Title
Essays on Environmental Policy and Climate Change

Author
Sun, Fanglin

Publication Date
2019

UNIVERSITY OF CALIFORNIA SAN DIEGO

Essays on Environmental Policy and Climate Change

A dissertation submitted in partial satisfaction of the
requirements for the degree
Doctor of Philosophy

in

Economics with a Specialization in Interdisciplinary Environmental Research

by

Fanglin Sun

Committee in charge:

Professor Richard T. Carson, Chair
Professor Sarah N. Giddings
Professor Joshua Graff Zivin
Professor Mark Jacobsen
Professor Richard Norris

2019

The dissertation of Fanglin Sun is approved, and it is acceptable in quality and form for publication on microfilm and electronically:

Chair

University of California San Diego

2019

DEDICATION

To my parents.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGEMENTS

I would like to thank my advisor, Richard Carson. You have inspired me to become an environmental economist. I will be forever grateful for so much of your time and it has been a pleasure working with you. Every time I talk with you, I feel tons of positive power. I would also like to thank my committee members Sarah Giddings, Mark Jacobsen, Joshua Graff Zivin, and Richard Norris for helping to improve my research and supporting me in my interdisciplinary interests. I also thank Yixiao Sun and Junjie Zhang for encouraging me during the difficult times. I also greatly appreciate my co-authors Teevrat Garg, Matthew Gibson, Rudai Yang, and Dong Yuan. It was a pleasure working with you – I have learned so much from you. I also thank Dodge Cahan for your support during the whole PhD life.

Chapter 1, in full, is currently being prepared for submission for publication of the material. Fanglin Sun; Richard Carson "Coastal Wetlands Reduce Property Damage during Tropical Cyclones." The dissertation author was the primary investigator and author of this material.

Chapter 2, in full, is currently being prepared for submission for publication of the material. Fanglin Sun; Rudai Yang; Dong Yuan "Green Stimulus: Tax Incentives in China's Automobile Market." The dissertation author was the primary investigator and author of this material.

Chapter 3, in full, is currently being prepared for submission for publication of the material. Teevrat Garg; Matthew Gibson; Fanglin Sun "Extreme Temperatures and Time-Use in China." The dissertation author was one of three co-authors of this material.

VITA

2013	B. S. in Environmental Economics and Policy, University of California, Berkeley
2019	Ph. D. in Economics with a Specialization in Interdisciplinary Environmental Research, University of California, San Diego

ABSTRACT OF THE DISSERTATION

Essays on Environmental Policy and Climate Change

by

Fanglin Sun

Doctor of Philosophy in Economics with a Specialization in Interdisciplinary Environmental Research

University of California San Diego, 2019

Professor Richard T. Carson, Chair

These essays study environmental policy and regulation, ecosystem service valuation, and the economic impacts of climate change. Chapter 1 explores the role of coastal wetlands in reducing property damage during tropical cyclones impacting the U.S. and estimates the economic value of this protective service. Chapter 2 investigates the effectiveness of a large-scale green stimulus measure in China: a major sales tax cut for greener vehicles. Chapter 3 studies the role of extreme weather in time-use decisions in China.

Chapter 1

Coastal Wetlands Reduce Property Damage during Tropical Cyclones

Abstract: Coastal wetlands dampen the impact of storm surge and strong winds. Studies on the economic valuation of this protective service provided by wetland ecosystems are, however, rare. Here we analyze property damage caused by 88 tropical storms and hurricanes hitting the U.S. between 1996 and 2016 and show that counties with more wetland coverage experienced significantly less property damage. The expected economic value of the protective effects of wetlands varies widely across coastal U.S. counties with an average value of about \$1.8 million/km^2 per year and a median value of \$91,000/km^2. Wetlands confer relatively more protection against weaker storms and in states with weaker building codes. Recent wetland losses are estimated to have increased property damage from Hurricane Irma by \$430 million. Our results suggest the importance of considering both natural and human factors in coastal zone defense policy.

1.1 Introduction

Traditional defensive measures against storm surge include building sea walls, levees and dams. However, such structures can fail (Hughes & Nadal 2009) and there are concerns about negative impacts of such structures on the local environment (Kennish 2001). Planners are looking at coastal wetlands as potential natural levees for storms due to their ability to reduce water velocity and wave turbulence (Christiansen, Wiberg, and Milligan 2000). Moreover, wetlands accumulate sediments providing protection against rising sea levels and local subsidence (Morris *et al.* 2002; Gedan *et al.* 2011).

Policymakers are often skeptical about employing wetlands as storm buffers, and hesitant to preserve or restore wetland systems as part of a storm defense strategy. Previous work has focused on mechanisms by which wetland plants attenuate storm surge (Christiansen *et al.* 2000; Morris *et al.* 2002; Gedan *et al.* 2011; Möller *et al.* 2014; Wamsley *et al.* 2010). Surprisingly few studies address the economic value of this protective service. These studies, which we build on, tend to be limited to a particular type of wetland, such as mangrove forests (Badola and Hussain 2005; Danielsen *et al.* 2005; Das and Vincent 2009; Barbier 2007), a few specific disasters (Badola and Hussain 2005; Danielsen *et al.* 2005; Das and Vincent 2009), or specific regions [i.e., certain tropical countries (Badola and Hussain 2005; Danielsen *et al.* 2005; Das and Vincent 2009; Barbier 2007) and Louisiana (Boutwell and Westra 2016; Farber 1987; Barbier *et al.* 2013; Barbier and Enchelmeyer 2014)]. The exception is the influential U.S. national study (Costanza *et al.* 2008), which finds that 1 km^2 of wetlands produce on average \$3.3 million annually in storm protection services. However, this study is limited by the coarse data employed and imprecise measure of the storm impact region.

Here we estimate the economic value of coastal wetlands in storm protection by analyzing all 88 tropical cyclones (of which 34 made landfall as hurricanes) impacting the counties along the entire Atlantic and Gulf Coasts of the U.S. between 1996 and 2016 (Fig. 1.4 and Fig. 1.5).

