability nor risk attitude significantly affects the subjects' performance on the car selection task. The result is presented in Column (2) of Table 2.7. Controlling for subjects' demographic characteristics and schools does not change this, as shown in Column (3). However, across all three specifications, having an EV as their dream car consistently correlates with their misoptimization. Subjects preferring an EV had on average an EC$ 2,563 to EC$ 3,057 higher payoffs, depending on the specification, than the ones who either do not have a dream car or have gasoline car as a dream car. A potential reason could be that those subjects are more familiar with nontraditional fuel type vehicles, like EV and PHEV, and thus have better knowledge of concepts like MPGe.

2.6 Conclusion

This paper simulates a complex information environment in an incentivized lab experiment in order to quantify the cost of attention in consumers' decision-making process when buying energy-using durables like cars. It evaluates the effectiveness of fuel economy labels and the fuel cost calculator, as provided by EPA, as a public good that lowers the effort costs for all automobile consumers. Using an incentive compatible mechanism allows me to measure subjects' willingness to pay for those information tools and services provided by the government, which provides insight into the policy evaluation of provisioning energy efficiency information. These results answer the four research questions proposed.

First, when subjects are asked to select one out of eight hypothetical cars that costs the least with sufficient financial incentives, around half of the subjects chose suboptimal options, which are also less fuel efficient, when having the fuel economy information presented to them in basic text format. This indicates an energy efficiency gap of EC$ 2943.44 (Experiment Currency), or $ 2.94 US dollars. Subjects with the fuel economy labels displayed to them misoptimized even more on average, although the difference in means is not statistically significant. Fuel economy labels present estimated fuel costs based on an average driver in the US for five years' driving, which can be misleading to consumers whose driving patterns are far away from the average driver. Access to a replica of the fuel cost calculator on the EPA's website significantly improved subjects' performance, with 65% of them choosing the optimal car and the remaining 35% choosing the second-best option. This treatment yielded a mean misoptimization of EC$ 1130.85 Experiment Currency, or $ 1.13 US dollars, almost 62% lower than subjects without it. This suggests that the fuel cost calculator is highly effective in reducing the potential energy efficiency gap, although 29% of the subjects reported having never heard of the EPA's fuel cost calculator.

Second, I elicit subjects' willingness to pay for fuel economy labels, fuel cost calculators and a service informing them their personalized optimal car in terms of costs. Subjects are willing to pay $1.50, $2.42, and $5.51 US dollars on average, which are roughly 3%, 5%, and up to 11% of their budget, for having access to these tools or services, respectively. The public good nature of these information provision tools and services also implies that further investment in the development and promotion of these tools and services could be justified.

From the elicited subjects' willingness to pay for the answer and the mean of misoptimization in the basic information group, an average effort cost of processing the fuel cost information of eight cars is estimated to be EC$ 2,517 Experiment Currency, which converts to $2.51 US dollars. The level misoptimization is found to be correlated with whether subjects possess a preference for electric vehicles in real life, but not with other factors I predicted, such as car ownership, experience in car purchase, risk preference or cognitive ability.

The result of this lab experiment suggests that if government were to address the energy efficiency gap in the automobile market by providing information tools and services, a fuel cost calculator is much more effective in delivering accurate information to each consumer than fuel economy labels. In addition to the mandated display of window stickers, EPA might want to consider promoting consumers' awareness of and accessibility to the fuel cost calculator or similar tools (e.g., mobile apps) that provide personalized information.

One limitation of this study is that the lab estimations of subjects' willingness to pay and cognitive effort costs may lack external validity, as subjects face much higher stakes when purchasing a car in real life. This is a drawback of utilizing the lab experiment method and a tradeoff for the advantage of exerting full control of other variables, such as consumers' preference for other features of a car and the uncertainty of their driving behavior. Conducting field experiments with more realistic incentives and information environments would likely improve on this aspect. Other potential directions for future research may include experiments with information treatments introducing general knowledge of EV and PHEV; alternative label treatments that eliminate numbers based on average drivers, which are potentially misleading; treatments with varying subsidy incentives; and treatments with variable driving patterns or gas prices, which address the future uncertainty in car purchasing decisions.

Chapter 3

Efficiency Wages, Unemployment, and Environmental Policy[26]

3.1 Introduction

The effects that environmental policies may have on labor markets, and whether and to what extent they kill jobs or create jobs, is of utmost importance to policymakers. Much popular aversion to environmental regulation comes from its perceived negative impact on jobs. Other distributional impacts of policy, like the sources-side and uses-side incidence, can depend on frictions in the labor market that yield unemployment. It is important for policymakers to understand the effect of environmental policies on unemployment and on both factor and output prices.

There are several ways to go about addressing the general question of how environmental policies affect labor markets and unemployment. Many papers empirically estimate the impact of specific environmental policies on employment, including Martin et al. (2014), Curtis (2018) and Colmer et al. (2018). Other papers use computable general equilibrium (CGE) models to quantify the large-scale effects that policies like an economy-wide carbon tax might have, including Böhringer et al. (2003), Hafstead et al. (2018), and Castellanos and Heutel (2019). A third approach uses analytical general equilibrium modeling, which can shed light on the mechanisms behind the effects that can be quantified through empirical or CGE models. Both Hafstead and Williams (2018) and Aubert and Chiroleu-Assouline (2019) introduce pollution

---

[26] Coauthored with Garth Heutel, published in Energy Economics 104 (2021): 105639. The published paper can be found at https://doi.org/10.1016/j.eneco.2021.105639.
We thank Spencer Banzhaf, Stefano Carattini, Kenneth Castellanos, Yuci Chen, Dan Karney, Stephie Fried, Don Fullerton, Chi Ta, and seminar participants at GSU, the AERE conference, and the ASSA conference for valuable comments.

policy and unemployment resulting from labor search frictions into an analytical general equilibrium model. Our paper follows this third approach.

The purpose of this paper is to study the effect of pollution taxes on unemployment and incidence using an analytical general equilibrium model where unemployment is endogenously generated via efficiency wages. Workers' effort is a function of the real wage and the economy's unemployment level. Pollution is modeled as a production input along with capital and labor. We find closed-form analytic solutions for the general equilibrium responses to a change in the pollution tax rate, including expressions for changes in the unemployment rate, factor prices (the sources-side incidence), output prices (the uses-side incidence), and worker effort. The model allows us to decompose the net effects into substitution effects, output effects, and effects from the efficiency wage specification. Lastly, we conduct numerical simulations using calibrated parameter values.

Our modeling approach dates back to the canonical tax incidence modeling of Harberger (1962). Like Agell and Lundborg (1992) and Rapanos (2006), our paper adds an efficiency wage theory of unemployment to the model, though those papers do not model pollution. Like Fullerton and Heutel (2007), our paper adds pollution and pollution taxes to the model, though that paper does not model unemployment.[27] We incorporate both efficiency wages and environmental policy into a Harberger-style analytical general equilibrium tax incidence model. Our paper is most similar to Hafstead and Williams (2018) and Aubert and Chiroleu-Assouline (2019), which both also model environmental policy and unemployment in an analytical general equilibrium setting. However, in both of those papers, unemployment arises from Diamond-

[27] Other papers that use a similar methodology to incorporate pollution policy into analytical general equilibrium modeling include Gonzalez (2012), Fullerton and Monti (2013), Dissou and Siddiqui (2014), and Baylis et al. (2014).

Mortensen-Pissarides-style search frictions (Pissarides 2000). In our paper, unemployment arises from efficiency wage theory (Akerlof 1982, Shapiro and Stiglitz 1984).[28]

Our theoretical results add new insights to the tax incidence literature. We identify effects that have been found in previous studies of environmental taxes, like the output and substitution effects. For example, an output effect exists such that the pollution tax disproportionately burdens the factor that is used more intensively in the polluting sector. These effects differ, though, when there is endogenous unemployment generated through efficiency wages. Along with these standard effects, we identify an effect that is new to the environmental tax literature, which we call the *efficiency wage effect*. The magnitude and direction of this effect depend on the form of the workers' effort function. Generally, the less elastic the workers' marginal effort response to the real wage is, the less burden labor bears, and the smaller increase in unemployment. With more structure on the effort function, we show that the crucial parameters of the effort function are the elasticities of effort with respect to the real wage and to unemployment. When effort responds more strongly to the real wage, then the magnitude of the efficiency wage effect is larger, which alleviates the tax burden on labor. When effort responds more strongly to unemployment, then the magnitude of the efficiency wage effect is smaller.

This key result depends on the efficiency wage specification causing unemployment, and so it is missing from previous studies that model unemployment through other causes. Our efficiency wage specification is general enough to accommodate different causes of efficiency wages and different effort functions. A gift exchange or fair wage efficiency wage model like Akerlof (1982) will lead to effort being very responsive to the real wage, and we find that this

[28] Furthermore, Hafstead and Williams (2018) do not provide analytical, closed-form solutions, just numerical simulations, and neither Hafstead and Williams (2018) nor Aubert and Chiroleu-Assouline (2019) include capital in their model.

implies that the efficiency wage effect will be large. A shirking and firing model like Shapiro and Stiglitz (1984) will lead to effort being very responsive to unemployment, and we find that this implies that the efficiency wage effect will be small. Thus, the structural origin of unemployment fundamentally affects how large of an effect the unemployment friction will have on standard tax incidence outcomes.

The calibrated numerical simulation results, based on a $40 per ton carbon tax, provide further insights into these effects. The disproportionate burden of the tax on labor from substitution effects is offset by the disproportionate burden on capital from the efficiency wage effect. Ignoring the efficiency wage effect, as in previous environmental tax incidence models, thus gets the sign of the sources-side incidence wrong. Because of the efficiency wage effect, the carbon tax burdens capital disproportionately higher than labor. The tax increases the unemployment rate by just under 1%; this effect is mainly driven by a substitution effect from the larger, untaxed clean sector, rather than substitution within the smaller, taxed dirty sector. Sensitivity analyses show that the effects on unemployment and on sources-side incidence depend on the effort function elasticities, the effect on sources-side incidence also depends on production elasticities, and the effect on uses-side incidence is relatively unaffected by these parameters. Both the analytical and the numerical results highlight the important role of the efficiency wage effect and the form of the effort function in the analysis of pollution tax incidence and unemployment effects.

The paper is organized as follows. Section 2 presents the model and derives a system of linearized equations. Section 3 presents and interprets the general solution, decomposing the net effect into separate effects. Section 4 calibrates and numerically simulates the model. The last section concludes.

3.2 Model

Our model is a two-sector, two-factor incidence model, in the spirit of Harberger (1962), with the addition of involuntary unemployment through an efficiency wage as in Agell and Lundborg (1992) and Rapanos (2006), and with the addition of pollution as in Fullerton and Heutel (2007, 2010). We consider a competitive two-sector economy using two factors of production: capital and labor. Both factors are perfectly mobile between sectors. A third variable input is pollution, Z, which is only used in production of one of the goods (the "dirty" good). The constant returns to scale production functions are:

$$X = X(K_X, E_X)$$

$$Y = Y(K_Y, E_Y, Z)$$

where X is the "clean" good, Y is the "dirty" good, K_X and K_Y are the capital used in each sector, and E_X and E_Y are the effective labor, in efficiency units, used in each sector.

The effective labor in each sector is defined as the actual amount of labor L times the effort level e:

$$E_X = e\left(\frac{w}{P}, U\right) \cdot L_X$$

$$E_Y = e\left(\frac{w}{P}, U\right) \cdot L_Y$$

where $e(\frac{w}{P}, U)$, the effort level of a representative worker, depends on the real wage rate $\frac{w}{P}$, and on the level of unemployment U.

This effort function is how we incorporate the efficiency wage theory of unemployment into our model. In structural models of efficiency wages, effort is an endogenously-determined optimal response of workers given the possibility of termination if caught shirking (Shapiro and Stiglitz 1984) or norms of fairness (Akerlof 1982). But here, the effort function is a reduced-form relationship between the wage, unemployment, and the level of effort. Our reduced-form effort function is identical to that of Rapanos (2006).[29]

Structural efficiency wage models predict that effort is positively related to the real wage ($\frac{w}{P}$) and to the economy-wide level of unemployment, so we impose that the first derivatives e_1 and e_2 are positive.[30] The effort level is identical across the two sectors (since neither the real wage nor unemployment are sector-specific). L_X and L_Y are the labor used in each sector in terms of the number of workers. Linearizing the two equations defining effective labor gives us:

$$\widehat{E_X} = \hat{e} + \widehat{L_X} \tag{1}$$

$$\widehat{E_Y} = \hat{e} + \widehat{L_Y} \tag{2}$$

We adopt the "hat" notation where a variable with a hat represents a proportional change in the variable. That is, $\widehat{E_X} \equiv dE_X/E_X$, and likewise for the other variables.

Both representative firms face the same effort function e, and they set their wages w to minimize the effective wage cost per worker $v \equiv w/e$. Formally, the optimization problem for the representative firm is:

$$\min_{w} v = \frac{w}{e\left(\frac{w}{P}, U\right)}$$

The first-order condition is

$$e - e_1 \frac{w}{P} = 0$$

where e_1 is the first derivative of the effort function with respect to the real wage. This condition can be written as $\varepsilon_1 \equiv \frac{e_1 w}{ep} = 1$, meaning that the wage is set so that the elasticity of effort with

---

[29] The reduced-form effort function in Agell and Lundborg (1992) is slightly different; effort is a function of the relative wages across industries and the ratio of the wage to capital rental rate.
[30] Empirical support for this reduced-form relationship is found in Raff and Summers (1987) and Cappelli and Chauvin (1991).

respect to the real wage is one. Totally differentiating this first-order condition, and employing the assumption that $e_{12} = \frac{\partial^2 e}{\partial\left(\frac{w}{P}\right)\partial U} = 0$, we obtain:

$$e_2 dU = \frac{e_{11} w^2}{P^2}\left(\frac{dw}{w} - \frac{dP}{P}\right)$$

which can be rewritten as

$$\hat{U} = \frac{e_{11} w^2}{e_2 U P^2}\left(\hat{w} - \hat{P}\right) = \frac{\frac{e_{11}}{e_1} \cdot \frac{w}{P}}{\frac{e_2}{e} \cdot U}\left(\hat{w} - \hat{P}\right)$$

$$\hat{U} = \frac{\varepsilon_{11}}{\varepsilon_2}\left(\hat{w} - \hat{P}\right) \tag{3}$$

where $\varepsilon_{11} \equiv \left(\frac{e_{11}}{e_1}\right)\left(\frac{w}{P}\right)$, and $\varepsilon_2 \equiv \left(\frac{e_2}{e}\right) U$. Since $e_2 > 0$, we also have $\varepsilon_2 > 0$, which is the elasticity of effort with respect to unemployment. We assume concavity of the effort function with respect to the real wage w/P to ensure an interior solution to the minimization problem, so $e_{11} < 0$, which implies that $\varepsilon_{11} < 0$. This parameter, ε_{11}, is important throughout the analysis and arises in the closed-form solutions presented below. It is a measure of the concavity of the effort function with respect to the real wage. If it is close to zero, the effort function is close to linear in the real wage. If it is large in absolute value, then the marginal effort with respect to the real wage (e_1) declines quickly as the wage increases.[31]

Totally differentiating the effort function $e = e(\frac{w}{P}, U)$ obtains

$$\hat{e} = \hat{w} - \hat{P} + \varepsilon_2 \hat{U} \tag{4}$$

From the definition of effective wage v, we have

$$\hat{v} = \hat{w} - \hat{e} \tag{5}$$

[31] Rapanos (2006) describes the parameter ε_{11} as "the rate at which workers get satisfied with real wages." (p. 481).

The first five equations of our model describe the labor market and are identical to those in the efficiency wage model of Rapanos (2006).

The resource constraints are:

$$K_X + K_Y = \overline{K}$$

$$L_X + L_Y = \overline{L} - U$$

where $\overline{K}$ and $\overline{L}$ are the fixed total amounts of capital and labor in the economy.[32] All capital is fully employed, while labor faces a level of unemployment U. Totally differentiating the resource constraints (noting that $\overline{K}$ and $\overline{L}$ remain fixed) yields

$$\widehat{K_X} \cdot \lambda_{KX} + \widehat{K_Y} \cdot \lambda_{KY} = 0 \tag{6}$$

$$\widehat{L_X} \cdot \lambda_{LX} + \widehat{L_Y} \cdot \lambda_{LY} = -\widehat{U} \cdot \lambda_{LU} \tag{7}$$

where λ_{ij} denotes sector j's share of factor i ($\lambda_{KX} = \frac{K_X}{\overline{K}}$). λ_{LU} denotes the unemployment rate ($\lambda_{LU} = \frac{U}{\overline{L}}$). Pollution Z has no equivalent resource constraint. As in Fullerton and Heutel (2007), we start with a preexisting positive tax τ_Z on pollution.

When modeling producer behavior, we consider the producers responding to the price and quantity of effective labor rather than actual labor. The price of a unit of effective labor is v, and the quantities are E_X and E_Y. Producers of X can substitute between factors in response to changes in the factor prices $p_K \equiv r(1 + \tau_K)$ and $p_E \equiv v(1 + \tau_E)$, where τ_K and τ_E are the *ad valorem* taxes on capital and effective labor. We will only consider a change in the pollution tax, not in any of the other taxes, so, $\widehat{p_K} = \hat{r}$ and $\widehat{p_E} = \hat{v}$.[33] The elasticity of substitution in production σ_X is defined to capture this response to factor price changes:

[32] As is standard in Harberger-type incidence models, total resources are fixed, though they can be re-allocated across sectors in response to policy. These models are thus sometimes described as "medium-run" adjustment models.

[33] Since we do not model changes in other pre-existing tax rates, like the labor tax, we do not consider revenue recycling (i.e. using the pollution tax revenues to reduce the labor tax rate). Pollution tax revenues are returned

$$\widehat{K_X} - \widehat{E_X} = \sigma_X(\hat{v} - \hat{r}) \tag{8}$$

where σ_X is defined to be positive.

Producers of Y use three inputs: capital, effective labor, and pollution. Firms face no market price for pollution, just a tax on per unit of pollution, so $p_Z = \tau_z$ and $\widehat{p_Z} = \widehat{\tau_z}$.[34] We model firm Y's behavior by assuming a constant elasticity of substitution (CES) production function, yielding:

$$\widehat{K_Y} - \hat{Z} = \sigma_Y(\widehat{\tau_Z} - \hat{r}) \tag{9}$$

$$\widehat{E_Y} - \hat{Z} = \sigma_Y(\widehat{\tau_Z} - \hat{v}) \tag{10}$$

where $\sigma_Y > 0$ is the elasticity of substitution in production. Equations (9) and (10) show how a change in any of the input prices affects the relative demand for the three inputs. The change in relative demand is a function of the change in relative prices and the substitution elasticity. A more complicated and general way of modeling production when the dirty sector has three inputs is to use Allen elasticities of demand, as in Fullerton and Heutel (2007). While that assumption is more general than CES, the resulting general solution is very long and complicated and does not add additional insight into the effect of the efficiency wage specification on outcomes. In the Appendix C, we present and analyze the full solution from the more general model, while here in the text we use the CES simplification.

Using the assumptions of perfect competition and constant returns to scale, we get

$$\widehat{p_X} + \hat{X} = \theta_{XK}(\hat{r} + \widehat{K_X}) + \theta_{XE}(\hat{v} + \widehat{E_X}) \tag{11}$$

$$\widehat{p_Y} + \hat{Y} = \theta_{YK}\left(\hat{r} + \widehat{K_Y}\right) + \theta_{YE}\left(\hat{v} + \widehat{E_Y}\right) + \theta_{YZ}\left(\hat{Z} + \widehat{\tau_Z}\right) \tag{12}$$

---

lump-sum and assumed to not affect equilibrium prices. CGE models, like Hafstead et al. (2018) and Castellanos and Heutel (2019), consider revenue recycling.

[34] Modeling pollution as an input allows for a very general form of substitutability between pollution, capital, and labor. One can alternatively interpret the pollution input as an energy input. In the numerical calibration below, we calibrate pollution factor shares and other parameters based on data on energy factor shares.

Here $\theta_{YK} \equiv \frac{r(1+\tau_K)K_Y}{p_Y \cdot Y}$, $\theta_{YE} \equiv \frac{v(1+\tau_E)E_Y}{p_Y \cdot Y}$ and $\theta_{YZ} \equiv \frac{\tau_Z \cdot Z}{p_Y \cdot Y}$ are the share of sales revenue from Y that is paid to capital, to effective labor, and to pollution (through the tax), respectively. Define θ_{XK} and θ_{XE} similarly to θ_{YK}. (Note that $\theta_{XK} + \theta_{XE} = 1$ and $\theta_{YK} + \theta_{YE} + \theta_{YZ} = 1$.) Totally differentiate each sector's production function and substitute in the conditions from the perfect competition assumption to get

$$\hat{X} = \theta_{XK}\widehat{K_X} + \theta_{XE}\widehat{E_X} \tag{13}$$

$$\hat{Y} = \theta_{YK}\widehat{K_Y} + \theta_{YE}\widehat{E_Y} + \theta_{YZ}\hat{Z} \tag{14}$$

The details of the derivation of equations 11 through 14 can be found in Fullerton and Heutel (2007, Appendix A).

Consumer preferences are modeled using σ_u, the elasticity of substitution between goods X and Y. The definition of this elasticity yields

$$\hat{X} - \hat{Y} = \sigma_u(\widehat{p_Y} - \widehat{p_X}) \tag{15}$$

Lastly, the price index P, which appears in the effort function, is defined to equal a weighted average of the output prices of the two goods, i.e. $P = {p_X}^{\eta} \cdot {p_Y}^{1-\eta}, (\eta < 1)$. Then the change in the price index can be written as

$$\hat{P} = \eta\widehat{p_X} + (1-\eta)\widehat{p_Y} \tag{16}$$

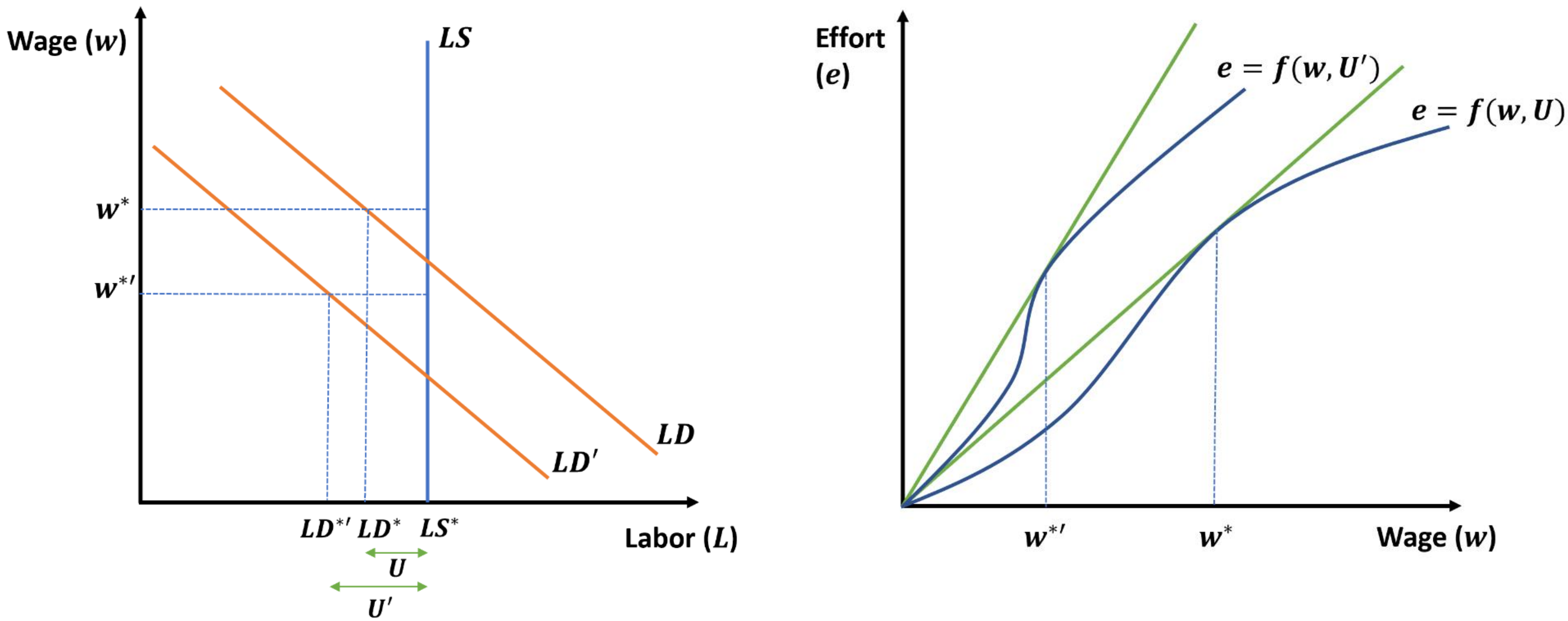
The full model is equations (1) through (16). It contains just one exogenous policy variable ($\hat{\tau}_Z$) and 17 endogenous variables. To solve it, we impose a normalization assumption by assuming that the price index P is the numeraire and unchanged, so that $\hat{P} = 0$.[35] Dropping $\hat{P}$ from the model thus yields 16 equations with 16 unknowns

[35] This normalization implies that all price changes analyzed in the model are price changes relative to the price index P. An increase in the pollution tax τ_Z is actually an increase in the ratio $\frac{\tau_Z}{P}$. By contrast, Fullerton and Heutel (2007) normalize by setting the clean good price change $\widehat{p_X} = 0$, and Rapanos normalizes by setting $\widehat{p_Y} = 0$. Garnache and Mérel (2020) demonstrate that choosing the overall price index P as numeraire is a more natural assumption that eliminates some counterintuitive cases.

$(\widehat{K_X}, \widehat{K_Y}, \widehat{E_X}, \widehat{E_Y}, \widehat{L_X}, \widehat{L_Y}, \hat{Z}, \widehat{U}, \hat{e}, \widehat{w}, \hat{v}, \widehat{p_X}, \widehat{p_Y}, \hat{r},\ \hat{X},\ \hat{Y})$. The model is solved with successive substitution, as described in Appendix C.

Figure 3.1 illustrate the intuition of the efficiency wage theory used in our model. On the left-hand side is the labor market, where supply is perfectly inelastic (since $\bar{L}$ is fixed). When labor demand is given by the curve LD, the equilibrium wage would be where demand and supply intersect. However, the right graph presents the effort function e as a function of the wage w on the x-axis. For a given effort function, the firm chooses the wage to maximize productivity per dollar paid. This is given by the tangent point of the effort function to a straight line starting at the origin, which yields the wage w^* for the effort function $e = f(w, U)$. This wage is higher than the market-clearing wage, and thus causes unemployment U (since quantity supplied at this wage, LS^*, exceeds quantity demanded at this wage, LD^*). Equilibrium is where the wage w^* chosen at the tangent line to the effort function in the right graph for unemployment level U also yields unemployment U in the labor market on the left graph.

Figure 3.1 Graphical Intuition of Efficiency Wage Model



Notes: These graphs demonstrate the intuition behind how a change in the pollution tax affects wages and employment in an efficiency wage model. The left graph is the labor market, where labor supply is perfectly inelastic. The right graph presents workers' effort function e as a function of the wage w on the x-axis. The firms set the wage where the effort function is tangent to a ray from the origin, maximizing productivity per dollar paid, and thus creating unemployment. A pollution tax can reduce labor demand from LD to LD'. Unemployment and thus the effort function change, and the equilibrium wage decreases from w^* to $w^{*\prime}$.

Suppose now that a pollution tax burdens the firms and therefore decreases labor demand to LD'. Without a change in the wage from w^*, unemployment would drastically increase. But the effort function also responds to unemployment, which changes the firm's optimal wage shown on the right graph. A new unemployment level yields a new optimal wage (from equation 3). The new, post-pollution-tax equilibrium involves an unemployment level U' such that the optimal wage $w^{*\prime}$ given U' from the effort function (right graph) yields unemployment U' in the labor market (left graph). As drawn in Figure 3.1, the pollution tax reduces labor demand, lowers the wage, and increases unemployment. However, both the magnitude and the direction of these changes depend on model parameters. For example, the effort function might be such that the new wage $w^{*\prime}$ is higher than the original wage w^*. We explore these effects in both the analytical solutions and numerical simulations below.[36]

The simplified analysis in Figure 3.1 omits several features of the model, including the two production sectors and the interaction between labor demand and capital demand. But it demonstrates that how workers' effort responds to changes in the wage and unemployment is crucial in determining the effects of the pollution tax. In an efficiency wage model, the wage is determined not only by the interaction of labor supply and demand. Rather, the wage affects both the workers' effort (internal margin) and the quantity of labor demanded (external margin). The inclusion of this margin has the potential to affect the incidence results from pollution policy.

[36] For more intuition on the microfoundations of the efficiency wage model, see Yellen (1984) or Weiss (2014).

3.3 Solution

Our focus is on incidence and unemployment effects, so we are most interested in solutions for changes in factor prices ($\widehat{w}$ and $\hat{r}$), output prices ($\widehat{p_X}$ and $\widehat{p_Y}$), and unemployment $\widehat{U}$.

We present three closed-form solutions. The first is $\widehat{U}$, which is the change in unemployment or the unemployment rate.[37] The second is $\widehat{w} - \hat{r}$, which represents the sources-side incidence, i.e., the relative burden on labor versus capital. If $\widehat{w} - \hat{r}$ is positive, then the wage increases more than the rental rate does (or decreases less), so the burden of the tax falls relatively more on capital than on labor. The third is $\widehat{p_Y} - \widehat{p_X}$, which represents the uses-side incidence, i.e. the relative burden on consumers of the dirty good versus consumers of the clean good. If $\widehat{p_Y} - \widehat{p_X}$ is positive, then the difference in these prices increases, so the burden of the tax falls relatively more on consumers of the dirty good versus consumers of the clean good. These solutions are:

$$\widehat{U} = \frac{\theta_{YZ}}{\varepsilon_2 D}\{\sigma_Y[A(1-\eta) + \eta_K(\gamma_K - \gamma_L)] + \sigma_u\theta_{XK}(\gamma_L - \gamma_K) + C\sigma_X(1-\eta)\}\,\widehat{\tau_Z} \tag{17}$$

$$\widehat{w} - \hat{r} = \frac{\theta_{YZ}}{\varepsilon_{11} D}\left\{\begin{matrix}\sigma_Y[(1-\eta)(A+\varepsilon_{11}B) + (\gamma_L - \gamma_K)(\varepsilon_{11}\eta_E - \eta_K)] \\ +\sigma_u(\gamma_L - \gamma_K)(\theta_{XK} - \varepsilon_{11}\theta_{XE}) + C\sigma_X(1-\eta)(1+\varepsilon_{11}) - (1-\eta)M\end{matrix}\right\}\widehat{\tau_Z} \tag{18}$$

$$\widehat{p_Y} - \widehat{p_X} = \frac{\theta_{YZ}}{D}\left\{\sigma_Y[\gamma_L\gamma_K + \gamma_L\theta_{XK} + \gamma_K\theta_{XE}] + C\sigma_X - M\frac{\theta_{XK}}{\varepsilon_{11}}\right\}\widehat{\tau_Z} \tag{19}$$

These solutions use the following definitions and simplifications: $\gamma_L \equiv \frac{\lambda_{LY}}{\lambda_{LX}}, \gamma_K \equiv \frac{\lambda_{KY}}{\lambda_{KX}}$, $\mathrm{A} \equiv \gamma_L\gamma_K + \gamma_L\theta_{YK} + \gamma_K(1-\theta_{YK})$, $\mathrm{B} \equiv \gamma_K\gamma_L + \gamma_K\theta_{YE} + \gamma_L(1-\theta_{YE})$, $C \equiv \theta_{XK}\gamma_K + \theta_{XE}\gamma_L + 1$, $\eta_K \equiv \theta_{XK}\eta + \theta_{YK}(1-\eta)$, $\eta_E \equiv \theta_{XE}\eta + \theta_{YE}(1-\eta)$, $M \equiv \frac{1}{\lambda_{KX}\lambda_{LX}}\Big[(1-\lambda_{LU}) +$

[37] U is the level of unemployment, so $\widehat{U}$ is defined as the percentage change in the level of unemployment. But since the total labor force is fixed, $\widehat{U}$ is also the percent change in the unemployment rate. It is not a percentage point change. For example, if the baseline unemployment rate is 4%, then $\widehat{U} = 0.1$ is a ten-percent increase in that baseline rate, to 4.4%.

$\varepsilon_{11}\left(1-\lambda_{LU}-\frac{\lambda_{LU}}{\varepsilon_2}\right)\Big]$, and $D \equiv \sigma_u(\gamma_L-\gamma_K)(\theta_{XK}\theta_{YE}-\theta_{XE}\theta_{YK})+\sigma_Y(A\eta_E+B\eta_K)+$ $C\sigma_X(\eta_E+\eta_K)-M\eta_K/\varepsilon_{11}$.

All three expressions are linear functions of the change of the pollution tax $\widehat{\tau_Z}$, since the model is linearized and $\widehat{\tau_Z}$ is the only exogenous policy variable. These expressions can be decomposed into several effects that can be separately analyzed.[38] In the following subsections, we decompose each expression into terms representing several intuitive effects, in the spirit of Mieszkowski (1967): an output effect, two substitution effects (one from the clean sector and one from the dirty sector), and an effect that we call the efficiency wage effect. The output effect is represented by the terms that include the elasticity of substitution in utility, σ_u. The clean sector substitution effect is represented by the terms that include the elasticity of substitution in production in the clean sector, σ_X. The dirty sector substitution effect is represented by the terms that include the elasticity of substitution in production in the dirty sector, σ_Y. Finally, the efficiency wage effect is represented by the terms that include M.[39] While assigning these names to each separable term, the efficiency wage effect that we identify does not capture all the channels of the pollution tax's impact related to workers' effort. The effort elasticity parameters ε_{11} and ε_2 are also in the coefficients in front of equations (17) and (18), as well as in the denominator D. We should interpret the terms including M as the identifiable part of the complex effect of the efficiency wage, while bearing in mind that the assumption of efficiency wage changes the sizes of all three other effects compared to the previous literature.

[38] Throughout the analysis below, we assume that the denominator D is positive, which it is in all of the numerical simulations. A sufficient but not necessary condition ensuring that D is positive is $\varepsilon_{11}>-1$.
[39] Since these results are so complicated, we also consider a simpler model that does not include capital. This model is presented in Appendix C. While the results are simpler than those from the main model, it cannot be used to analyze sources-side incidence or to see how substitution between labor and capital affects unemployment.

3.3.1 *Efficiency Wage Effect*

Our main result is the interpretation of an effect that we call the efficiency wage effect. This effect of course is absent in previous models without an efficiency wage or endogenous unemployment. It is present in previous models with efficiency wage-driven unemployment, for instance Rapanos (2006) derives a similar effect that he calls the "unemployment effect." But in those papers, the effect arises not from a pollution tax (since there is no pollution in those models) but rather from factor income taxes.