Tropical storms are defined as tropical cyclones with maximum sustained winds of 34 to 63 knots, while hurricanes are those with at least 64 knots (National Hurricane Center). Among the 232 coastal counties experiencing at least tropical storm level winds, 203 experienced property damage at least once, and 38% of counties suffered damage when hit by tropical cyclone winds (Table 1.2 -1.3). Many tropical cyclones hitting the U.S. are below hurricane strength – the focus of most previous work. We show wetlands reduce property damage proportionately more at the lower end of the tropical cyclone classification scale, although the absolute magnitude of damage reduction is larger at the high end of the scale.

By using all the tropical storms and hurricanes affecting the U.S. since 1996, when consistently defined county estimates of property damage become available, we avoid sample selection bias issues, whereby damage data was generally available earlier only for more destructive storms. Areas subject to flood risk in a county are more accurately estimated, based on local elevation data and detailed information on individual storm trajectories that more precisely spatially delineate storm paths and wind speeds at different distances and directions from the eye (see Fig. 1.1 for the example of Hurricane Katrina). Wetland coverage varies over time and space within a county due to natural or anthropogenic factors (Kennish 2001). It also effectively varies because each storm's flooding area is a function of (i) storm path and (ii) wind intensity. State characteristics remaining largely unchanged over time and year-level economic shocks potentially influencing property damage are controlled by using a fixed-effects statistical framework.

Annual expected property damage caused by tropical cyclones depends on: first, the probability that a county experiences tropical cyclones of different wind velocities – the wind velocity, in turn, determines the area likely to be flooded by storm surge; second, the probability that, on experiencing a given wind speed, damage is nonzero. These relationships are described by:

$$E(D|X_{-v}) = \int P(D>0|v,X_{-v})E(D|v,X_{-v},D>0)f(v)dv, \tag{1.1}$$

where D represents a county's property damage when experiencing wind speed v during a tropical cyclone, $f(v)$ represents the annual probability of experiencing wind speed v, and X_{-v} represents other factors affecting property damage besides wind intensities. Applying the damage function approach developed by (Das and Vincent 2009), coastal wetlands may influence property damage during storms in two ways: first, through the likelihood of a county experiencing damage in a storm surge; second, if damage occurs, the amount.

1.2 Results

Coastal wetland coverage is associated with statistically significant reductions in cyclone-related property damage. A loss of 1 km^2 of wetland coverage increases the predicted probability of experiencing property damage during storms by 0.02% ($P < 0.05$) in a county with the average wetland coverage, wind speed, and flooding area (Table 1.4). For coastal communities suffering from property damage from a storm, a 1% loss of coastal wetlands is associated with a 0.6% increase in property damage ($P < 0.01$), controlling for storm specific characteristics, property value under flooding risk, state specific time invariant determinants of property damage, and year-level shocks (Table 1.1, Fig. 1.6). Coefficient estimates of wind, potential storm surge area, property value under flooding risk and being located to the right-hand of the storm path are positive and significant. The wind effect is particularly large (a 1% increase increases damage by 7%) and counties on the storm path's right-side experience 140% ($P < 0.01$) more property damage than those on the left. The estimated storm protection effects of wetlands are broadly robust to the statistical model used (see Materials and Methods), and do not change substantially when time trends are included instead of year fixed effects or whether the two largest disasters, Hurricanes Katrina and Sandy, are excluded (Table 1.5).

Coastal wetlands' protective effects are non-linear in wind intensity, conditional on damage. This may be because once wetland vegetation is fully saturated with water, wave dissipation effects are weaker (Resio and Westerink 2008; Möller *et al.* 1999). To detect this type of nonlinearity, wetland effects are decomposed by the wind speeds experienced by a county. Wetlands are effective against storms of all different magnitudes. The elasticity of property damage with respect to wetlands is -0.58 for a tropical storm (a 1% decrease in wetlands is associated with a 0.58% reduction in property damages), -0.55 for a Category 1 hurricane, -0.40 for a Category 2 hurricane, and -0.35 for a Category 3-5 hurricane (Fig. 1.2A, Table 1.6). This pattern is consistent with lab experiments (Möller *et al.* 2014). The preventative effect is especially strong for tropical storms, which happen twice as often as hurricanes. However, because property damage is rapidly increasing in storm strength, the absolute magnitude of damages prevented is predicted to be largest for major hurricanes.

Saltwater wetlands are located closer to the shore than freshwater wetlands (Fig. 1.7), providing the first line of defense against storm surges. Nevertheless, freshwater wetlands typically have more coverage than saltwater wetlands, providing a wider buffer zone, as freshwater wetlands constitute about 85% of total coastal wetland coverage. We find significant reductions in property damage for both freshwater and saltwater wetlands. The difference between their contributions is small and not significantly different from zero (Fig. 1.2B, Column 3 of Table 1.1). This is not surprising since storm surge can extend miles inland and encompass both types of wetlands.

Forested wetlands, having rougher woody vegetation, may provide a more effective buffer than emergent or scrub/shrub wetlands (Gedan *et al.* 2011, Barbier 2007, Barbier *et al.* 2013; Barbier and Enchelmeyer 2014). Costanza *et al.* (2008) did not find significant evidence that forested wetlands reduced economic losses, perhaps due to data limitations. We find forested and non-forested wetlands play similarly protective roles (estimated elasticities are: -0.58 and -0.56, respectively). We cannot reject the hypothesis that forested wetland reduces damage more than non-forested wetlands, as suggested by simulation studies (Barbier *et al.* 2013; Barbier and Enchelmeyer 2014), although our result is consistent with (Gedan *et al.* 2011), who survey field observation studies and find mangroves and marshes confer comparable wave attenuation.

Coastal states take different strategies in terms of disaster relief and preparedness. Some adopt more stringent building codes, e.g., requiring building on stilts or setting a minimum construction elevation, while others do not. To investigate whether state level policy factors induce heterogeneity in wetland protective effects, coastal states were separated into two groups based on being above or below the median assessment score for strictness of the residential building code and enforcement system (see Materials and Methods). Virginia, Florida, South Carolina and New Jersey rank as the top four states, while Texas, Mississippi, Alabama and Delaware have no mandatory statewide building code directed toward storm damage prevention. Wetland effects on property damage reduction are significantly lower in states with more stringent building codes and enforcement systems, suggesting that building codes are a partial substitute for wetlands in terms of storm protection (stricter code estimate: -0.50; less strict code estimate: -0.81), though wetlands still have a sizable effect even with stricter building codes (Fig. 1.2D, Table 1.6).

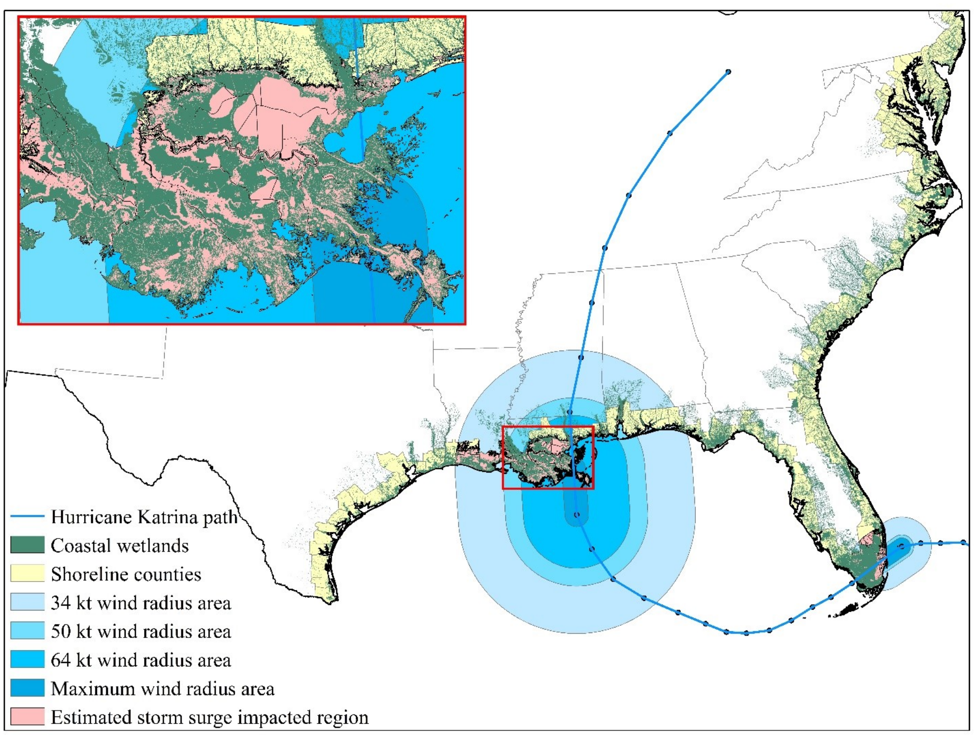

Figure 1.1: Coastal wetland distribution and estimated storm surge area near Hurricane Katrina landfall.

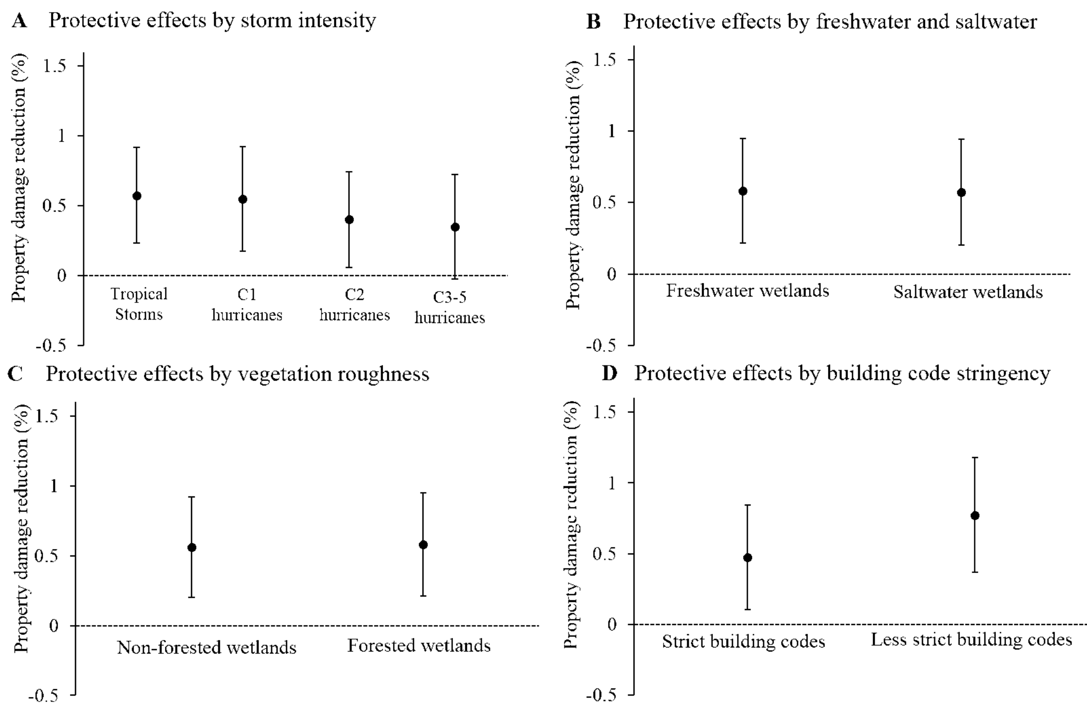

Figure 1.2: Elasticity of property damage with respect to coastal wetland coverage. Percent reduction (with 95% CI) in property damage per 1% increase in wetland coverage.

We estimate the marginal value of coastal wetlands for storm protection for each shoreline county along the Atlantic and Gulf Coasts. Assuming the local probability of experiencing different tropical cyclone intensities provided in (Klotzbach *et al.*) follows a gamma distribution, estimated annual marginal values range from less than \$800 to \$100 million per km^2, with an average of about \$1.8 million and a median value of \$91,000 (Fig. 1.3, Table 1.7,1.8 and 1.9). The heterogeneity in the storm protection value of wetlands (Fig. 1.8 and Fig. 1.9) across counties is due to the property values at risk, local wetland coverage, coastline shape, local elevation, building codes, and the probability of experiencing different wind intensities.