This efficiency wage effect is absent from the equation for unemployment, equation (17) (there is no term with M in that equation). That may seem counterintuitive since of course the efficiency wage component of the model must affect unemployment. However, the coefficient $\frac{1}{\varepsilon_2}$ in front of equation (17) captures this relationship. The substitution and output effects are scaled by this coefficient, which shows how the form of the effort function translates these effects into unemployment. When workers' effort is more responsive to unemployment, ε_2 is large, so the equilibrium effect on unemployment is smaller in magnitude, all else equal. The intuition for this effect is clearer in the simplified model in Appendix C, where the effect on unemployment is also scaled by $\frac{1}{\varepsilon_2}$.

The efficiency wage effect is its own term in the expressions for the sources-side and uses-side incidence; it is represented by the terms with M in it. As defined earlier, $M \equiv \frac{1}{\lambda_{KX}\lambda_{LX}}\left[(1-\lambda_{LU}) + \varepsilon_{11}\left(1-\lambda_{LU}-\frac{\lambda_{LU}}{\varepsilon_2}\right)\right]$, which is strictly positive if $\varepsilon_{11} > -1$. The efficiency wage effect in the expression for sources-side incidence (equation 18) is $-\frac{\theta_{YZ}}{\varepsilon_{11}D}(1-\eta)M$ and so is the same sign of M. If workers' marginal effort with respect to the real wage does not decline too fast as the wage increases (i.e. $\varepsilon_{11} > -1$), then the efficiency wage effect on $\hat{w}-\hat{r}$ is strictly positive, meaning that a pollution tax disproportionately burdens capital. The uses-side efficiency wage effect from equation (19) is $-\frac{\theta_{YZ}\theta_{XK}}{\varepsilon_{11}D}M$. Under the same assumption that $\varepsilon_{11} > -1$, this effect is strictly positive, which means the dirty good price increases more than the clean good price, and the uses-side incidence falls more on consumers of the dirty good.

To further interpret this effect, we can impose a functional form on the worker's effort function:

$$e\left(\frac{W}{P}, U\right) = \phi\left(\frac{W}{P}\right)^{\alpha} + \psi U^{\beta}$$

where $\phi > 0$, $0 < \alpha < 1$, $\psi < 0$, and $\beta < 0$.[40] These parameter restrictions ensure that $e_1 > 0$, $e_2 > 0$, $e_{12} = 0$, $e_{11} < 0$, and $e_{22} < 0$. The elasticity of effort with respect to the wage is $\varepsilon_1 = \frac{\alpha\phi\left(\frac{W}{P}\right)^{\alpha}}{\phi\left(\frac{W}{P}\right)^{\alpha}+\psi U^{\beta}}$. The first-order condition that this elasticity is one amounts to $\phi(\alpha - 1)\left(\frac{W}{P}\right)^{\alpha} = \psi U^{\beta}$. The elasticity of effort with respect to unemployment is $\varepsilon_2 = \frac{\beta\psi U^{\beta}}{\phi\left(\frac{W}{P}\right)^{\alpha}+\psi U^{\beta}} = \frac{\beta(\alpha-1)}{\alpha} > 0$. The concavity of the effort function with respect to wage is $\varepsilon_{11} = \alpha - 1 < 0$. Under this functional form assumption, $M = \frac{\alpha}{\lambda_{KX}\lambda_{LX}}\left(1 - \left(1 + \frac{1}{\beta}\right)\lambda_{LU}\right)$. This expression is strictly positive, and its magnitude depends on both the unemployment rate λ_{LU} and the elasticities of the effort function. These elasticities ultimately depend on the values of α and β, which represent the responsiveness of effort with respect to the real wage and to unemployment, respectively.

We explore how the magnitude of M, and thus of the efficiency wage effect on both the sources-side and uses-side incidence, depends on these parameters. First, $\frac{\partial M}{\partial \alpha} =$

[40] A more natural functional form assumption is Cobb-Douglas, but a Cobb-Douglas effort function does not satisfy the assumption that $e_{12} = 0$, and the first-order condition that $\varepsilon_1 = 1$ demands that effort is linear in the real wage.

$\frac{1}{\lambda_{KX}\lambda_{LX}}\left(1-\left(1+\frac{1}{\beta}\right)\lambda_{LU}\right)$. This derivative is strictly positive (since $\beta < 0$). The efficiency wage effect becomes larger in magnitude (M increases) as workers' effort becomes more responsive to the real wage (α increases). Second, $\frac{\partial M}{\partial \beta} = \frac{\lambda_{LU}}{\lambda_{LX}\lambda_{KX}}\frac{\alpha}{\beta^2}$. This derivative is strictly positive. The efficiency wage effect becomes smaller in magnitude (M decreases) as workers' effort becomes more responsive to unemployment (β decreases).[41] These two derivatives demonstrate how the source of the efficiency wage matters greatly to incidence effects. A high α means effort is very responsive to the real wage, which is likely to be true in a gift exchange or fair wage efficiency wage model like Akerlof (1982). A high β means effort is very responsive to unemployment, which is likely to be true in a shirking and firing model like Shapiro and Stiglitz (1984). If a fair wage model is more accurate, then the efficiency wage incidence effect is large, whereas if a shirking and firing model is more accurate, then the efficiency wage incidence effect is smaller.

We provide intuition for this key result that the efficiency wage effect on both sources-side and uses-side incidence is larger when effort is more responsive to the real wage and is smaller when effort is more responsive to unemployment. When effort is very responsive to the real wage, then the efficiency wage effect on sources-side incidence, which increases the relative burden on capital, is large, because in equilibrium the wage must rise high enough to provide the incentive for worker effort. Thus, workers' effort being highly responsive to the wage benefits workers by forcing the wage to increase. When effort is very responsive to the unemployment rate, then the efficiency wage effect on sources-side incidence is small, because in equilibrium the effort can be incentivized through unemployment rather than through the wage. Thus,

[41] Because $\beta < 0$ and the elasticity of effort with respect to unemployment is proportional to the absolute value of β, a lower value of β (more negative) represents more elastic effort.

workers' effort being highly responsive to the unemployment rate hurts workers by decreasing the wage.

The intuition is similar for the efficiency wage effect on uses-side incidence. When effort is very responsive to the real wage, then the efficiency wage effect on uses-side incidence, which increases the relative burden on consumers of the dirty good, is large, because the increase in the wage necessary to induce equilibrium effort is partially passed through to output prices and disproportionately to the dirty good price. When effort is very responsive to the unemployment rate, then the efficiency wage effect on uses-side incidence is small, because effort need not be induced through a change in the wage but instead can be induced through equilibrium unemployment, and less of a price change passes through to output prices.

We also explore how the unemployment rate affects the efficiency wage effect: $\frac{\partial M}{\partial \lambda_{LU}} = \frac{-\alpha}{\lambda_{KX}\lambda_{LX}}\left(1 + \frac{1}{\beta}\right)$. This is positive if and only if $-1 < \beta < 0$, and negative if and only if $\beta < -1$. All else equal, one might predict that a larger baseline unemployment rate will increase the magnitude of the efficiency wage effect. But if effort is very responsive to unemployment (β is large in absolute value) then this might not be the case.

While the efficiency wage effect is represented by the term with M in the expression for sources-side incidence, the entire expression for sources-side incidence (equation 18) is scaled by the factor $\frac{1}{\varepsilon_{11}}$. This scale factor also appears in the corresponding expression in the simpler model in Appendix C. As in that model, this factor shows that all of the effects on the sources-side incidence depend on the magnitude of ε_{11}. If it is large in absolute value, then workers' marginal effort is highly responsive to the wage, so that all of the effects on the wage (and thus on the sources-side incidence) are dampened.

3.3.2 Output Effect

The remaining effects in equations (17), (18), and (19) are the output effect and two substitution effects. These are standard effects found in the tax incidence literature dating back to Harberger (1962) and Mieszkowski (1967). Here, we focus on how the inclusion of pollution and unemployment modifies these effects.

In both equations (17) and (18), the terms that include σ_u, the substitution elasticity of demand between the two goods X and Y, represent an output effect. Through the output effect, the pollution tax disproportionately affects the dirty sector — because the dirty sector is the only sector that uses pollution as an input — and reduces its output in a way that depends on consumer preferences via σ_u. Less output means less demand for all inputs, but particularly the input used intensively in that sector.

The output effect caused by a one-unit change in the pollution tax ($\widehat{\tau_Z}$) on unemployment $\widehat{U}$ is $\frac{\theta_{YZ}}{\varepsilon_2 D}\{\sigma_u \theta_{XK}(\gamma_L - \gamma_K)\}$. This term is negative whenever $\gamma_K > \gamma_L$, which holds whenever the dirty sector Y is relatively capital-intensive.[42] The dirty sector being capital-intensive means that the pollution tax will impose a larger burden on capital than on labor, which translates to a decrease in unemployment, captured in this term.

In the expression for sources-side incidence $\widehat{w} - \hat{r}$, equation (18), the output effect $\frac{\theta_{YZ}}{\varepsilon_{11} D}\{-\sigma_u(\gamma_L - \gamma_K)(-\theta_{XK} + \varepsilon_{11}\theta_{XE})\}$ is positive whenever $\gamma_K > \gamma_L$. If the dirty sector is relatively capital-intensive ($\gamma_K > \gamma_L$), then this output effect will decrease the price of capital relative to the wage ($\widehat{w} - \hat{r} > 0$). The magnitude of this effect is proportional to the substitution elasticity of demand between the two goods, σ_u.

[42] $\gamma_K > \gamma_L$ implies $\frac{\lambda_{KY}}{\lambda_{KX}} > \frac{\lambda_{LY}}{\lambda_{LX}}$, which implies $\frac{K_Y}{K_X} > \frac{L_Y}{L_X}$.

There is no output effect on the uses-side incidence $\widehat{p_Y} - \widehat{p_X}$; the relative factor intensities do not affect uses-side incidence, only sources-side incidence.

3.3.3 Clean Sector Substitution Effect

Next, we identify two kinds of substitution effects. In equations (17), (18), and (19), the terms that include σ_X, the substitution elasticity of input demand between capital and labor for the clean (X) sector, are what we call the clean sector substitution effect. This captures the response of the clean sector to the change of relative input prices. Because the model is general equilibrium and total factor quantities (capital and labor) across sectors are fixed, the effect of substitutability within the clean industry impacts the incidence of a tax levied only on the dirty industry.

In the expression for the change in unemployment $\widehat{U}$ (equation 17), the clean sector substitution effect is $\frac{\theta_{YZ}}{\varepsilon_2 D}\{C\sigma_X(1-\eta)\}$. This term is unambiguously positive. An increase in the pollution tax unambiguously increases unemployment through the clear sector substitution effect. Similarly, for the sources-side incidence (equation 18), the clean sector substitution effect is $\frac{\theta_{YZ}}{\varepsilon_{11} D}\{C\sigma_X(1-\eta)(1+\varepsilon_{11})\}$. This term is unambiguously negative, so when the pollution tax increases, this effect decreases $\hat{w} - \hat{r}$ and places more burden of the tax on labor.

The clean sector substitution effect's impact on both unemployment $\widehat{U}$ and sources-side incidence $\hat{w} - \hat{r}$ arises from the same intuition. The tax increase is an overall distortion to the economy. While the total amount of capital employed is fixed, the total amount of labor employed varies because of endogenous unemployment. The overall distortion from the pollution tax thus exacerbates the tax wedge affecting unemployment, increasing overall unemployment and disproportionately burdening labor income (due to the link between unemployment and labor income from the effort function).

The clean sector substitution effect on the uses-side incidence $\widehat{p_Y} - \widehat{p_X}$ is $\frac{\theta_{YZ}}{D}\{C\sigma_X\}$ which is always positive. An increase in the pollution tax burdens consumers of the dirty good more than it burdens consumers of the clean good through this effect.

The clean sector substitution effect's magnitude on all three outcomes is scaled by the magnitude of σ_X. The easier it is for the clean sector to substitute between capital and labor (larger σ_X), the larger is the size of each of the effects described above.[43]

3.3.4 *Dirty Sector Substitution Effect*

The other substitution effect comes from substitutability among inputs in the dirty sector. It is represented by the terms that contain the dirty sector's substitution elasticity, σ_Y. The dirty sector substitution effect on the change in unemployment in equation 17 is $\frac{\theta_{YZ}}{\varepsilon_2 D}\sigma_Y[A(1-\eta) + \eta_K(\gamma_K - \gamma_L)]$. This effect contains two parts. The first, $A(1-\eta)$, is strictly positive, so this part of the effect increases the unemployment rate. The second part, $\eta_K(\gamma_K - \gamma_L)$, is of the same sign as $\gamma_K - \gamma_L$, and so it is positive whenever the dirty sector is capital-intensive, and it is negative whenever the dirty sector is labor-intensive. When the dirty sector is capital-intensive, then the pollution tax unambiguously increases the unemployment rate via the dirty sector substitution effect, but when the dirty sector is labor-intensive, then the dirty sector substitution effect contains offsetting terms on unemployment.

[43] A similar effect is found in Rapanos (2006). For example, the first term in equation 34 in Rapanos (2006) is the clean sector substitution effect on sources-side incidence, and it also is scaled by the substitution elasticity in consumption between the two goods (denoted by σ_D in his model).

The dirty sector substitution effect on sources-side incidence in equation 18 is $\frac{\theta_{YZ}}{D}\sigma_Y\left[(1-\eta)\left(\frac{A}{\varepsilon_{11}}+B\right)+(\gamma_L-\gamma_K)\left(\eta_E-\frac{\eta_K}{\varepsilon_{11}}\right)\right]$. The second half of this effect, $(\gamma_L-\gamma_K)\left(\eta_E-\frac{\eta_K}{\varepsilon_{11}}\right)$, is of the same sign as $\gamma_L-\gamma_K$, and so is positive when the dirty sector is labor-intensive. The first half of the effect is of ambiguous sign, depending on the sign of $\frac{A}{\varepsilon_{11}}+B$. Like the dirty sector substitution effect on unemployment, the dirty sector substitution effect on sources-side incidence can have ambiguous sign.

However, the dirty sector substitution effect on uses-side incidence in equation 19, $\frac{\theta_{YZ}}{D}\sigma_Y[\gamma_L\gamma_K+\gamma_L\theta_{XK}+\gamma_K\theta_{XE}]$, is unambiguously positive. This effect increases the burden of the pollution tax disproportionately for consumers of the dirty good.

Appendix C presents results from a more general model that does not impose the CES assumption about production in the dirty sector; as a result the dirty sector substitution effect is much more complicated. It depends on the relative substitutability among inputs (for example, whether labor or capital is a better substitute for pollution), which is missing under the CES assumption.

3.3.5 Other Outcomes

The focus of our model is the effect of the pollution tax on unemployment, sources-side incidence, and uses-side incidence, which are given in equations 17-19. Two other outcomes may also be of interest: the effect on worker effort and on pollution. In a standard tax incidence model, the sources-side burden on workers is fully captured by the change in the wage. Here, workers' burden is more complicated, since the tax affects the wage, unemployment, and worker effort, all of which contribute to worker welfare.[44] The effect on effort is:

$$\hat{e} = \frac{(\varepsilon_{11} + 1)\theta_{YZ}}{\varepsilon_{11} D} \{\sigma_Y [A(1-\eta) + \eta_K(\gamma_K - \gamma_L)] + \sigma_u \theta_{XK}(\gamma_L - \gamma_K) + C\sigma_X(1-\eta)\} \widehat{\tau_Z} \quad (20)$$

Equations 3 and 4 show that the equilibrium change in effort is just a multiple of the equilibrium change in unemployment: $\hat{e} = \varepsilon_2 \left(\frac{1+\varepsilon_{11}}{\varepsilon_{11}}\right) \widehat{U}$. Since $\varepsilon_2 \left(\frac{1+\varepsilon_{11}}{\varepsilon_{11}}\right) < 0$, if $\varepsilon_{11} > -1$ (always true under the effort function form $e\left(\frac{w}{P}, U\right) = \phi \left(\frac{w}{P}\right)^{\alpha} + \psi U^{\beta}$), the sign of the change in effort $\hat{e}$ is always opposite of the sign of the change of unemployment $\widehat{U}$. These two effects on worker welfare move in opposite directions; an increase in unemployment always coincides with a decrease in effort (among those with jobs). Equations 3 and 4 also show that the change in the wage is a multiple of the change in effort: $\hat{e} = (1 + \varepsilon_{11})\widehat{w}$. When $\varepsilon_{11} > -1$, the wage and the effort move in the same direction so have opposite effects on worker welfare; an increase in the wage coincides with an increase in effort.[45]

Since $\hat{e} = \varepsilon_2 \left(\frac{1+\varepsilon_{11}}{\varepsilon_{11}}\right) \widehat{U}$, the effect of the pollution tax on effort can be decomposed into the substitution effects and output effect that appear in equation 17 for unemployment. For example, the clean sector substitution effect is $\frac{(\varepsilon_{11}+1)\theta_{YZ}}{\varepsilon_{11} D}\{C\sigma_X(1-\eta)\}$, which is unambiguously negative. An increase in the pollution tax unambiguously decreases workers' effort through this effect. The output effect on the effort level $\hat{e}$ is $\frac{(\varepsilon_{11}+1)\theta_{YZ}}{\varepsilon_{11} D}\{\sigma_u \theta_{XK}(\gamma_L - \gamma_K)\}$, which is positive whenever $\gamma_K > \gamma_L$ and $\varepsilon_{11} > -1$. If the dirty sector is capital-intensive and workers' marginal

[44] Our model does not have an explicit utility function that can be used to measure worker welfare. Fullerton and Ta (2020) is an analytical general equilibrium that does have a utility function, and their section 10 considers welfare implications. Bartik (2015) and Kuminoff et al. (2015) discuss the welfare implications of unemployment caused by environmental regulations.