The marginal value of coastal wetlands for storm protection over a fixed time period, the relevant quantity for benefit-cost assessments involving development projects, can be estimated by discounting the future annual value of wetland over the desired time frame assuming the current annual marginal value remains constant. Using a discount rate of 2.8% (US Army Corps

Table 1.1: Conditional damage model estimates. Standard errors (in parentheses) are clustered two-ways at the county and storm level. N=946. All models include state and year fixed effects. $^{*}P < 0.10$, $^{**}P < 0.05$, $^{***}P < 0.01$.

	(1)	(2)	(3)	(4)	(5)
	log(damage)	log(damage)	log(damage)	log(damage)	log(damage)
log(wetland)	-0.5756***	-0.5752***	-0.5805***	-0.5598***	-0.8055***
	(0.1840)	(0.1718)	(0.1836)	(0.1805)	(0.2029)
C1 hurricanes × log(wetland)		0.0261			
		(0.0769)			
C2 hurricanes × log(wetland)		0.1724*			
		(0.1029)			
C3-C5 hurricanes × log(wetland)		0.2251*			
		(0.1208)			
Saltwater wetlands × log(wetland)			0.0073		
			(0.0409)		
Forested wetlands × log(wetland)				-0.0198	
				(0.0390)	
Strict building code × log(wetland)					0.3011*
					(0.1545)
log(wind)	7.1885***	6.4122***	7.1928***	7.1953***	7.1929***
	(0.5653)	(0.9744)	(0.5683)	(0.5668)	(0.5668)
Right	0.8821***	0.8749***	0.8828***	0.8880***	0.8825***
	(0.3129)	(0.3200)	(0.3147)	(0.3183)	(0.3128)
log(storm area)	0.4793**	0.4767**	0.4811**	0.4595**	0.4558*
	(0.2249)	(0.2180)	(0.2248)	(0.2235)	(0.2293)
log(property at risk)	0.3205***	0.3135***	0.3190***	0.3194***	0.3179***
	(0.0622)	(0.0599)	(0.0638)	(0.0624)	(0.0617)
adj. R^2	0.52	0.52	0.52	0.52	0.52

Engineers 2008), expected storm protection services provided by 1 km^2 of coastal wetlands over a 30-year (100-year) period are on average worth about \$36 million (\$60 million). The median value is \$2 million (\$3 million).

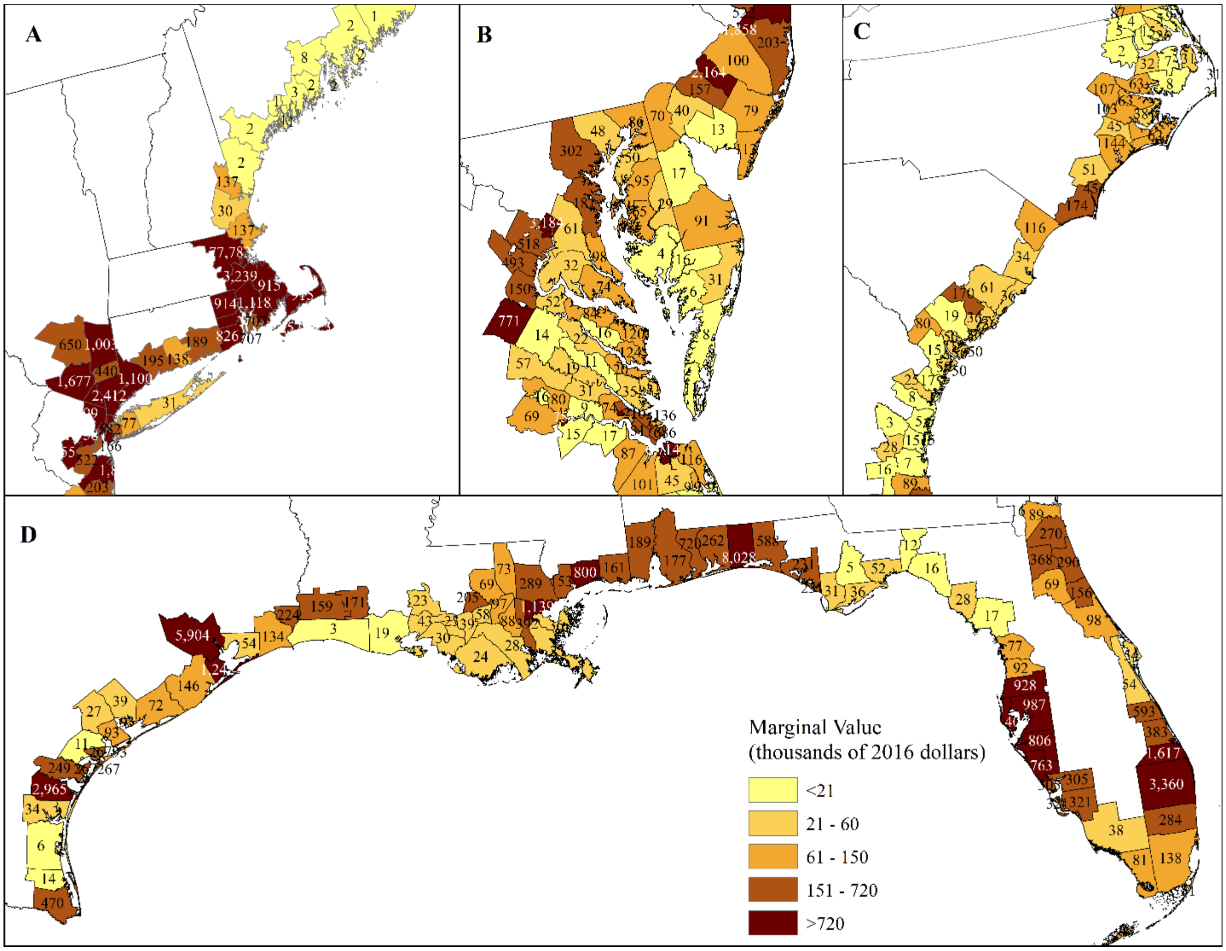

Figure 1.3: Annual county-level marginal value of coastal wetlands for storm protection.

1.3 Discussion

Estimates of the marginal economic value of wetland services in protecting property value can serve many purposes. Federal, state, and local agencies responsible for wetland management could employ our estimated expected marginal value when determining the amount and the optimal site of required compensatory mitigation. To achieve the goal of "no net loss" in both wetland acreage and function, Section 404 of the Clean Water Act requires development projects that could have adverse impacts on wetlands to offset wetland loss by restoring, creating, enhancing or preserving wetlands within the same watershed (Davlasheridze *et al.*). To determine the amount of compensatory mitigation for each project, the Army Corps of Engineers conducts a case-by-case evaluation and sets a compensatory mitigation ratio. The expected marginal value of wetlands in reducing storm damages estimated in this study should be useful to a federal agency making such assessments. One of our main findings is that location is a crucial factor storm protection services provided by wetlands. This should be accounted for when evaluating off-site compensatory mitigations since even relatively small differences in location between the wetlands lost and the new wetlands created can substantively influence the storm protection services provided. Further, a replacement wetland may take decades to fully develop the functions provided by the original wetlands. The approach developed here, for a given discount rate, can be used to obtain a consistent estimate of the economic value of the storm protection service lost during the time it takes for the new wetland to fully reach the capacity of the lost wetland.

Our model can be used to estimate property damage under different wetland loss scenarios. To illustrate this use, we consider the question of how much property damage from Hurricane Irma, in 2017, which occurred just outside of our sample period, might have been prevented if there had been no loss of wetlands in Florida between 1996 and 2016. In the 19 coastal counties that experienced tropical storm level wind speeds when Hurricane Irma made landfall, wetland coverage was reduced by 2.8% between 1996 and 2016. Absent this reduction in wetlands, we estimate property damage in these counties would have been lower by about $430 million (see Materials and Methods). This is substantial for a single storm. For a comparison, FEMA spent $10 billion on preventative hurricane, storm, and flood mitigation programs from 1989-2017 (Davlasheridze *et al.*). This suggests that wetland preservation is likely to be a comparatively effective way of protecting coastal communities against tropical cyclones. Restoring wetlands may also be a cost-effective policy, but that action needs to consider the time path noted earlier for such wetlands to provide storm protection services. The interaction between building codes, restrictions on building in high risk locations, and wetland coverage locations deserves further attention from a policy perspective.

Our model can also be used to predict the storm protection value of coastal wetlands in the context of different climate change scenarios. This can be done in a straightforward manner for the winds associated with tropical cyclone activity by simply replacing the actual wind distribution at each location with the forecast wind distribution based on a particular climate change scenario and reintegrating property damages estimates over the desired spatial locations and time frame. It is also possible to use our model to look at the interaction between changing sea levels and wetlands in coastal counties by holding the estimated parameters constant and substituting in a new detailed topographic map of areas at risk under different storm conditions. With projections of rising sea levels and increasingly intense storms associated with climate change (Knutson *et al.* 2010), low-lying coastal communities are likely to become more vulnerable to flooding. Model-based estimates can be calculated for the economic value of preventing future property damage under specific climate change and mitigation scenarios under different assumptions about wetland coverage.

It is important to recognize storm protection for property is just one of the ecological services that wetlands provide. Other ecosystem services delivered by wetlands include habitat for fish and wildlife, filtration of industrial, residential, and agricultural runoff, outdoor recreational opportunities, and carbon sequestration, all of which we do not value here. These services are at the heart of the current controversy over the U.S. Clean Water Act (US Army Corps Engineers 2008; Boyle *et al.* 2017). While we have provided comprehensive estimates for a major component of wetland services, having values for the entire suite of these services is needed for effective policy decisions (Guerry *et al.* 2015), particularly when unmonetized benefits of wetland services are likely to be ignored.

1.4 Materials and Methods

1.4.1 Data

Information on data sources can be found in the Appendix.

1.4.2 Construction of Potential Flooding Area for Each Storm

For each tropical cyclone, the maximum sustained wind speed experienced by each affected county was estimated based on distance from the storm center and the radii of different wind intensities. Potential flooding areas for each tropical cyclone wind category are estimated based on local elevation since inland penetration of storm surge is highly dependent on local topography. For each county, we map the area below each elevation from 0 to 8 meters in 0.5 meter increments. We then compare the area with the Storm Surge Inundation Map developed by NOAA Map (Zachry *et al.* 2015), which provides the flooding inland extent for different hurricane categories based on simulated storms, taking into account local topography, elevation, and other environmental features. We select the elevation for which these two maps coincide the closest. For tropical storms and Category 1 hurricanes, we select locations with elevation below 1 to 1.5 meters as the potential flooding areas. For Category 2 to Category 5 hurricanes, we choose elevations ranging from 2 to 8 meters to create the flooding areas. The estimated storm surge impact region for a specific storm is the intersection of the potential flooding areas and the areas exposed to at least tropical storm strength wind. The property value at risk of flooding is the value of total housing, estimated based on U.S. Census Bureau block group housing value data, within the flood risk area.

1.4.3 Regression Models

To estimate the marginal effects of coastal wetlands in storm protection along both the extensive and intensive margins, we employ a Cragg lognormal hurdle model (Cragg 1971; Wooldrige 2010) that consists of two parts: a probit model estimating whether coastal wetlands reduce the likelihood that a county experiences damage in a storm, and a conditional damage model estimating to what extent coastal wetlands reduce property damage when damage occurs. The two models can be expressed as follows:

$$\begin{aligned} P(damage_{csht} > 0|X) = \Phi(&\gamma_0 + \gamma_1 wetland_{csht} + \gamma_2 wind_{csht} + \gamma_3 stormarea_{csht} \\ &+ \gamma_4 riskproperty_{csht} + \gamma_5 right_{csht} + \eta_{csht}), \end{aligned} \tag{1.2}$$

$$\begin{aligned} ln(damage)_{csht} = \beta_0 &+ \beta_1 ln(wetland)_{csht} + \beta_2 ln(wind)_{csht} + \beta_3 ln(stormarea)_{csht} \\ &+ \beta_4 ln(riskproperty)_{csht} + \beta_5 right_{csht} + \gamma_s + \lambda_t + \varepsilon_{csht}, \end{aligned} \tag{1.3}$$