[45] This relationship holds for the change in the wage $\widehat{w}$, relative to the numeraire, but not necessarily for the relative change in the wage compared to the rental rate, $\widehat{w} - \hat{r}$, presented in equation 18.

effort with respect to the real wage does not decline too fast as the wage increases, workers' effort will increase when the pollution tax increases.

Another outcome of interest is the effect of the pollution tax on pollution itself, Z. Unfortunately, a closed-form solution for $\hat{Z}$ is too complicated to be able to interpret. In Appendix C, we present intermediate steps in the solution method, including an equation (equation A.2) in which the change in pollution $\hat{Z}$ can be expressed in terms of other endogenous variables. Instead of an analytical solution, the effect of the pollution tax on pollution will be considered below using numerical simulations.

3.4 Numerical Simulations

Here we numerically simulate the model by assigning parameter values calibrated from data and taken from the previous literature. Ours is a simple two-sector, two-input model, not a CGE model, so the purpose of these simulations is not to pin down plausible quantitative values for the magnitudes of these effects. Rather, the purpose is to explore how the net effects are decomposed into the effects identified in the previous section and how sensitive the magnitudes are to various parameter values. We begin by presenting base-case simulations decomposed into the effects from the analytical model. Then we vary parameter values, including the effort function elasticities.

3.4.1 Calibration

We use the 2017 Integrated Industry-Level Production Account (KLEMS) data provided by the U.S. Bureau of Economic Analysis for the calibration of the factor share and factor intensity parameters.[46]

First, we use the energy inputs (in millions of dollars) as a measurement of the pollution input Z in our dirty sector. There are very few places with prices on pollution, so we do not calibrate pollution based on market-based pollution policies; instead we interpret the pollution input as an energy input. The KLEMS data contains 64 major industries. We rank them based on their ratios of energy inputs to gross outputs, and we assign the top 16 energy-intensive industries as the dirty sector and the remaining industries as the clean sector. The dirty sector includes utilities (with energy inputs at 17.63% of output), rail transportation (10.08%), and truck transportation (9.39%). The 47 clean industries range from accommodation (energy inputs at 2.63% of output) to insurance carriers and related activities (0.06%). This assignment implies that the dirty sector makes up about 30 percent of gross outputs. We let the weight of the price of X on the price index P, η = 0.7, mirroring the fact that the clean sector is 70% of income.

Second, the shares of each sector's revenue paid to labor, capital, and energy are measured using the ratios of compensation to labor, capital, and energy to the outputs of each sector. The clean sector is more labor-intensive, with about 61% of its revenue paid to labor, so $\theta_{XK} = 0.39$ and $\theta_{XE} = 0.61$. The dirty sector is more capital-intensive and pays about 7% of its revenue to energy inputs, so we have $\theta_{YZ} = 0.07$, $\theta_{YK} = 0.56$ and $\theta_{YE} = 0.37$.

Third, we use the different factor intensities of the two sectors and their share of gross output to calculate each sector's share of capital and labor. Sector X's share of capital is $\lambda_{KX} =$

[46] U.S. Bureau of Economic Analysis, "Production Account Tables, 1998-2017," https://www.bea.gov/data/special-topics/integrated-industry-level-production-account-klems (accessed December 12, 2019).

0.62 and sector Y's is $\lambda_{KY} = 0.38$, showing that even though the dirty sector Y is capital-intensive, it still uses a smaller share of the economy's capital because it only accounts for 30% of the economy. We set the unemployment rate λ_{LU} to be 0.04 to roughly coincide with the average U.S. monthly unemployment rate (4.35%) in 2017. Thus, we get $\lambda_{LX} = 0.76$, $\lambda_{LY} = 0.20$. These imply that $\gamma_L = 0.26$ and $\gamma_K = 0.61$.

Fourth, we use unity for the elasticity of substitution between capital and labor in the clean sector ($\sigma_X = 1$) and the elasticity of substitution in consumption between the clean and dirty goods ($\sigma_u = 1$), following Fullerton and Heutel (2007). For the elasticity of substitution in production in the dirty sector σ_Y, we use 0.5 based on Fullerton and Heutel (2010).[47]

Table 3.1 Base Case Parameter Values

Parameter	Value	Parameter	Value
θ_{XK}	0.39	λ_{KX}	0.62
θ_{XE}	0.61	λ_{KY}	0.38
θ_{YK}	0.56	λ_{LX}	0.76
θ_{YE}	0.37	λ_{LY}	0.20
θ_{YZ}	0.07	λ_{LU}	0.04
γ_K	0.61	γ_L	0.26
η	0.7	σ_X	1
ε_{11}	–0.5	σ_u	1
ε_2	0.5	σ_Y	0.5

Note: These values are calibrated based on data and on the previous literature as described in the text.

[47] Fullerton and Heutel (2010) model production in the dirty sector using Allen elasticities instead of CES (see our Appendix C), and they use $e_{KE} = 0.5, e_{KZ} = 0.5$, and $e_{EZ} = 0.3$ for the three cross-price Allen elasticities. This indicates that capital is a slightly better substitute for pollution than is labor ($e_{KZ} > e_{EZ}$). With CES, though, these Allen elasticities must all be equal to each other, so we choose 0.5 for their value (σ_Y). In Table 3.4 below we will consider alternate values that do not assume CES. In Fullerton and Heutel (2010), there is no effective labor E, just labor L, so we assume that their e_{KL} is equal to our e_{KE}, etc.

Finally, we found no source for the parameter values related to the effort function, ε_{11} and ε_2. When we impose the functional form described earlier in the text, $e\left(\frac{w}{P}, U\right) = \phi\left(\frac{w}{P}\right)^{\alpha} + \psi U^{\beta}$, these parameters are $\varepsilon_{11} = \alpha - 1$ and $\varepsilon_2 = \frac{\beta(\alpha-1)}{\alpha}$. So, for the base case, we arbitrarily assume α to be 0.5 and β to be -0.5, implying that $\varepsilon_{11} = -0.5$ and $\varepsilon_2 = 0.5$. Table 1 summarizes the base-case parameter values.

The exogenous policy choice variable is the change in the pollution tax $\widehat{\tau_Z}$. We model the change in the price of energy under a carbon tax set at the social cost of carbon (SCC). The federal Interagency Working Group on Social Cost of Greenhouse Gases provides an updated estimate of the SCC based on new versions of three IAM models (DICE, PAGE, and FUND) in 2016. We adopt an estimate of \$40 per metric ton of CO_2 based on the report (Interagency Working Group on Social Cost of Greenhouse Gases, 2016). Then we calculate the weighted average energy price with and without a carbon tax at \$40 per metric ton CO_2. The calculation is based on the fuel price calculator provided by Hafstead and Picciano (2017), and we use the 2015 energy price and industrial sector energy usage data provided by the U.S. Energy Information Administration.[48] In 2015, the energy generated from coal, petroleum, and natural gas is 1.38, 8.25, and 9.43 quadrillion British thermal units (BTU), respectively. The average percentage increase of prices for coal (all types), petroleum products, and natural gas is 264%, 25%, and 50%, respectively. Weighted by the energy usage amount, we get that the \$40 carbon tax increases the energy price by 35% on average. Therefore, we present simulation results with $\widehat{\tau_Z} = 0.35$. This choice of $\widehat{\tau_Z}$ allows us to compare our model's results to other models that consider a carbon tax set at the SCC.[49]

[48] U.S. Energy Information Administration, "U.S. industrial sector energy use by source, 1950-2018," https://www.eia.gov/energyexplained/use-of-energy/industry.php (accessed December 12, 2019).
[49] Our model is linear, so the effects of a smaller pollution price change are scaled linearly.

3.4.2 Results

We first present results under the base-case parameterization. In Table 3.2, and all of the numerical simulation tables, we present the effects of a 35% increase in the pollution tax on unemployment ($\widehat{U}$), the sources-side incidence ($\hat{w} - \hat{r}$), and the uses-side incidence ($\widehat{p_Y} - \widehat{p_X}$), which are the three main results from our model. Table 3.2 also presents the effect of the pollution tax on effort ($\hat{e}$), and the subsequent tables also present the effect on effort and on pollution ($\hat{Z}$). The last row of Table 3.2 (row 5) presents the net effect of the tax, and rows 1 through 4 decompose this net effect into the four effects discussed earlier.

Table 3.2 Base Case Simulation Results

Row		$\boldsymbol{\widehat{U}}$	$\boldsymbol{\hat{w} - \hat{r}}$	$\boldsymbol{\widehat{p_Y} - \widehat{p_X}}$	$\boldsymbol{\hat{e}}$
1	Output Effect	–0.25%	0.44%	–	0.12%
2	Clean Sector Substitution Effect	0.76%	–0.38%	1.27%	–0.38%
3	Dirty Sector Substitution Effect	0.30%	–0.31%	0.29%	–0.15%
4	Efficiency Wage Effect	–	0.60%	0.78%	–
5	Net Effect	0.81%	0.35%	2.35%	–0.41%

Note: This table presents the simulated effects on unemployment, sources-side incidence, and uses-side incidence of a $40 per metric ton carbon tax (a 35% increase in the pollution tax) under the base case parameter values (listed in Table 3.1).

From the theoretical results, there is no efficiency wage effect in the expression for unemployment and workers' effort, and there is no output effect in the expression for uses-side incidence (so these entries in Table 3.2 are blank).

The net effect of the 35% increase in the pollution tax on unemployment is to increase unemployment by 0.81% (a percent change in the unemployment rate, not a percentage-point change). This is small, because the dirty (taxed) sector is just 30% of the overall economy, and pollution is just 7% of the value of its inputs, and the tax rate increase is just 35%. The increase in unemployment is mainly driven by the clean sector substitution effect (0.76% increase) versus the dirty sector substitution effect (0.30% increase). Even though the dirty sector is the taxed sector, substitution among inputs in the clean sector has a larger effect on unemployment. This is because the clean sector is the larger sector (70%), and in general equilibrium, its substitution possibility is more important for employment than is the dirty sector's substitution. The output effect is negative since the dirty (taxed) sector is capital-intensive.

For the sources-side incidence, the efficiency wage effect plays a significant role. Both dirty and clean sector substitution effects serve to increase the relative burden on labor ($\hat{w} - \hat{r} < 0$). From these two effects alone, the wage relative to the capital rental rate decreases by 0.7%. The output effect offsets these effects somewhat, again since the dirty sector is capital-intensive. But the efficiency wage effect reverses the sign and completely offsets the substitution effects and decreases the relative burden on labor. The sources-side incidence goes from favoring capital to favoring labor.

For the uses-side incidence (the relative burden on output prices), we see a positive sign from all three effects; each puts more of the burden on consumers of the dirty good than on consumers of the clean good. Ignoring the efficiency wage effect would miss about 30% of this net effect.

The net effect of a pollution tax on workers' effort level is that they work 0.41% less hard, which implies a small utility gain if effort is costly. Just like the effect on unemployment, this net effect is dominated by the clean sector substitution effect. Finally, Table 3.2 does not present the base-case effect of the pollution tax increase on pollution, because that change cannot be decomposed into the different effects. The net effect of the 35% pollution tax increase is to decrease pollution by 19%.

We compare our base-case results to those from CGE papers that simulate the effects of carbon taxes on unemployment. In Hafstead et al. (2018), unemployment is generated through search frictions, not efficiency wages. According to their Figures 2 and 3, a $40 per metric ton carbon price with lump-sum rebate results in a 30% emission reduction and a 0.3 percentage-point change in the unemployment rate. Given their 5% base steady-state unemployment rate, the new unemployment rate is 5.3%, so the percent change is 6%.[50] Castellanos and Heutel's (2019) CGE model generates unemployment through a wage curve. They find that a $35 per ton carbon tax increases unemployment by 4.4% and decreases emissions by 30%. Our $40 per metric ton carbon tax results in a roughly 19% pollution reduction and 0.81% increase in the unemployment rate, which is from our base 4% to 4.0324% (= 4 times 1.0081%). Thus, for roughly the same pollution tax increase, those CGE models find a decrease in pollution about twice as large as ours, and an increase in unemployment about five to six times as large as ours.

Several explanations could account for this difference in the magnitudes of the results. First, in those other models, unemployment is generated differently than in our model. In Hafstead et al. (2018), unemployment is generated via search frictions, and in Castellanos and Heutel (2019), unemployment is generated via a wage curve. In our model, it is generated via efficiency wages. Second, those models are multisector calibrated CGE models, while ours is a two-sector analytical model. Third, our model is linearized, so the 35% tax rate change that we model may create non-linearities. Fourth, our results could be sensitive to the choice of the

[50] Hafstead et al. (2018) also find that a roughly $15 per metric ton carbon price with lump-sum rebate induces a 15% emission reduction and a roughly 3% increase in the unemployment rate (percent not percentage-point). Hafstead and Williams (2018) also model unemployment through search frictions, though their model is a two-sector general equilibrium model rather than a CGE model. They find that a $20 per ton carbon tax increases unemployment by 3% (5% to 5.16%) and decreases emissions by 13.6%.

effort function parameters ε_{11} and ε_2, for which we were unable to find a calibration source. We investigate this in the sensitivity analysis below.

The base-case results depend on the base-case parameters, so we next conduct sensitivity analysis over parameter values. First, we vary the effort function elasticity parameters ε_{11} and ε_2. These results are presented in Table 3.3, which presents the outcomes when all of the parameters are at the base case, except for these two parameters. In Table 3.3 and the remaining tables, we also present the resulting change in pollution, $\hat{Z}$.

In Table 3.3, unemployment increases the least when the elasticity of marginal effort with respect to wage (ε_{11} in absolute value) is small and the elasticity of effort with respect to unemployment (ε_2) is large. The explanation is that if ε_{11} is large in absolute value, workers' marginal reduced effort increases quickly as the wage drops. This restrains the magnitude of the wage dropping relative to capital price because the reduced wage will cause extra loss of productivity due to a quickly decreased effort level. If ε_2 is large, workers are more sensitive to unemployment and work much harder, then their extra productivity will offset the rising cost of energy and there will be less increase in unemployment. In row seven, where the magnitude of ε_{11} is highest and ε_2 is smallest, we see the largest increase in unemployment of 5%. This is about the same magnitude change found for the same carbon tax increase in Hafstead et al. (2018).

The uses-side incidence always falls disproportionately on consumers of the dirty good and is not much affected by the effort function elasticities. Likewise, the fall in pollution is largely unaffected by these elasticities: a 35% increase in the tax rate yields a pollution reduction of about 19%. The effort level always decreases when varying effort function elasticities, and its change correlates more strongly with ε_{11}. The effort decreases the least when the elasticity of marginal effort with respect to wage (ε_{11} in absolute value) is large.

Table 3.3 Sensitivity Analysis – Varying Effort Function Elasticities

Row	$\boldsymbol{\varepsilon_{11}}$	$\boldsymbol{\varepsilon_2}$	$\widehat{\boldsymbol{U}}$	$\widehat{\boldsymbol{w}}-\widehat{\boldsymbol{r}}$	$\widehat{\boldsymbol{p_Y}}-\widehat{\boldsymbol{p_X}}$	$\widehat{\boldsymbol{Z}}$	$\widehat{\boldsymbol{e}}$
1	−0.1	0.1	1.08%	0.46%	2.21%	−19.22%	−0.97%
2	−0.1	0.5	0.22%	0.42%	2.22%	−19.22%	−1.00%
3	−0.1	0.9	0.12%	0.42%	2.22%	−19.22%	−1.00%
4	−0.5	0.1	3.67%	0.49%	2.33%	−18.99%	−0.37%
5	−0.5	0.5	0.81%	0.35%	2.35%	−18.96%	−0.41%
6	−0.5	0.9	0.46%	0.34%	2.35%	−18.95%	−0.41%
7	−0.9	0.1	5.00%	0.50%	2.39%	−18.87%	−0.06%
8	−0.9	0.5	1.16%	0.32%	2.43%	−18.80%	−0.06%
9	−0.9	0.9	0.66%	0.29%	2.43%	−18.79%	−0.07%

Note: This table presents the simulated effects on unemployment, sources-side incidence, uses-side incidence, and pollution of a $40 per metric ton carbon tax (a 35% increase in the pollution tax) for different values of the effort function elasticities. Their base-case values are used in row 5. All the other parameters are kept at their base case values (listed in Table 3.1).

Next, in Table 3.4, we investigate the effect of substitution elasticities in the dirty sector. Rather than simply varying the CES elasticity σ_Y, we employ the more complicated model of dirty sector production from Appendix C, where production is modeled using Allen elasticities of substitution. We vary the Allen cross-price elasticities in Table 3.4. We keep the elasticity between labor and capital, e_{KE}, equal to its base-case value of 0.5, and we vary the other two cross-price elasticities e_{KZ} and e_{EZ} to vary among 0, 0.5, and 1. All of the other parameters are kept at their base case values, except that the own-price elasticities e_{KK}, e_{EE}, and e_{ZZ} must also vary with the cross-price elasticities. To demonstrate, we also include in the third column of Table 3.4 the resulting value of the own-price elasticity e_{ZZ}.