where $damage_{csht}$ is the property damage caused by tropical cyclone h in year t in county c of state s, $wetland_{csht}$ is the coastal wetland area in county c within the estimated storm surge impact region of storm h, $wind_{csht}$ is the maximum sustained wind speed experienced by the county, $stormarea_{csht}$ is the area of each county within the potential storm surge impact zone, and X is a vector of all the regressors in the probit model. $riskproperty_{csht}$ controls for the total property value under the risk of coastal flooding for each county. Counties with more property value within the potential flooding areas are likely to experience greater losses because the property to be potentially destroyed is of greater value. To control for the location of a county relative to the storm track, an indicator variable, $right_{csht}$, is included in the model. $right_{csht}$ equals 1 if a county is located to the right of the storm path, and 0 otherwise. Coastal flooding impacts are expected to be greater on the right side of the storm path since tropical cyclones rotate counterclockwise in the Northern Hemisphere with strong winds pushing water onshore to the right of the storm path, while blowing water away from the coast to the left (Morton 2002). γ_s is a state fixed effect, which captures state specific characteristics that are largely fixed across time. One example is the shape of the coastline of each state, which is relatively stable over time – a state with a coastline curved inward may experience higher surge levels (thus, more damage) when a tropical cyclone makes landfall, compared to states with a convex coastline (NOAA National Hurricane Center). γ_s also includes factors such as each state's historical exposure to storm surges and residents' culture and attitudes towards storms. λ_t is a year fixed effect, which mainly picks up year specific factors that affect all counties in the U.S. η_{csht} and ε_{csht} are error terms, which capture random component with limited long-term forecast in advance such as tides, very specific storm track, wind gusts, and rainfall. β_1 is the coefficient of interest, which captures the elasticity of storm damage to existing wetland coverage when a county suffers from positive property damage.

1.4.4 Alternative Specifications

Estimation results of Eq. (2), as well as a few alternative specifications are shown in Table S4. Adding linear and quadratic time trends as controls instead of time fixed effects does not substantively change the estimation of the protective effects of wetlands (Column 2). Figure 1.5 reflects one important feature of tropical cyclones – a highly skewed distribution of outcomes (Nordhaus 2010). To check whether the regression results in Table 1 are driven primarily by only a few extremely large disasters, observations corresponding to the highest and second highest damage storms are dropped (Columns 3-4). The coefficient estimates remain stable across the columns, suggesting that the main regression results are not largely driven by a few devastating storms. To capture the observed and unobserved features specific to a county, county fixed effects are included in the model instead of state fixed effects (Column 5). The identifying variation comes from within-county differences in wetland coverage across storms, induced by differences in the flooding area at risk. The elasticity of property damage with respect to wetlands changes to -1.69. That is, rather than controlling for time invariant factors that may affect damage at the state level, when we attempt to more precisely control for such factors at the county level, the wetland effect becomes larger. While this may suggest the elasticity in the main specification is underestimated, the sample is effectively different because many counties appear only for one storm and, more generally, the identification of the county-level fixed effects is tenuous (with state-level fixed effects, New Hampshire is the only state that effectively drops out of the model).

The appropriateness of the log-log damage model specification was checked by estimating a Box-Cox model (Box and Box 1964). We found that the null hypothesis of a log-log specification cannot be rejected ($P = 0.88$). To check for whether it was necessary to account for possible correlation, conditional on included covariates, between the first and second stages of the Cragg lognormal hurdle model, we estimated a Heckman model which allows for potential correlation between the two stages. We can not reject the null hypothesis using a Wald test that the error terms of the two stages are independent ($P = 0.55$). Hence, we use the Cragg lognormal hurdle model as our main model in the analysis.

1.4.5 Potential Endogeneity

The potential for endogeneity naturally arises in any consideration of property damage, due to moral hazard and other concerns. This is largely due to locational and insurance decisions. However, the housing units at risk have already been built at their particular location when a storm strikes; each tropical cyclone's path is exogenous, providing the randomly assigned wind treatment. In addition, our damage measure includes total losses, not just insured losses, and there are reasons to expect the two measures to be quite different – for example, the probability of households in areas at high risk of coastal flooding having flood insurance was found to be only about 63% (Dixon *et al.* 2006). Further, the government strongly favors an ex post response to property damage, even though ex ante actions are considerably more effective, a contradiction largely driven by political considerations (Davlasheridze *et al.* 2017).

Another possible source of possible endogeneity is that units in areas at high risk of being hit by tropical cyclones may be better built or located in areas that are better protected by wetlands and other natural defenses against storm surge and flooding, although ex ante the opposite scenario is also plausible. To a large extent, this should be captured by the property value at risk. Also state fixed effects capture time invariant state level factors influencing damages. The model results shown in Table S4, Column 5, go even further by including county level fixed effects (but see substantive discussion and qualification above), suggesting that, if anything, our main estimates for the marginal value of wetlands may be underestimated.

1.4.6 Marginal Value of Wetlands in Storm Protection

Let D_{csht}, W_{csht}, V_{csht}, S_{csht}, P_{csht}, and R_{csht} refer to $damage_{csht}$, $wetland_{csht}$, $wind_{csht}$, $stormarea_{csht}$, $riskproperty_{csht}$, and $right_{csht}$, and let α stand for $\beta_0 + \gamma_s + \lambda_t$. Based on the conditional damage model, the expected damage to a county when the wind speed is v, conditional on experiencing property damage, will be (omitting subscripts)

$$E(D|v, X_{-v}, D > 0) = W^{\beta_1} v^{\beta_2} S^{\beta_3} P^{\beta_4} e^{\alpha} E(e^{\varepsilon}). \tag{1.4}$$

The underlying statistical framework here is a survival model where the expected value depends on both the estimated regression parameters and the estimated variance. There are two standard approaches to obtaining the estimate of $E(e^{\varepsilon})$. First, we can assume the residuals are normally distributed, effectively treating the regression model as the maximum likelihood estimator, which can be sensitive to outliers. Second, we can estimate this quantity by bootstrapping the empirical residual distribution of the observed data. This latter approach is more flexible and, in this instance, more conservative. It produces an estimated value of 10.81 for $E(e^{\varepsilon})$, and estimates of marginal wetland values that are 17% lower than those obtained under the assumption that the error terms are normally distributed. We report the more conservative estimates. The annual expected property damage due to tropical cyclones to a shoreline county can be calculated by integrating the expected property damage over all the possible storm wind speeds that could affect the county:

$$E(D|X_{-v}) = \int E(D|v, X_{-v}, D > 0)P(D > 0|v, X_{-v}) f(v)dv \tag{1.5}$$

The marginal value of wetlands in storm protection will be $\frac{\partial E(D|X_{-v})}{\partial W}$, which can be expressed as:

$$\int [\frac{\partial E(D|v, X_{-v}, D > 0)}{\partial W} P(D > 0|v, X_{-v}) + \frac{\partial P(D > 0|v, X_{-v})}{\partial W} E(D|v, X_{-v}, D > 0)] f(v)dv \tag{1.6}$$

This can be estimated using the expression:

$$\int \hat{D}\Big(\frac{\widehat{\beta_1}}{W} P(D > \widehat{0|}v, X_{-v}) + \frac{\partial P(D > \widehat{0|}v, X_{-v})}{\partial W}\Big) f(v)dv, \tag{1.7}$$

where $\hat{D}$ is the predicted property damage when county c experiences a storm with wind speed v based on the estimation results of the model in Eq. (2). In a few instances, the predicted value exceeds total property value under risk. To control the over-prediction problem, $\hat{D}$ is capped by the total property value under flooding risk for each wind category. $P(D > \widehat{0|}v, X_{-v})$ and $\frac{\partial P(D > \widehat{0|}v, X_{-v})}{\partial W}$ are the predicted likelihood of a county experiencing damage when hit by wind velocity v and the estimated marginal effect of wetlands in reducing the probability of suffering property damage based on the estimation results of the model in Eq. (1).

The annual distribution of wind speeds projected for each county from (Klotzbach) is assumed to follow a gamma distribution, and we impose 152 kt as the upper bound wind force (strongest wind speed recorded post World War II in the U.S., which was during Hurricane Camille in 1969). The Landfalling Hurricane Probability Project estimated the probability of one or more events bringing three wind intensities, i.e., $P(v \geq 34kt)$, $P(v \geq 65kt)$, and $P(v \geq 100kt)$, for eleven coastal regions covering all counties in our analysis. These eleven coastal regions group counties based on the frequency of major hurricane landfalls from 1900 to 1999. For each region, using these points on the cumulative distribution function of wind speeds, the parameters of the best fit gamma probability distribution function of wind speeds are backed out using the minimum distance estimation method (Drossos and Philippou 1980). The R-squared reported is the average over regressions from 11 different wind regions (Klotzbach). As a robustness check, Weibull and log-normal distributions are fit for each county as well. These have slightly lower R^2 compared with that of the gamma distribution and generate similar estimates for the marginal value of wetlands (Table 1.10).

The annual expected property damage due to tropical cyclones to a shoreline county can be calculated by integrating the expected property damage over all the possible storm wind speeds that could affect the county. It would be straightforward to use alternative projections for future wind intensities in the modeling framework put forward here.

The marginal value of coastal wetlands across time is estimated by discounting the future annual value of wetland to the current period. Assuming that the annual marginal value of wetlands for storm protection stays the same in the future, then the formula can be expressed as:

$$\sum_{t=0}^{T} \frac{1}{(1+r)^t} \frac{\partial E(D|X_{-v})}{\partial W}, \tag{1.8}$$

where r is the discount rate and t refers to year.

1.4.7 Wetland Loss in Florida and Hurricane Irma

The expected change in property damage can be forecasted under different wetland loss scenarios for a given storm. Hurricane Irma made landfall in Florida on September 10, 2017, as a Category 4 Hurricane (NOAA National Hurricane Center 2017) and influenced 19 coastal counties at its landfall locations (Fig. 1.10). Since the storm path and wind speed radius data from (Knapp *et al.* 2010, Demuth *et al.* 2006) have not been updated, we estimated wind intensity experienced by each affected county using Hurricane Irma Advisory Archive data from the National Hurricane Center (NOAA National Hurricane Center 2017). We used our usual methodology for the remaining explanatory variables. Total property damage caused by Hurricane Irma is also not yet known, therefore we predict it using the model for two different scenarios: first, using 2010 coastal wetland coverage; second, using coverage in 1996, that is, assuming no loss. From 1996 to 2010, the total wetland coverage within the potential flooding area was reduced by about 500 km^2 (from 17900 km^2 to 17400 km^2), a loss about 2.8% of wetland coverage in 1996. The forecasted property damage is $19.07 billion based on the wetland coverage in 1996 and $19.50 billion based on the wetland coverage in 2010. Thus, our model predicts that property damage caused by Irma would have been reduced by $430 million, if the 500 km^2 of wetlands lost between 1996 and 2010 had been maintained.

1.5 Appendix

1.5.1 Additional Data Descriptions

Coastal wetlands. Included in this study are saltwater and freshwater wetlands located within the coastal watershed boundary of U.S. states (U.S. Environmental Protection Agency). The wetland coverage data is extracted from digital land cover maps provided by the NOAA Coastal Change Analysis Program (C-CAP Land Cover Atlas). These land cover maps are created based on 30-meter Landsat imagery and are updated every five years since 1996. Wetlands are classified to palustrine and estuarine wetlands based on the salinity level where they located, and each group is further categorized based on their vegetation types – forested, scrub/shrub, and emergent wetlands. This analysis includes counties with more than a de minimis [over .2 km^2 (50 acres)] coastal wetland coverage within the flooding area during a Category 5 hurricane.

Tropical cyclones. Storm trajectories, intensities and radii of various wind speeds are collected from the International Best Track Archive for Climate Stewardship Dataset (Knapp *et al.* 2010) and the Extended Best Track Dataset (Demuth *et al.* 2006).

Storm damage. Storm property damage for each coastal county is from the Storm Event Database, from NOAA (Storm Events Database). Note that the cost of economic disruption included in (Costanza *et al.* 2008) is not covered here. These costs tend to be inaccurately estimated and, given the need to evacuate people in the face of high winds and large scale loss of utility services, may not be heavily influenced by wetland coverage. There are also injuries and deaths associated with tropical cyclones but again these are less clearly tied to wetland coverage than evacuation success. To the extent economic disruption cost and direct harm to people are influenced by wetland coverage, our estimates will represent a lower bound.