Table 3.4 Sensitivity Analysis – Varying Dirty Sector Substitution Elasticities

Row	e_{KZ}	e_{EZ}	e_{ZZ}	$\widehat{U}$	$\widehat{w}-\widehat{r}$	$\widehat{p_Y}-\widehat{p_X}$	$\widehat{Z}$	$\widehat{e}$
1	0	0	0	0.66%	0.60%	2.32%	−1.85%	−0.33%
2	0	0.5	−2.64	0.49%	0.88%	2.28%	−8.43%	−0.25%
3	0	1	−5.29	0.32%	1.15%	2.24%	−14.99%	−0.16%
4	0.5	0	−4	0.99%	0.08%	2.39%	−12.31%	−0.49%
5	0.5	0.5	−6.64	0.81%	0.35%	2.35%	−18.96%	−0.41%
6	0.5	1	−9.29	0.64%	0.63%	2.31%	−25.57%	−0.32%
7	1	0	−8	1.31%	−0.44%	2.46%	−22.66%	−0.65%
8	1	0.5	−10.64	1.13%	−0.16%	2.42%	−29.37%	−0.57%
9	1	1	−13.29	0.96%	0.12%	2.38%	−36.04%	−0.48%

Note: This table presents the simulated effects on unemployment, sources-side incidence, uses-side incidence, and pollution of a $40 per metric ton carbon tax (a 35% increase in the pollution tax) for different values of the substitution elasticities e_{KZ} and e_{EZ}. Their base-case values are used in row 5. All the other parameters are kept at their base case values (listed in Table 3.1).

In Table 3.4, unemployment always increases with the 35% increase in the carbon tax, and it increases the most when capital is a better substitute for pollution relative to labor ($e_{KZ} > e_{EZ}$). The value of $\widehat{w}-\hat{r}$ varies across different parameter values, and it is small or even negative when $e_{KZ} > e_{EZ}$. The change in pollution $\hat{Z}$ is always negative, but its magnitude varies considerably. The pollution tax is much more effective in reducing pollution when inputs are strong substitutes. When e_{ZZ} is large in absolute value (as in the last row), then the change in pollution is large in absolute value. The percent change in pollution in these rows from the 35% pollution tax increase is similar to that found in Hafstead et al. (2018). The effort level decreases the most in row 7 when capital is a much better substitute for pollution than is labor. The effort decreases the least in row 3 when labor is a much better substitute for pollution than is capital.

Lastly, in Table 3.5, we hold the factor substitution elasticities and the effort function elasticities fixed at their base-case values and consider the impact of changes in factor intensities. We vary the value of $\gamma_K-\gamma_L$ from —0.35 to 0.55; this measures the capital intensity of the dirty sector ($\gamma_K-\gamma_L$ is positive if the dirty sector is more capital intensive than the clean sector). We maintain the assumption that the clean sector is 70% of income, and we set the ratio of total capital to labor in the economy to be 0.45/0.55 to be roughly consistent with the base case.

Table 3.5 Sensitivity Analysis – Varying Factor Intensities

Row	$\gamma_K - \gamma_L$	$\widehat{U}$	$\hat{w} - \hat{r}$	$\widehat{p_Y} - \widehat{p_X}$	$\widehat{Z}$	$\hat{e}$
1	−0.35	1.10%	−0.11%	2.59%	−19.11%	−0.55%
2	−0.25	1.06%	−0.04%	2.57%	−19.09%	−0.53%
3	0	0.95%	0.13%	2.50%	−19.04%	−0.48%
4	0.25	0.86%	0.29%	2.41%	−18.97%	−0.43%
5	0.35	0.82%	0.35%	2.36%	−18.95%	−0.41%
6	0.55	0.75%	0.46%	2.27%	−18.90%	−0.38%

Note: This table presents the simulated effects on unemployment, sources-side incidence, uses-side incidence, and pollution of a $40 per metric ton carbon tax (a 35% increase in the pollution tax) for different values of relative factor intensities. All the other parameters are kept at their base case values (listed in Table 3.1). Their base-case values (rounded to the nearest hundredth) are used in row 5.

As the dirty sector becomes more capital-intensive (as $\gamma_K - \gamma_L$ increases), the increase in unemployment declines, capital bears an increasing share of the burden ($\hat{w} - \hat{r}$ increases), and workers' effort level decreases less. Varying capital intensities yields only minor variation in the relative change in output prices and the change in pollution.

The calibration is based on US data, but one could also apply this model to other countries with different parameters. For example, China has a proportionately larger manufacturing sector than the US. China's manufacturing industry contributes about 40.5% of its GDP in 2017 and employs 28.1% of its workers.[51] In the US, the manufacturing sector takes up only 19.1% of the GDP, which is only half of China's, with the service sector being the largest contributor to GDP (80%). The employed US population in manufacturing sector is only 19.7%. Without carefully recalibrating our simulation using industry-specific data, we can roughly take

[51] National Bureau of Statistics of China, "China Statistical Yearbook 2019," http://www.stats.gov.cn/tjsj/ndsj/2019/indexch.htm

the manufacturing sector as the dirty sector to find that $\gamma_K - \gamma_L$ for China is around -0.2, which is more labor-intensive than the US. This means Row 2 of Table 3.5 will more closely reflect the impact on China's economy.

In summary, the purpose of these simulations is not to pin down point estimates of the pollution tax's effects (this is not a CGE model), but rather to explore how the net effects are decomposed into different channels and to explore how sensitive the effects are to parameter values. From the decomposition (Table 3.2), we learn that the efficiency wage effect has a substantial influence on the sources-side incidence of the tax. From the sensitivity analyses (Tables 3 through 5), we learn that the net effect on unemployment is highly sensitive to the elasticities of the effort function but relatively insensitive to substitution elasticities in production or factor shares. The sources-side incidence is highly sensitive to both substitution elasticities in production and factor shares, while the uses-side incidence is generally insensitive to any of these parameters. The effect of the pollution tax on pollution only depends on the substitution elasticities in production.

3.5 Conclusion

We use an analytical general equilibrium model with unemployment generated through efficiency wages to analyze the effect of a pollution tax on unemployment and on sources-side and uses-side incidence. Worker effort depends on unemployment and the real wage. Pollution is modeled as an input to production. We decompose the general equilibrium impact of the tax on unemployment and incidence into several effects, including an output effect, substitution effects, and an effect that we call the efficiency wage effect. The efficiency wage effect reduces the tax's burden on labor. The magnitude of this efficiency wage effect depends crucially on how workers' effort responds to both the real wage and unemployment. When workers are more responsive to the real wage, the efficiency wage effect is larger, and when workers are more responsive to unemployment, the efficiency wage effect is smaller.

We further illustrate our results through calibrated numerical simulations. At the base-case parameterization, the new efficiency wage effect offsets the substitution and output effects on the sources-side incidence. Ignoring the efficiency wage effect, the burden of a pollution tax increase falls mostly on labor, while including it, the burden falls mostly on capital. On unemployment, the output effect reduces unemployment since the dirty sector is capital-intensive, but it is dominated by substitution effects that increase unemployment. The magnitudes of the effects on unemployment and on sources-side incidence depend greatly on the structure of the effort function, though the magnitude of the uses-side incidence is largely independent of that. The uses-side incidence always falls disproportionately on consumers of the dirty good. The effect on pollution reduction only varies drastically when we change the substitutability between the three inputs of dirty sector. A pollution tax increase is most effective when both labor and capital are strong substitutes for pollution.

We employ a parsimonious model to interpret the intuition behind our results, so there are many ways in which the model could be extended by relaxing various assumptions. For example, further work could consider other effort functions, including one that depends on the wage to rental rate ratio (Agell and Lundborg 1992), or could include heterogeneity among workers (Fullerton and Monti 2013). We do not consider the benefit of pollution reduction and its incidence or effect on unemployment. We do not consider the effects of different choices of revenue recycling, for example using pollution tax revenue to reduce the pre-existing labor tax rate. Future work could consider including various labor market policies, such as the minimum wage or pre-existing labor taxes.

Nevertheless, our results provide theoretical insights into the impact of environmental policy on labor markets that could inform policymakers. A key takeaway is that the effect of policy on unemployment depends on *how* unemployment is generated in the economy. Our model is an efficiency wage model, rather than a search-and-matching model (Hafstead and Williams 2018, Aubert and Chiroleu-Assouline 2019) or another model of unemployment. But our model nests several different structural causes of efficiency wages. Under a fair wage model, worker effort may respond greatly to the real wage, while under a shirking and firing model, worker effort may respond greatly to unemployment. We show that how effort responds is a crucial determinant of how overall unemployment will be affected by a pollution tax, as well as its incidence.

APPENDICES

Appendix A. Appendix for Chapter 1

Appendix A.1 The Scaling of Google Trends Index

To be more specific, let us assume the keywords of interest are A, B, C, D, E, F, G, H, for the purpose of illustration. These eight keywords could correspond to a foreign disaster or any domestic trending searches. Because Google Trends provides comparable "interest over time" of only up to five keywords at once, I group the keywords into groups of four, together with a "numeraire keyword", "image", which I use for scaling. "Image" is a commonly searched word that has a relatively stable search volume comparable to other keywords of interest.

Group	Keywords	Week1	Week2	Week3	Week4
1	A	0	0	5	5
	B	8	15	5	2
	C	1	20	**100**	40
	D	22	8	5	35
	Image	*15*	*10*	*10*	*15*
2	E	35	**100**	88	65
	F	20	5	2	0
	G	0	1	2	1
	H	40	25	20	12
	Image	*12*	*8*	*8*	*12*

To make the data of keywords in two groups comparable, I can multiply all the indexes in Group 2 by 1.25, based on the ratio of the indexes of "image" that are in both groups. The interest over time of the 8 keywords are as follows:

Keywords	Week1	Week2	Week3	Week4
A	0	0	4	4
B	6	12	4	2
C	1	16	80	32
D	18	6	4	28
E	43.75	125	110	81.25
F	25	6.25	2.5	0
G	0	1.25	2.5	1.25
H	50	31.25	25	15
Image	15	10	10	15

The process above is an extremely simplified representation of the method. In practice, I used two different numeraire keywords - “dog vs cat” and “image”. These keywords are carefully chosen to be of relatively little volatility and to be comparable to keywords with search volume of drastically different scales. “Image” has very high search volume overall, so I use “image” as the numeraire keyword when requesting “interest over time” data of the daily top trending keywords and the keywords of hurricanes (such as “Hurricane Dorian”), which also have high search volume. Hurricane keywords are separated from other foreign disasters because they often end up hitting the U.S. territory as well as other countries in the Caribbean[52], and thus they receive much more public attention within the U.S. than other foreign disasters.

I did not use “image” when requesting “interest over time” data of disaster keywords other than hurricanes, because the search volume of “image” is so high that the index of those disaster keywords would be rounded to zero by Google. Instead, I used “dog vs cat”, the search volume of which is more comparable to those disaster keywords.

To bridge these two different scales together, I used the “interest over time” data of two *bridge keywords*: “gallons to liters” and “inches to cm”, that are also of little volatility. On

[52] The term “hurricane” is specific to the tropical cyclones originating from the Caribbean, or more broadly in the North Atlantic, central North Pacific, and eastern North Pacific. The same type of phenomenon in the Northwest Pacific is called a “*typhoon”* or a “tropical cyclone”.

average, the search volume of “gallons to liters” is about 9.3 times of “dog vs cat”, the search volume of “inches to cm” is about 8.8 times of “gallons to liters”, and the search volume of “image” is about 5.6 times of “inches to cm”. This means that the search volume of “image” is around 458.3 times of “dog vs cat”. If grouping keywords comparable to “dog vs cat” together with keywords comparable to “image” when requesting the raw “interest over time” data, all the index of the former would be rounded to zero by Google. Therefore, I used the aforementioned two “numeraire keywords” and two “bridge keywords” and the relative ratio between them to finally obtain the search index of both top daily top trending keywords and disaster keywords of all types (including hurricanes) in a consistently scaled manner.

Appendix A.2 Google Year in Search

As an alternative to the "top trending" keywords, I also explore using Google's "Year in Search"[53] keywords as the instruments. Every year, Google publishes the top 10 keywords in its Searches, News, and some other categories. Table A1 presents the "Year in Search" keywords under the category "Searches" and "News" from 2017 to 2020. There are 68 unique keywords in total. I then query Google Trends and obtain the weekly news pressure measured using the scaled indices of these keywords and repeat the regressions for the Google Trends analysis in the main body of this paper. These keywords represent relatively more significant events – the top ten of each year – compared to the average "daily top trending" keywords that essentially are just significant events within a few days. The results are presented in Table A2 and A3.

[53] https://about.google/stories/year-in-search/

Table A1. Google's "Year in Search" Keywords in Searches and News (2017-2022)

	2017		2018		2019		2020	
Rank	**Searches**	**News**	**Searches**	**News**	**Searches**	**News**	**Searches**	**News**
1	Hurricane Irma	Hurricane Irma	World Cup	World Cup	Disney Plus	Hurricane Dorian	Election results	Election results
2	Matt Lauer	Las Vegas shooting	Hurricane Florence	Hurricane Florence	Cameron Boyce	Notre Dame Cathedral	Coronavirus	Coronavirus
3	Tom Petty	Solar Eclipse	Mac Miller	Mega Millions	Nipsey Hussle	Women's World Cup	Kobe Bryant	Stimulus checks
4	Super Bowl	Hurricane Harvey	Kate Spade	Election Results	Hurricane Dorian	Area 51 raid	Coronavirus update	Unemployment
5	Las Vegas shooting	Bitcoin Price	Anthony Bourdain	Hurricane Michael	Antonio Brown	Copa America	Coronavirus symptoms	Iran
6	Mayweather vs McGregor fight	North Korea	Black Panther	Kavanaugh Confirmation	Luke Perry	El Paso shooting	Zoom	Hurricane Laura
7	Solar eclipse	Hurricane Jose	Mega Millions Results	Florida Shooting	Avengers: Endgame	Sri Lanka	Who is winning the election	Super Tuesday
8	Hurricane Harvey	Hurricane Maria	Stan Lee	Royal Wedding	Game of Thrones	Government shutdown	Naya Rivera	Stock market
9	Aaron Hernandez	April the Giraffe	Demi Lovato	Olympic Medal Count	iPhone 11	Equifax data breach settlement	Chadwick Boseman	Murder hornet
10	Fidget Spinner	DACA	Election Results	Government Shutdown	Jussie Smollett	California earthquake	PlayStation 5	Australia fires

Table A2. Effects of News Pressure on Disaster Index and Relief
(Google Trends with "Search in Year", with missing data imputed)

	(1)	(2)	(3)	(4)
	First Stage	**First Stage**	**Reduced Form**	**Reduced Form**
Variables	Disaster Trend	Disaster Trend	Relief	Relief
News Pressure	38.7	46.8	-0.00872	-0.00539
('000000)	(90.7)	(84.8)	(0.0258)	(0.0281)
Total Deaths Imputed	715		1.01***	
('000)	(879)		(0.243)	
Total Affected Imputed	19.5		0.0939***	
('000000)	(27.8)		(0.0296)	
Total Damages Imputed	120		0.00695	
('000000 USD)	(90.0)		(0.0133)	
Log Deaths Imputed		33.96		0.0424***
		(38.51)		(0.0148)
Log Affected Imputed		34.87**		0.0308***
		(17.46)		(0.00685)
Log Damages Imputed		52.31*		2.55e-05
		(30.89)		(0.00976)
Constant	-200.0	-1,075*	0.0280	-0.173
	(226.3)	(586.2)	(0.223)	(0.227)
Observations	367	367	367	367
R-squared	0.997	0.997	0.435	0.388

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

Table A3. 2SLS Regression Results
(Google Trends with "Search in Year", with missing data imputed)

Variables	(1) IV	(2) IV
Disaster Week Trend Index	-0.000225	-0.000115
	(0.000700)	(0.000522)
Total Deaths Imputed	1.17*	
('000)	(0.679)	
Total Affected Imputed	0.0983***	
('000000)	(0.0299)	
Total Damages Imputed	0.0341	
('000000 USD)	(0.0963)	
Log Deaths Imputed		0.0463*
		(0.0236)
Log Affected Imputed		0.0349*
		(0.0195)
Log Damages Imputed		0.00604
		(0.0316)
Constant	0.342	0.0395
	(0.315)	(0.724)
Observations	367	367
R-squared	0.305	0.351

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

Appendix B. Appendix for Chapter 2

Appendix B.1 Car Choice Task Information

Subjects are presented the following information about their budget, the assigned driving patterns and the fuel prices that are relevant to their decision.

Again, you have a budget of experiment currency **EC$ 50,000**.

You plan to drive this car for **8 years**.
For most of a year, you drive **15 miles every day (7 days a week, for 50 weeks)** for your daily commute and errands. About **60%** of these trips are in city stop-and-go traffic, and **40%** are on the highway.
For the remaining **2 weeks** of each year, you take **one road trip** as your vacation. A typical road trip is about **1000 miles' driving**, with **10%** of such trips in city stop-and-go traffic and **90%** on the highway.
Your home's garage is equipped to charge electric vehicles or plug-in hybrid vehicles. Your workplace is **not** equipped with charging ports.
Your road trips are very laid-back and traverse areas with sufficient facilities like gas stations and electric vehicle / plug-in hybrid vehicle charging stations, which allow you to charge your car up to **10 times** for each road trip if needed.

Suppose you know that gasoline prices for the future 8 years will be,
for **regular** gasoline, **EC$ 3.50 / gallon** and, for **premium** gasoline, **EC$ 4.10 / gallon**.
The current electricity price for you is Georgia Power's basic rate plan for residential service with prices fluctuating throughout the year. However, if you choose a plug-in hybrid car or an electric car, you could sign up for Georgia Power's Plug-in Electric Vehicle rate. This rate offers lower prices from 11 p.m. – 7 a.m. to encourage nighttime EV charging. You can safely assume the **average electricity price** in this plan will be **EC$ 0.07 /kWh**.

The formula for Mile per gallon equivalent can be calculated like this: **33.7 kWh of electricity = 1 gallon of gas.**

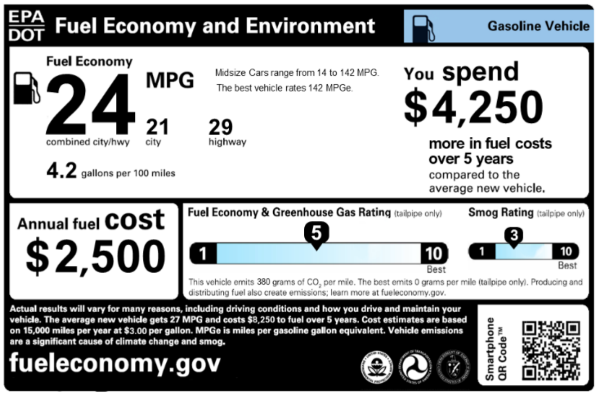
Then a list of 8 hypothetical cars with their MSRP, tax breaks, fuel types and fuel economy data are presented to them in a drop-down menu. Table B1 lists the details of the 8 cars.

Table B1. Car Options Used in the Experiment

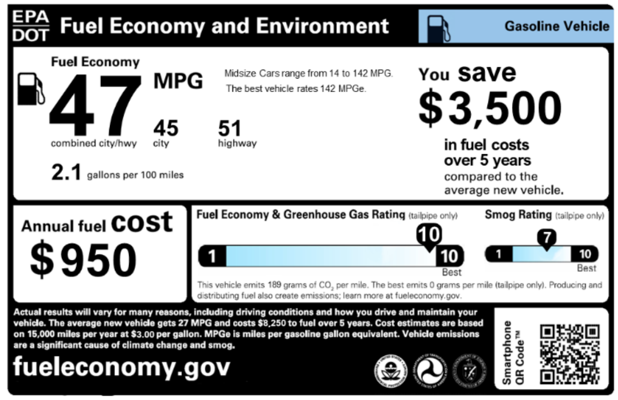
Car Name in Experiment	Real Car Make and Model	Vehicle Type	Combined MPG	City MPG	Highway MPG	Gallon per 100 mi	Combined MPGe	City MPGe	Highway MPGe	kWh per 100 mi	Electricity Range (mi)	Car Price	Tax Break
Roamer	Kia Stinger AWD	Gasoline Premium	24	21	29	4.2						34000	0
Twister	Hyundai Sonata	Gasoline	31	27	37	3.2						28100	0
Serpent	Hyundai Sonata hybrid	Hybrid	47	45	51	2.1						28759	0
Evolution	Honda Accord Hybrid	Hybrid	48	48	47	2.1						34879	0
Moonlight	Honda Clarity	PHEV	42			2.4	110			31	48	35355	7500
Aeon	Hyundai Ioniq Plug-in Hybrid	PHEV	52			1.9	119			28	29	38292	3500
Millennium	Tesla Model 3 standard range	EV					131	138	124	26	220	44099	0
Flux	Hyundai Ioniq Electirc	EV					133	145	121	25	170	43650	7500

Appendix B.2 Fuel Economy Label Examples

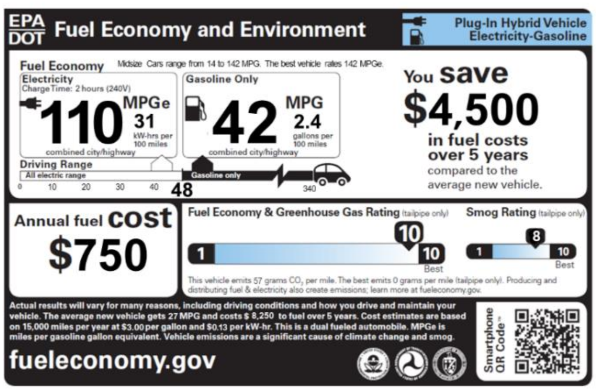
Figure A1. Examples of the Fuel Economy Labels



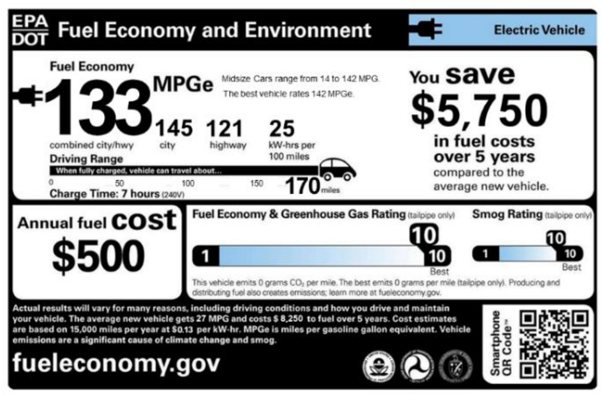
Roamer (gasoline car)



Serpent (hybrid gasoline car)

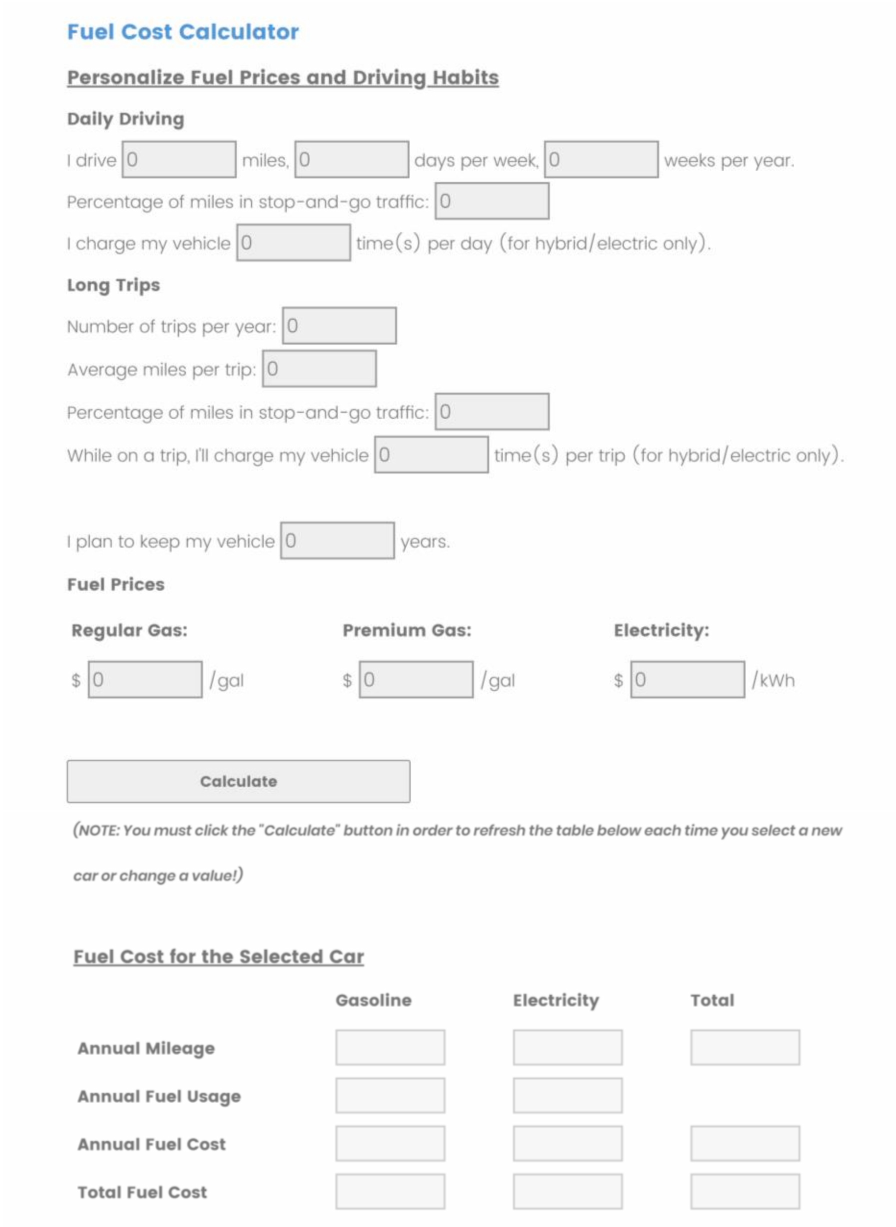


Moonlight (PHEV)



Flux (EV)

Appendix B.3 Fuel Cost Calculator Interface



Appendix B.4 Risk Preference Test Instruction

Below are the 6 gambling games: coin-flips with 6 combinations of payoffs. You can choose only one game to play. The subsequent result of the gamble you choose will be a bonus added to your final experiment payoff.

Gamble 1: flip the coin, and if it is heads, you will get EC$560, or if it is tails, you will get EC$560.

Gamble 2: flip the coin, and if it is heads, you will get EC$480, or if it is tails, you will get EC$720.

Gamble 3: flip the coin, and if it is heads, you will get EC$400, or if it is tails, you will get EC$880.

Gamble 4: flip the coin, and if it is heads, you will get EC$320, or if it is tails, you will get EC$1040.

Gamble 5: flip the coin, and if it is heads, you will get EC$240, or if it is tails, you will get EC$1200.

Gamble 6: flip the coin, and if it is heads, you will get EC$40, or if it is tails, you will get EC$1400.

The coin is standard, which means there are 50/50 chances between the two payoffs. Which gamble would you like to play?

Appendix B.5 Instructions and Consent

Instructions

Thank you for participating in this experiment!
Please read these instructions carefully.

1. Please finish the experiment independently without consulting others.

2. You are **not** allowed to share the questions from the experiment or your result with others after the experiment.

3. Please silence your phone.

4. You are allowed to use the basic Windows calculator displayed on the screen if you find it helpful. It is set to float above the experiment interface. Please do **not** close it or click the top left button on it, as that will cause you to lose access to it. If you accidentally close it, please raise your hand and notify the experimenter.

5. You are allowed to use pencil and paper to take notes during the experiment if you find them helpful.

6. You are **not** allowed to use any tools beyond these, such as your phone, websites, or software that might help you make your decision.

7. Your decisions in the experiment will determine the **Experiment Currency (EC$)** you have at the end of the experiment, which will be converted into US dollars using the exchange rate: **EC$ 1000 = US$ 1**.

8. At the end of the experiment, you will be paid in cash. Once you have finished the experiment, please **remain in your seat and raise your hand**. The experimenter will come to assist you and process the payment based on your result.

9. Please read through each page carefully. Once you click the ">>" button, You will **not** be allowed to go back to the previous page.

10. If you have any questions during the experiment, please raise your hand and the experimenter will come to assist you.

Appendix C. Appendix for Chapter 3

Appendix C.1 Solution Method

We begin by eliminating through successive substitution several of the endogenous variables from the system of equations. Output quantities $\hat{X}$ and $\hat{Y}$ can be eliminated with equations (13) and (14); effort and the effective wage $\hat{e}$ and $\hat{v}$ can be eliminated with equations (4) and (5); and the effective labor levels $\widehat{E_X}$ and $\widehat{E_Y}$ can be eliminated with equations (1) and (2). Then, capital and labor used in each sector ($\widehat{K_X}, \widehat{K_Y}, \widehat{L_X}, \widehat{L_Y}$) can be eliminated with equations (6), (7), (9), and (10), after substitution in for the variables that had already been eliminated. That leaves six remaining endogenous variables – $\hat{Z}$, $\widehat{U}$, $\widehat{w}$, $\hat{r}$, $\widehat{p_X}$, and $\widehat{p_y}$ – and the following six equations:

$$\widehat{U} = \frac{\varepsilon_{11}}{\varepsilon_2}\widehat{w} \qquad (A1)$$

$$\begin{aligned}(\gamma_L - \gamma_K)\big(\hat{Z} + \sigma_Y\widehat{\tau_Z}\big) - \big(1 + \gamma_L(1 - \sigma_Y\varepsilon_{11})\big)\widehat{w} + (\gamma_K\sigma_Y + \sigma_X)\hat{r} \\ = \left[\varepsilon_2(1 + \gamma_L - \sigma_X) - \frac{\lambda_{LU}}{\lambda_{LX}}\right]\widehat{U}\end{aligned} \qquad (A2)$$

$$\widehat{p_X} = \theta_{XK}\hat{r} - \theta_{XE}\varepsilon_{11}\widehat{w} \qquad (A3)$$

$$\widehat{p_Y} = \theta_{YK}\hat{r} - \theta_{YE}\varepsilon_{11}\widehat{w} + \theta_{YZ}\widehat{\tau_Z} \qquad (A4)$$

$$0 = \eta\widehat{p_X} + (1 - \eta)\widehat{p_Y} \qquad (A5)$$

$$\begin{aligned}&\sigma_u(\widehat{p_Y} - \widehat{p_X}) = \\ &-(\theta_{XK}\gamma_K + \theta_{XE}\gamma_L + 1)\hat{Z} + (\theta_{XK}\gamma_K + \theta_{YK})\sigma_Y\hat{r} + \theta_{XE}\left[(1 + \gamma_L)\varepsilon_2 - \frac{\lambda_{LU}}{\lambda_{LX}}\right]\widehat{U} \\ &+[\theta_{XE}(\gamma_L + 1) - (\theta_{XE}\gamma_L + \theta_{YE})\sigma_Y\varepsilon_{11}]\widehat{w} - (\theta_{XK}\gamma_K + \theta_{YK} + \theta_{XE}\gamma_L + \theta_{YE})\sigma_Y\widehat{\tau_Z}\end{aligned} \qquad (A6)$$

We then successively solve for the remaining variables.

Appendix C.2 Model without Capital

We consider a competitive two-sector economy using only one factor of production: labor, which is perfectly mobile between sectors. The second variable input, pollution, is only used in the production of the dirty good (sector Y). This simpler model allows us to more easily some of the effects found in the more complicated general solutions presented in the main text.

The constant-returns-to-scale production functions become:

$$X = X(E_X)$$

$$Y = Y(E_Y, Z)$$

The labor market equations are the same as equations (1) – (5) in the original model. There is now only one resource constraint, which is on labor and is the same as equation (7). Producers of Y choose between labor and pollution. The elasticity of substitution in production σ_Y is defined to capture this response to factor price changes:

$$\hat{Z} - \widehat{E_Y} = \sigma_Y(\hat{v} - \widehat{\tau_z}) \qquad (A7)$$

where σ_Y is defined to be positive.

Using the assumptions of perfect competition and constant returns to scale, we get

$$\widehat{p_X} + \hat{X} = \hat{v} + \widehat{E_X} \qquad (A8)$$

$$\widehat{p_Y} + \hat{Y} = \theta_{YE}\left(\hat{v} + \widehat{E_Y}\right) + \theta_{YZ}\left(\hat{Z} + \widehat{\tau_Z}\right) \qquad (A9)$$

Totally differentiate each sector's production function and substitute in the conditions from the perfect competition assumption to get

$$\hat{X} = \widehat{E_X} \qquad (A10)$$

$$\hat{Y} = \theta_{YE}\widehat{E_Y} + \theta_{YZ}\hat{Z} \qquad (A11)$$

The consumer side is the same as in our original model, represented by equations (15) and (16). We also normalize the overall price level so that $\hat{P} = 0$, and we drop that variable out of the system.

The full model is equations (1) – (5), (7), (15), (16) from the main text model, and (A7) through (A11). It contains one exogenous policy variable (τ_Z), 13 equations and 13 endogenous variables ($\widehat{E_X}, \widehat{E_Y}, \widehat{L_X}, \widehat{L_Y}, \hat{Z}, \hat{U}, \hat{e}, \hat{w}, \hat{v}, \widehat{p_X}, \widehat{p_Y}, \hat{X}, \ \hat{Y}$). The model is solved with successive substitution similar to the method described in Appendix A.I.

The results are as follows.

$$\hat{U} = \frac{(1-\eta)\theta_{YZ}\widehat{\tau_Z}}{\varepsilon_2((1-\eta)\theta_{YE}+\eta)} \qquad (A12)$$

$$\hat{w} = \frac{(1-\eta)\theta_{YZ}\widehat{\tau_Z}}{\varepsilon_{11}((1-\eta)\theta_{YE}+\eta)} \qquad (A13)$$

$$\widehat{p_Y} - \widehat{p_X} = \frac{\theta_{YZ}\widehat{\tau_Z}}{(1-\eta)\theta_{YE}+\eta} \qquad (A14)$$

$$\hat{e} = \frac{(\varepsilon_{11}+1)(1-\eta)\theta_{YZ}\widehat{\tau_Z}}{\varepsilon_{11}\big((1-\eta)\theta_{YE}+\eta\big)} \qquad (A15)$$

Note that there is no σ_X, σ_Y, or σ_u in the expressions, which means there is no clean sector substitution effect, dirty sector substitution effect, or output effect in an economy with no capital. Therefore, equations A12 through A15 fully capture the efficiency wage effect of the pollution tax on the change of unemployment, wage, relative output prices, and workers' effort. To interpret the results, we need to take a closer look at the term $\frac{(1-\eta)\theta_{YZ}}{(1-\eta)\theta_{YE}+\eta}$. The term η represents the weight of the clean good's price in the overall price level, or the share of the clean sector in the economy. Therefore, if the overall revenue of the economy is 1 unit, then the compensation to effective labor is $(1-\eta)\theta_{YE} + \eta\theta_{XE} = (1-\eta)\theta_{YE} + \eta$, since all the clean sector's revenue is paid to labor ($\theta_{XE} = 1$). The compensation to pollution or energy is $(1 - \eta)\theta_{YZ}$. Then equation A12 becomes

$$\widehat{U} = \frac{revenue\ paid\ to\ energy}{revenue\ paid\ to\ labor} \frac{\widehat{\tau_Z}}{\varepsilon_2} > 0$$

which is very straightforward. The effect of an increase in the pollution tax on unemployment is determined by the share of revenue paid to energy compared to labor in the economy, but its effect will be restrained by the elasticity of workers' effort with respect to unemployment (ε_2). An increase in the pollution tax will increase unemployment more for a more energy-intensive economy. If workers' effort is more sensitive to unemployment (ε_2 is large), then their extra productivity will offset the rising cost of energy and there will be less increase in unemployment. In the solution to the full model in the text (equation 17), the overall effect is also scaled by $\frac{1}{\varepsilon_2}$ for the same reason, though the terms inside the bracket are much more complicated.

Similarly,

$$\widehat{w} = \frac{revenue\ paid\ to\ energy}{revenue\ paid\ to\ labor} \frac{\widehat{\tau_Z}}{\varepsilon_{11}} < 0$$

The effect on the wage is determined by the share of revenue paid to energy compared to labor, restrained by the rate at which workers get satisfied with the wage (ε_{11}). The more energy-intensive the economy is, the carbon tax increase will lead to lower wages to compensate for the rising costs on energy. If ε_{11} is large in absolute value, workers' marginal effort declines quickly as the wage increases, or equivalently, as the wage decreases the marginal reduced effort increases quickly. This restrains the magnitude of the wage dropping, because the reduced wage will cause an increasing loss of productivity. This effect is also seen in the analogous solution to the full model (equation 18), which is scaled by $\frac{1}{\varepsilon_2}$.

Likewise,

$$\widehat{p_Y} - \widehat{p_X} = \frac{\theta_{YZ}\widehat{\tau_Z}}{(1-\eta)\theta_{YE} + \eta} = \frac{revenue\ paid\ to\ energy}{revenue\ paid\ to\ labor}\frac{\widehat{\tau_Z}}{1-\eta} > 0$$

The increase of the dirty good price relative to the clean good price is proportional to the ratio of revenue paid to energy compared to labor, whose effect will be restrained by the share of the dirty sector in the economy $(1-\eta)$.

Lastly,

$$\hat{e} = \frac{(\varepsilon_{11}+1)(1-\eta)\theta_{YZ}\widehat{\tau_Z}}{\varepsilon_{11}\big((1-\eta)\theta_{YE} + \eta\big)} = \left(\frac{\varepsilon_{11}+1}{\varepsilon_{11}}\right)\frac{revenue\ paid\ to\ energy}{revenue\ paid\ to\ labor}\widehat{\tau_Z}$$

Since $\varepsilon_{11} < 0$, $\hat{e}$ is negative as long as $\varepsilon_{11} > -1$, consistent with Cobb-Douglas effort. The effect of a pollution tax increase on workers' effort is determined by the share of revenue paid to energy compared to labor, factored by $(\frac{\varepsilon_{11}+1}{\varepsilon_{11}})$. If ε_{11} is large in absolute value, workers' marginal effort declines quickly as the wage increases, then workers' equilibrium effort will become only slightly lower. If ε_{11} is closer to zero, which means the effort is closer to a linear function of wage, then workers' equilibrium effort will become much smaller. In other words, since the policy reduces the wage ($\widehat{w} < 0$) workers will work less hard, but "how much less" depends on their effort elasticity to wage. Curiously, the effect on effort is independent of effort's responsiveness to unemployment, ε_2, even though unemployment is also changed by the pollution tax. In the main model in the paper, the elasticity ε_2 affects effort through its effect on the equilibrium change in the wage, but that effect is missing in this simpler model.

These results help us tease out the meaning of the efficiency wage effect: the weight of energy or pollution expenditures in the economy adjusted by the workers' response to the changing real wage and unemployment rate due to the tax. However, this model cannot be used to analyze sources-side incidence or to see how substitution between labor and capital affects unemployment, which is why the more complicated model with capital is the focus of this paper.

Appendix C.3 Model with Allen Elasticities in Dirty Sector

Instead of assuming a CES production function in the dirty sector, we can be more general by modeling production using Allen elasticities of substitution e_{ij}. This elasticity is positive for two substitutes and negative for two complements, and the own price Allen elasticity must always be negative. We assume that cross-price Allen elasticities are always positive, so that any two inputs are substitutes for each other. The magnitudes of the Allen elasticities determine which inputs are better substitutes. For example, if $e_{KZ} > e_{EZ}$, then capital is a better substitute for pollution than is labor.

Following Fullerton and Heutel (2007) (see their Appendix A for the derivation), we arrive at two equations describing the dirty sector's production decisions:

$$\widehat{K_Y} - \hat{Z} = \theta_{YK}(e_{KK} - e_{ZK})\hat{r} + \theta_{YE}(e_{KE} - e_{ZE})\hat{v} + \theta_{YZ}(e_{KZ} - e_{ZZ})\widehat{\tau_Z} \tag{9'}$$

$$\widehat{E_Y} - \hat{Z} = \theta_{YK}(e_{EK} - e_{ZK})\hat{r} + \theta_{YE}(e_{EE} - e_{ZE})\hat{v} + \theta_{YZ}(e_{EZ} - e_{ZZ})\widehat{\tau_Z} \tag{10'}$$

All the other equations remain the same as in the general model. This is a more general case of our original model that can greatly complicate the solutions. The equations (9') and (10') simplify to equations (9) and (10) from the main model when all of the cross-price elasticities e_{ij} are equal to each other and equal σ_Y.[54]

Solving the model, we get the closed form solutions:

$$\widehat{U} = \frac{\theta_{YZ}}{\varepsilon_2 D'} \left\{ \begin{matrix} A[-\theta_{YK}(1-\eta)(e_{KK} - e_{ZK}) + \eta_K(e_{KZ} - e_{ZZ})] \\ +B[\theta_{YK}(1-\eta)(e_{KE} - e_{ZK}) - \eta_K(e_{EZ} - e_{ZZ})] \\ +\sigma_u\theta_{XK}(\gamma_L - \gamma_K) + C\sigma_X(1-\eta) \end{matrix} \right\} \widehat{\tau_Z} \tag{17'}$$

[54] Karney (2016) shows that production can also be characterized by Morishima elasticities rather than Allen elasticities, and his equations 19 and 20 demonstrate how Morishima elasticities can also be transformed into CES production.

$$\hat{w} - \hat{r} =$$

$$\frac{\theta_{YZ}}{\varepsilon_{11} D'} \left\{ \begin{matrix} -A[\theta_{YK}(1-\eta)(e_{KK} - e_{ZK}) - (\eta_K - \varepsilon_{11}\eta_E)(e_{KZ} - e_{ZZ}) - \theta_{YE}(1-\eta)\varepsilon_{11}(e_{KE} - e_{ZE})] \\ -B[-\theta_{YK}(1-\eta)(e_{KE} - e_{ZK}) + (\eta_K - \varepsilon_{11}\eta_E)(e_{EZ} - e_{ZZ}) + \theta_{YE}(1-\eta)\varepsilon_{11}(e_{EE} - e_{ZE})] \\ -\sigma_u(\gamma_L - \gamma_K)(-\theta_{XK} + \varepsilon_{11}\theta_{XE}) + C\sigma_X(1-\eta)(1+\varepsilon_{11}) - (1-\eta)M \end{matrix} \right\} \widehat{\tau_Z} \quad (18')$$

$$\widehat{p_Y} - \widehat{p_X} = \frac{\theta_{YZ}}{D'} \left\{ \begin{matrix} -\theta_{XE}\theta_{YK}[A(e_{KK} - e_{ZK} + e_{ZZ} - e_{KZ}) + B(e_{ZK} - e_{KE} + e_{EZ} - e_{ZZ})] \\ -\theta_{XK}\theta_{YE}[A(e_{ZE} - e_{KE} + e_{KZ} - e_{ZZ}) + B(e_{EE} - e_{ZE} + e_{ZZ} - e_{EZ})] \\ +C\sigma_X - M\dfrac{\theta_{XK}}{\varepsilon_{11}} \end{matrix} \right\} \widehat{\tau_Z} \quad (19')$$

These solutions use the same constants defined in the main solution, except that here the denominator is $D' \equiv A[-\theta_{YK}(e_{KK} - e_{ZK})\eta_E + \theta_{YE}(e_{KE} - e_{ZE})\eta_K] + B[\theta_{YK}(e_{KE} - e_{ZK})\eta_E - \theta_{YE}(e_{EE} - e_{ZE})\eta_K] + \sigma_u(\gamma_L - \gamma_K)(\theta_{XK}\theta_{YE} - \theta_{XE}\theta_{YK}) - M\frac{\eta_K}{\varepsilon_{11}} + C\sigma_X(\eta_K + \eta_E)$.

The efficiency wage effect, the output effect, and the clean sector substitution effect are all identical in these equations to what they were in the original model's equations. The dirty sector substitution effect here is different; it is all of the terms that contain the Allen elasticities of substitution e_{ij}. This effect in each outcome is long and complicated and difficult to interpret, which is why in the main model we chose to employ the CES assumption. The relative magnitudes of the various Allen elasticities affects the sign and magnitude of this effect.

The dirty sector substitution effect can be simplified under an additional assumption. The simplifying assumption is that the two sectors have equal factor intensities; that is, $\gamma_K = \gamma_L \equiv \gamma$. Then we have $A = B = (1+\gamma)\gamma$ and $C = \gamma + 1$. This eliminates the output effect. It also greatly simplifies the complicated dirty sector substitution effect. The solutions under this assumption are:

$$\hat{U} = \frac{\theta_{YZ}}{\varepsilon_2 D}(1+\gamma)\{-\gamma[\theta_{YK}(1-\eta)(e_{KK} - e_{KE}) + \eta_K(e_{EZ} - e_{KZ})] + \sigma_X(1-\eta)\} \widehat{\tau_Z}$$

$$\hat{w} - \hat{r} = \frac{\theta_{YZ}}{\varepsilon_{11} D} \left\{ \begin{matrix} -\gamma(1+\gamma)\big[(1-\eta)\big(-2e_{KE}(1-\theta_{YZ})\big) - \theta_{YZ}(e_{KZ} + e_{EZ}) + (\eta_K - \varepsilon_{11}\eta_E)(e_{EZ} - e_{KZ})\big] \\ +(1+\gamma)\sigma_X(1-\eta)(1+\varepsilon_{11}) - (1-\eta)M \end{matrix} \right\} \widehat{\tau_Z}$$

$$\widehat{p_Y} - \widehat{p_X} = \frac{\theta_{YZ}}{D} \left\{ \begin{matrix} -\gamma(1+\gamma)[\theta_{XE}\theta_{YK}(e_{KK} - e_{KE} + e_{KZ} + e_{EE})] \\ +(1+\gamma)\sigma_X - M\dfrac{\theta_{XK}}{\varepsilon_{11}} \end{matrix} \right\} \widehat{\tau_Z}$$

The dirty sector substitution effect on unemployment $\widehat{U}$ is $-\frac{\theta_{YZ}}{\varepsilon_2 D}(1+\gamma)\gamma[\theta_{YK}(1-\eta)(e_{KK}-e_{KE})+\eta_K(e_{EZ}-e_{KZ})]$. We can sign the following parts: $-\frac{\theta_{YZ}}{\varepsilon_2 D}(1+\gamma)\gamma<0$ and $\theta_{YK}(1-\eta)(e_{KK}-e_{KE})<0$. Therefore, as long as $e_{EZ}-e_{KZ}<0$, this effect is positive. If capital is a better substitute for pollution than is labor ($e_{EZ}-e_{KZ}<0$), then an increase in the pollution tax increases unemployment through this effect. However, if labor is a better substitute for pollution than is capital ($e_{EZ}-e_{KZ}>0$), we cannot say with certainty whether it increases or decreases the unemployment through this effect.

The dirty sector substitution effect on $\widehat{w}-\hat{r}$ is $-\frac{\theta_{YZ}}{\varepsilon_{11} D}\gamma(1+\gamma)\big[(1-\eta)\big(-2e_{KE}(1-\theta_{YZ})\big)-\theta_{YZ}(e_{KZ}+e_{EZ})+(\eta_K-\varepsilon_{11}\eta_E)(e_{EZ}-e_{KZ})\big]$. If capital is a better substitute for pollution than is labor ($e_{EZ}-e_{KZ}<0$), then this effect is strictly negative, so the pollution tax imposes more burden on labor.

When it comes to the uses-side incidence, the dirty sector substitution effect is $-\frac{\theta_{YZ}}{D}\gamma(1+\gamma)[\theta_{XE}\theta_{YK}(e_{KK}-e_{KE}+e_{KZ}+e_{EE})]$. The sign of this term is determined by $e_{KK}-e_{KE}+e_{KZ}+e_{EE}$. Since e_{KK} and e_{EE} are negative, one simple case is that if capital and labor are better substitutes than are capital and pollution ($e_{KE}>e_{KZ}$), then the dirty sector substitution effect on $\widehat{p_Y}-\widehat{p_X}$ is positive, which means the price of the dirty good increases more than the clean good through this effect.

References

Abeler, Johannes, and Simon Jäger. "Complex tax incentives." *American Economic Journal: Economic Policy* 7, no. 3 (2015): 1-28.

Acemoglu, D., Hassan, T. A., & Tahoun, A. (2018). The power of the street: Evidence from Egypt's Arab Spring. *The Review of Financial Studies*, *31*(1), 1-42.

Agell, Jonas, and Per Lundborg. "Fair wages, involuntary unemployment and tax policies in the simple general equilibrium model." *Journal of Public Economics* 47, no. 3 (1992): 299-320.

Akerlof, George A. "Labor contracts as partial gift exchange." *The Quarterly Journal of Economics* 97.4 (1982): 543-569.

Allcott, H., & Gentzkow, M. (2017). Social media and fake news in the 2016 election. *Journal of economic perspectives*, *31*(2), 211-36.

Allcott, Hunt, and Dmitry Taubinsky. "Evaluating behaviorally motivated policy: Experimental evidence from the lightbulb market." *American Economic Review* 105, no. 8 (2015): 2501-38.

Allcott, Hunt, and Nathan Wozny. "Gasoline prices, fuel economy, and the energy paradox." *Review of Economics and Statistics* 96, no. 5 (2014): 779-795.

Allcott, Hunt, and Richard L. Sweeney. "The role of sales agents in information disclosure: evidence from a field experiment." *Management Science* 63, no. 1 (2016): 21-39.

Allcott, Hunt, Sendhil Mullainathan, and Dmitry Taubinsky. "Energy policy with externalities and internalities." *Journal of Public Economics* 112 (2014): 72-88.

Allcott, Hunt. "Social norms and energy conservation." *Journal of public Economics* 95, no. 9-10 (2011): 1082-1095.

Allcott, Hunt. "The welfare effects of misperceived product costs: Data and calibrations from the automobile market." *American Economic Journal: Economic Policy* 5, no. 3 (2013): 30-66.

Annen, K., & Strickland, S. (2017). Global Samaritans? Donor election cycles and the allocation of humanitarian aid. *European Economic Review*, *96*, 38-47.

Aubert, Diane, and Mireille Chiroleu-Assouline. "Environmental tax reform and income distribution with imperfect heterogeneous labour markets." *European Economic Review* 116 (2019): 60-82.

Ayres, Ian, Sophie Raseman, and Alice Shih. "Evidence from two large field experiments that peer comparison feedback can reduce residential energy usage." *The Journal of Law*, Economics, and Organization 29, no. 5 (2013): 992-1022.

Barone, G., D'Acunto, F., & Narciso, G. (2015). Telecracy: Testing for channels of persuasion. *American Economic Journal: Economic Policy*, *7*(2), 30-60.

Bartik, Timothy J. "The social value of job loss and its effect on the costs of US environmental regulations." *Review of Environmental Economics and Policy* 9, no. 2 (2015): 179-197.

Baylis, Kathy, Don Fullerton, and Daniel H. Karney. "Negative leakage." *Journal of the Association of Environmental and Resource Economists* 1, no. 1/2 (2014): 51-73.

Besley, T., & Burgess, R. (2002). The political economy of government responsiveness: Theory and evidence from India. *The quarterly journal of economics*, *117*(4), 1415-1451.

Besley, T., & Prat, A. (2006). Handcuffs for the grabbing hand? Media capture and government accountability. *American economic review*, *96*(3), 720-736.

Böhringer, Christoph, Klaus Conrad, and Andreas Löschel. "Carbon taxes and joint implementation. an applied general equilibrium analysis for Germany and India." *Environmental and Resource Economics* 24, no. 1 (2003): 49-76.

Bolsen, T., & Shapiro, M. A. (2018). The US news media, polarization on climate change, and pathways to effective communication. *Environmental Communication*, *12*(2), 149-163.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer. "Salience and consumer choice." *Journal of Political Economy* 121, no. 5 (2013): 803-843.

Boykoff, M. T., & Boykoff, J. M. (2004). Balance as bias: Global warming and the US prestige press. *Global environmental change*, *14*(2), 125-136.

Busse, Meghan R., Christopher R. Knittel, and Florian Zettelmeyer. "Are consumers myopic? Evidence from new and used car purchases." *American Economic Review* 103, no. 1 (2013): 220-56.

Cagé, J. (2020). Media competition, information provision and political participation: Evidence from French local newspapers and elections, 1944–2014. *Journal of Public Economics*, *185*, 104077.

Caplin, Andrew, and Mark Dean. "Revealed preference, rational inattention, and costly information acquisition." *American Economic Review* 105, no. 7 (2015): 2183-2203.

Cappelli, Peter, and Keith Chauvin. "An interplant test of the efficiency wage hypothesis." *The Quarterly Journal of Economics* 106.3 (1991): 769-787.

Castellanos, Kenneth A., and Garth Heutel. "Unemployment, labor mobility, and climate policy." Working paper No. w25797, National Bureau of Economic Research, 2019.

Cheremukhin, Anton, Anna Popova, and Antonella Tutino. "Experimental evidence on rational inattention." *Federal Reserve Bank of Dallas Working Paper* 1112 (2011).

Chiang, C. F., & Knight, B. (2011). Media bias and influence: Evidence from newspaper endorsements. *The Review of economic studies*, *78*(3), 795-820.

Choi, H., & Varian, H. (2012). Predicting the present with Google Trends. *Economic record*, *88*, 2-9.

Colmer, Jonathan, Ralf Martin, Mirbelle Muûls, and Ulrich Wagner. "Emissions trading, firm behavior, and the environment: evidence from French manufacturing firms." Paper presented at NBER Summer Institute 2018 environmental & energy economics, Cambridge, MA, USA, 2018.

Costa, Dora L., and Matthew E. Kahn. "Energy conservation “nudges” and environmentalist ideology: Evidence from a randomized residential electricity field experiment." *Journal of the European Economic Association* 11, no. 3 (2013): 680-702.

Cox, J. C., Kreisman, D., & Dynarski, S. (2020). Designed to fail: Effects of the default option and information complexity on student loan repayment. *Journal of Public Economics*, *192*, 104298.

Curtis, E. Mark. "Who loses under cap-and-trade programs? the labor market effects of the NOx budget trading program." *Review of Economics and Statistics* 100, no. 1 (2018): 151-166.

Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *The Journal of Finance*, *66*(5), 1461-1499.

Dave, Chetan, Catherine C. Eckel, Cathleen A. Johnson, and Christian Rojas. "Eliciting risk preferences: When is simple better?." *Journal of Risk and Uncertainty* 41, no. 3 (2010): 219-243.

Davis, Lucas W., and Gilbert E. Metcalf. "Does better information lead to better choices? Evidence from energy-efficiency labels." *Journal of the Association of Environmental and Resource Economists* 3, no. 3 (2016): 589-625.

Dean, Mark, and Nate Leigh Neligh. "Experimental tests of rational inattention." (2017).

DellaVigna, S., & Gentzkow, M. (2010). Persuasion: empirical evidence. *Annu. Rev. Econ.*, *2*(1), 643-669.

DellaVigna, S., & Kaplan, E. (2007). The Fox News effect: Media bias and voting. *The Quarterly Journal of Economics*, *122*(3), 1187-1234.

DellaVigna, S., & Pollet, J. M. (2009). Investor inattention and Friday earnings announcements. *The Journal of Finance*, *64*(2), 709-749.

Dissou, Yazid, and Muhammad Shahid Siddiqui. "Can carbon taxes be progressive?" *Energy Economics* 42 (2014): 88-100.

Dolan, Paul, and Robert Metcalfe. "Neighbors, knowledge, and nuggets: two natural field experiments on the role of incentives on energy conservation." *Becker Friedman Institute for Research in Economics Working Paper* 2589269 (2015).

Drago, F., Nannicini, T., & Sobbrio, F. (2014). Meet the press: How voters and politicians respond to newspaper entry and exit. *American Economic Journal: Applied Economics*, *6*(3), 159-88.

Dranove, David, and Ginger Zhe Jin. "Quality disclosure and certification: Theory and practice." *Journal of Economic Literature* 48, no. 4 (2010): 935-63.

Drury, A. C., Olson, R. S., & Van Belle, D. A. (2005). The politics of humanitarian aid: US foreign disaster assistance, 1964–1995. *The Journal of Politics*, *67*(2), 454-473.

Durante, R., Pinotti, P., & Tesei, A. (2019). The political legacy of entertainment tv. *American Economic Review*, *109*(7), 2497-2530.

Eckel, Catherine C., and Philip J. Grossman. "Sex differences and statistical stereotyping in attitudes toward financial risk." *Evolution and human behavior* 23, no. 4 (2002): 281-295.

Eisensee, T., & Strömberg, D. (2007). News droughts, news floods, and US disaster relief. *The Quarterly Journal of Economics*, *122*(2), 693-728.

Enikolopov, R., Makarin, A., & Petrova, M. (2020). Social media and protest participation: Evidence from Russia. *Econometrica*, *88*(4), 1479-1514.

Enikolopov, R., Petrova, M., & Sonin, K. (2018). Social media and corruption. *American Economic Journal: Applied Economics*, *10*(1), 150-74.

Enikolopov, R., Petrova, M., & Zhuravskaya, E. (2011). Media and political persuasion: Evidence from Russia. *American Economic Review*, *101*(7), 3253-85.

Falck, O., Gold, R., & Heblich, S. (2014). E-lections: Voting Behavior and the Internet. *American Economic Review*, *104*(7), 2238-65.

Fischer, Carolyn, Winston Harrington, and Ian WH Parry. "Should automobile fuel economy standards be tightened?." *The Energy Journal* (2007): 1-29.

Frederick, Shane. "Cognitive reflection and decision making." *Journal of Economic perspectives* 19, no. 4 (2005): 25-42.

Fullerton, Don, and Chi L. Ta. "Costs of energy efficiency mandates can reverse the sign of rebound." *Journal of Public Economics* 188 (2020): 104225.

Fullerton, Don, and Garth Heutel. "The general equilibrium incidence of environmental taxes." *Journal of Public Economics* 91, no. 3-4 (2007): 571-591.

Fullerton, Don, and Garth Heutel. "The general equilibrium incidence of environmental mandates." *American Economic Journal: Economic Policy* 2, no. 3 (2010): 64-89.

Fullerton, Don, and Holly Monti. "Can pollution tax rebates protect low-wage earners?" *Journal of Environmental Economics and Management* 66, no. 3 (2013): 539-553.

Gabaix, Xavier, and David Laibson. "Shrouded attributes, consumer myopia, and information suppression in competitive markets." *The Quarterly Journal of Economics* 121, no. 2 (2006): 505-540.

Gabaix, Xavier, David Laibson, Guillermo Moloche, and Stephen Weinberg. "Costly information acquisition: Experimental analysis of a boundedly rational model." *American Economic Review* 96, no. 4 (2006): 1043-1068.

Gabaix, Xavier. "A sparsity-based model of bounded rationality." *The Quarterly Journal of Economics* 129, no. 4 (2014): 1661-1710.

Gailmard, S., & Patty, J. W. (2012). Formal models of bureaucracy. *Annual Review of Political Science*, *15*, 353-377.

Garnache, Cloé, and Pierre Mérel. "Environmental Policy in General Equilibrium: When the Choice of Numeraire Matters." CESifo Working Paper No. 8354, 2020.

Gentzkow, M. (2006). Television and voter turnout. *The Quarterly Journal of Economics*, *121*(3), 931-972.

Gentzkow, M., & Shapiro, J. M. (2008). Competition and Truth in the Market for News. *Journal of Economic perspectives*, *22*(2), 133-154.

Gentzkow, M., Shapiro, J. M., & Sinkinson, M. (2011). The effect of newspaper entry and exit on electoral politics. *American Economic Review*, *101*(7), 2980-3018.

Gillingham, Kenneth, and Karen Palmer. "Bridging the energy efficiency gap: Policy insights from economic theory and empirical evidence." *Review of Environmental Economics and Policy* 8, no. 1 (2014): 18-38.

Gillingham, Kenneth, Richard G. Newell, and Karen Palmer. "Energy efficiency economics and policy." *Annu. Rev. Resour. Econ.* 1, no. 1 (2009): 597-620.

Ginsberg, J., Mohebbi, M. H., Patel, R. S., Brammer, L., Smolinski, M. S., & Brilliant, L. (2009). Detecting influenza epidemics using search engine query data. *Nature*, *457*(7232), 1012-1014.

Goecke, Henry, Wolfgang J. Luhan, and Michael WM Roos. "Rational inattentiveness in a forecasting experiment." *Journal of Economic Behavior & Organization* 94 (2013): 80-89.

Gonzalez, Fidel. "Distributional effects of carbon taxes: The case of Mexico." *Energy Economics* 34, no. 6 (2012): 2102-2115.

Greene, David L. How consumers value fuel economy: A literature review. No. EPA-420-R-10-008. 2010.

Grigolon, Laura, Mathias Reynaert, and Frank Verboven. "Consumer valuation of fuel costs and the effectiveness of tax policy: Evidence from the European car market." (2014).

Hafstead, Marc AC, and Roberton C. Williams. "Unemployment and environmental regulation in general equilibrium." *Journal of Public Economics* 160 (2018): 50-65.

Hafstead, Marc AC, Roberton C. Williams III, and Yunguang Chen. *Environmental Policy, Full-Employment Models, and Employment: A Critical Analysis*. No. w24505. National Bureau of Economic Research, 2018.

Hafstead, Marc, and Paul Picciano. "Calculating various fuel prices under a carbon tax." Common Resources (blog), Resources for the Future, November 28, 2017, https://www.resourcesmag.org/common-resources/calculating-various-fuel-prices-under-a-carbon-tax/.

Handel, Benjamin, and Joshua Schwartzstein. "Frictions or Mental Gaps: What's Behind the Information We (Don't) Use and When Do We Care?." *Journal of Economic Perspectives* 32, no. 1 (2018): 155-78.

Harberger, Arnold C. "The incidence of the corporation income tax." *Journal of Political Economy* 70, no. 3 (1962): 215-240.

Hausman, Jerry A. "Individual discount rates and the purchase and utilization of energy-using durables." *The Bell Journal of Economics* (1979): 33-54.

Heutel, Garth. "Optimal policy instruments for externality-producing durable goods under present bias." *Journal of Environmental Economics and Management* 72 (2015): 54-70.

Hirshleifer, D., Lim, S. S., & Teoh, S. H. (2009). Driven to distraction: Extraneous events and underreaction to earnings news. *The Journal of Finance*, *64*(5), 2289-2325.

Houde, Sébastien. How consumers respond to environmental certification and the value of energy information. No. w20019. National Bureau of Economic Research, 2014.

Howarth, Richard B., and Bo Andersson. "Market barriers to energy efficiency." *Energy Economics* 15, no. 4 (1993): 262-272.

Howarth, Richard B., Brent M. Haddad, and Bruce Paton. "The economics of energy efficiency: insights from voluntary participation programs." *Energy Policy* 28, no. 6-7 (2000): 477-486.

Interagency Working Group on Social Cost of Greenhouse Gases. "Current Technical Support Document (2016): Technical Update of the Social Cost of Carbon for Regulatory Impact Analysis Under Executive Order 12866." Environmental Protection Agency (2016). https://archive.epa.gov/epa/climatechange/social-cost-carbon-technical-documentation.html EPA's Web Archive, Dec 12, 2019.

Johnson, M., Brace, P., & Arceneaux, K. (2005). Public opinion and dynamic representation in the American states: The case of environmental attitudes. *Social science quarterly*, *86*(1), 87-108.

Joly, J. (2014). Do the media influence foreign aid because or in spite of the bureaucracy? A case study of Belgian aid determinants. *Political Communication*, *31*(4), 584-603.

Karney, Daniel H. "General equilibrium models with Morishima elasticities of substitution in production." *Economic Modelling* 53 (2016): 266-277.

Klemick, Heather, Ann Wolverton, and Jason Shogren. "Energy-efficiency gap." Encyclopedia of Energy, Natural Resource, and Environmental Economics 1 (2013): 74-81.

Kling, J. R., Mullainathan, S., Shafir, E., Vermeulen, L. C., & Wrobel, M. V. (2012). Comparison friction: Experimental evidence from Medicare drug plans. *The quarterly journal of economics*, *127*(1), 199-235.

Kuminoff, Nicolai V., Todd Schoellman, and Christopher Timmins. "Environmental regulations and the welfare effects of job layoffs in the United States: A spatial approach." *Review of Environmental Economics and Policy* 9, no. 2 (2015): 198-218.

Larrick, Richard P., and Jack B. Soll. "The MPG illusion." *SCIENCE-NEW YORK THEN WASHINGTON-* 320, no. 5883 (2008): 1593.

Lim, C. S., Snyder Jr, J. M., & Strömberg, D. (2015). The judge, the politician, and the press: newspaper coverage and criminal sentencing across electoral systems. *American Economic Journal: Applied Economics*, *7*(4), 103-35.

Maggetti, M., & Papadopoulos, Y. (2018). The principal–agent framework and independent regulatory agencies. *Political studies review*, *16*(3), 172-183.

Martin, Daniel. "Rational inattention in games: experimental evidence." *Available at SSRN 2674224* (2016).

Martin, G. J., & Yurukoglu, A. (2017). Bias in cable news: Persuasion and polarization. *American Economic Review*, *107*(9), 2565-99.

Martin, Ralf, Laure B. De Preux, and Ulrich J. Wagner. "The impact of a carbon tax on manufacturing: Evidence from microdata." *Journal of Public Economics* 117 (2014): 1-14.

Mieszkowski, Peter M. "On the theory of tax incidence." *Journal of Political Economy* 75, no. 3 (1967): 250-262.

Millner, A., & Ollivier, H. (2016). Beliefs, politics, and environmental policy. *Review of Environmental Economics and Policy*, *10*(2), 226-244.

Munger, K. (2020). All the news that's fit to click: The economics of clickbait media. *Political Communication*, *37*(3), 376-397.

Newell, Richard G., and Juha Siikamäki. "Nudging energy efficiency behavior: The role of information labels." *Journal of the Association of Environmental and Resource Economists* 1, no. 4 (2014): 555-598.

Pissarides, Christopher A. *Equilibrium unemployment theory*. MIT press, 2000.

Qin, B., Strömberg, D., & Wu, Y. (2017). Why does China allow freer social media? Protests versus surveillance and propaganda. *Journal of Economic Perspectives*, *31*(1), 117-40.

Raff, Daniel MG, and Lawrence H. Summers. "Did Henry Ford pay efficiency wages?" *Journal of Labor Economics* 5.4, Part 2 (1987): S57-S86.

Rapanos, Vassilis T. "Tax Incidence in a Model with Efficiency Wages and Unemployment." *International Economic Journal* 20, no. 4 (2006): 477-494.

Ripberger, J. T. (2011). Capturing curiosity: Using internet search trends to measure public attentiveness. *Policy studies journal*, *39*(2), 239-259.

Sallee, James M. "Rational inattention and energy efficiency." *The Journal of Law and Economics* 57, no. 3 (2014): 781-820.

Sallee, James M., Sarah E. West, and Wei Fan. "Do consumers recognize the value of fuel economy? Evidence from used car prices and gasoline price fluctuations." *Journal of Public Economics* 135 (2016): 61-73.

Schultz, Wesley P., Azar M. Khazian, and Adam C. Zaleski. "Using normative social influence to promote conservation among hotel guests." *Social influence* 3, no. 1 (2008): 4-23.

Shapiro, Carl, and Joseph E. Stiglitz. "Equilibrium unemployment as a worker discipline device." *The American Economic Review* 74.3 (1984): 433-444.

Snyder Jr, J. M., & Strömberg, D. (2010). Press coverage and political accountability. *Journal of political Economy*, *118*(2), 355-408.

Sood, Gaurav; Laohaprapanon, Suriyan, 2020, "Vanderbilt TV News Abstracts", https://doi.org/10.7910/DVN/BP2JXU, Harvard Dataverse, V3

Strömberg, D. (2004). Radio's impact on public spending. *The Quarterly Journal of Economics*, *119*(1), 189-221.

Strömberg, D. (2007). Natural disasters, economic development, and humanitarian aid. *Journal of Economic perspectives*, *21*(3), 199-222.

Tsvetanov, Tsvetan, and Kathleen Segerson. "Re-evaluating the role of energy efficiency standards: A behavioral economics approach." *Journal of Environmental Economics and Management* 66, no. 2 (2013): 347-363.

Turrentine, Thomas S., and Kenneth S. Kurani. "Car buyers and fuel economy?." *Energy policy* 35, no. 2 (2007): 1213-1223.

Van Belle, D. A. (2003). Bureaucratic responsiveness to the news media: Comparing the influence of the New York Times and network television news coverage on US foreign aid allocations. *Political Communication*, *20*(3), 263-285.

Weiss, Andrew. *Efficiency wages: Models of Unemployment, Layoffs, and Wage Dispersion*. Princeton University Press, 2014.

Yanagizawa-Drott, D. (2014). Propaganda and conflict: Evidence from the Rwandan genocide. *The Quarterly Journal of Economics*, *129*(4), 1947-1994.

Yellen, Janet. "Efficiency Wage Models of Unemployment." *American Economic Review* 74, no. 2 (1984): 200-205.

Vita

Xin Zhang was born in June 1992, in People's Republic of China. She graduated from Renmin University of China with a bachelor's degree in Economics in 2015. Xin began pursuing for a PhD in Economics at Georgia State University in August 2016. Her primary research fields are environmental economics, experimental economics, and behavioral economics.

During Xin Zhang’s graduate studies at Andrew Young School of Policy Studies, she worked as a Graduate Research Assistant and an instructor of Principles of Microeconomics and Principles of Macroeconomics. She was awarded AYSPS Excellence in Teaching award for her exceptional performance in the classroom. She also received GSU Provost’s Dissertation Fellowship and GSU Dissertation Grant.

Xin’s paper *Efficiency Wage, Unemployment and Environmental Policy*, coauthored with Dr. Garth Heutel, has been presented on various conferences such as ASSA and AERE, and published on *Energy Economics.*

Xin has accepted a postdoctoral lecturer position at New York University.