Property value. Property value is estimated based on Census block group level housing data from the 2000 and 2010 U.S. Censuses and the American Community Survey 5-Year Estimates from 2005 to 2015. The 2000 U.S. Census data is retrieved from the IPUMS National Historical Geographic Information System (Manson *et al.* 2017), while the rest of the housing data is from the U.S. Census Bureau Topologically Integrated Geographic Encoding and Referencing (TIGER) Product (U.S. Census Bureau). Linear interpolation is used to estimate housing value in years not covered by these surveys.

Elevation. Elevation data is based on the National Elevation Dataset (NED) produced by the United States Geological Survey (National Elevation Dataset).

Storm probability. Annual storm probability data for each coastal county is collected from the United States Landfalling Hurricane Probability Project (Klotzbach *et al.*).

Building codes. The stringency of building codes for Atlantic and Gulf Coast states is measured based on an assessment report by the Insurance Institute for Business and Home Safety in 2015 (Insurance Institute for Business & Home Safety 2015). This report ranks hurricane-prone states on a scale of 0-100 based on the effectiveness of the states' residential building code adoption and enforcement systems. The building code stringency dummy variable "code" equals to 1 for states with an assessment score above the median score and 0 otherwise.

1.5.2 Additional Figures

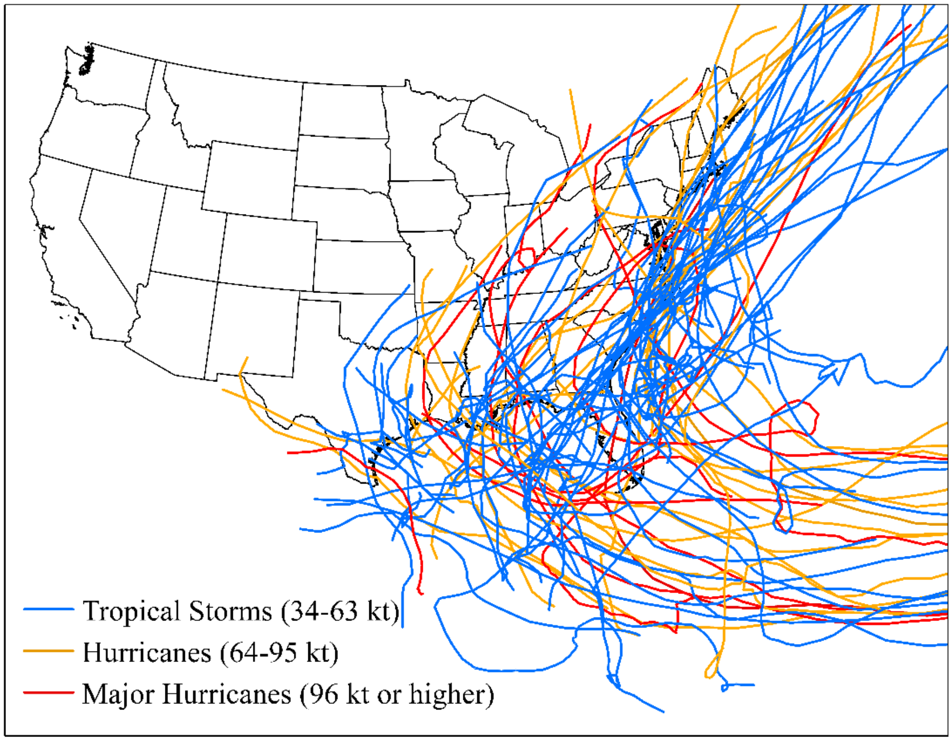

Figure 1.4: Paths of tropical cyclones hitting the United States (1996-2016).

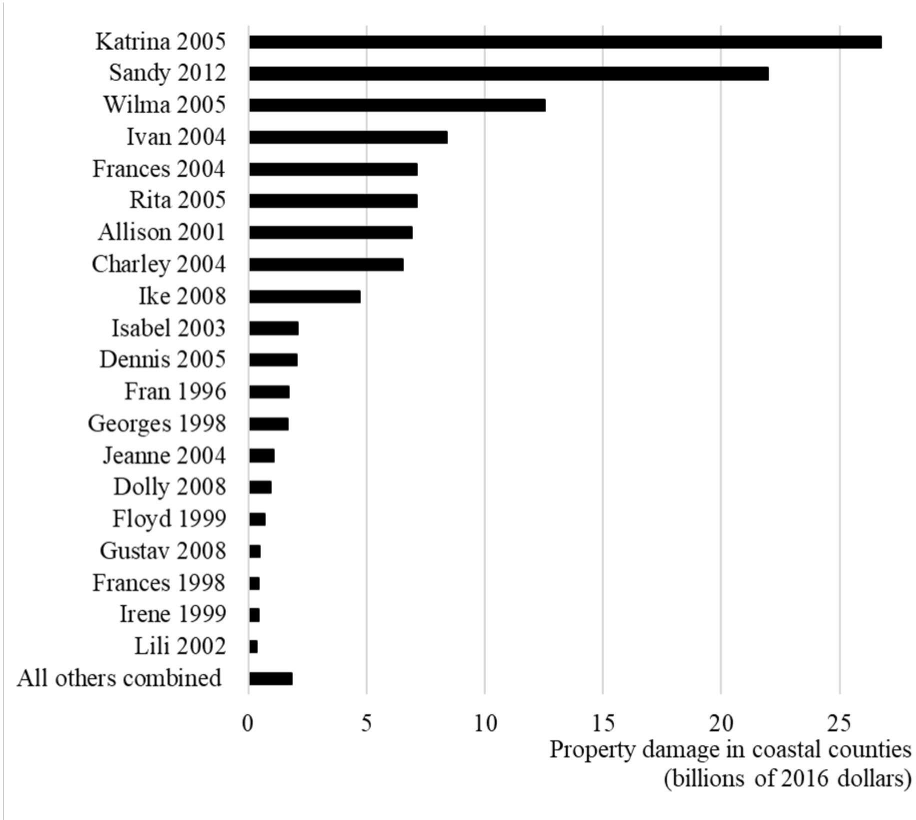

Figure 1.5: Property damage to U.S. shoreline counties during tropical cyclones from 1996 to 2016.

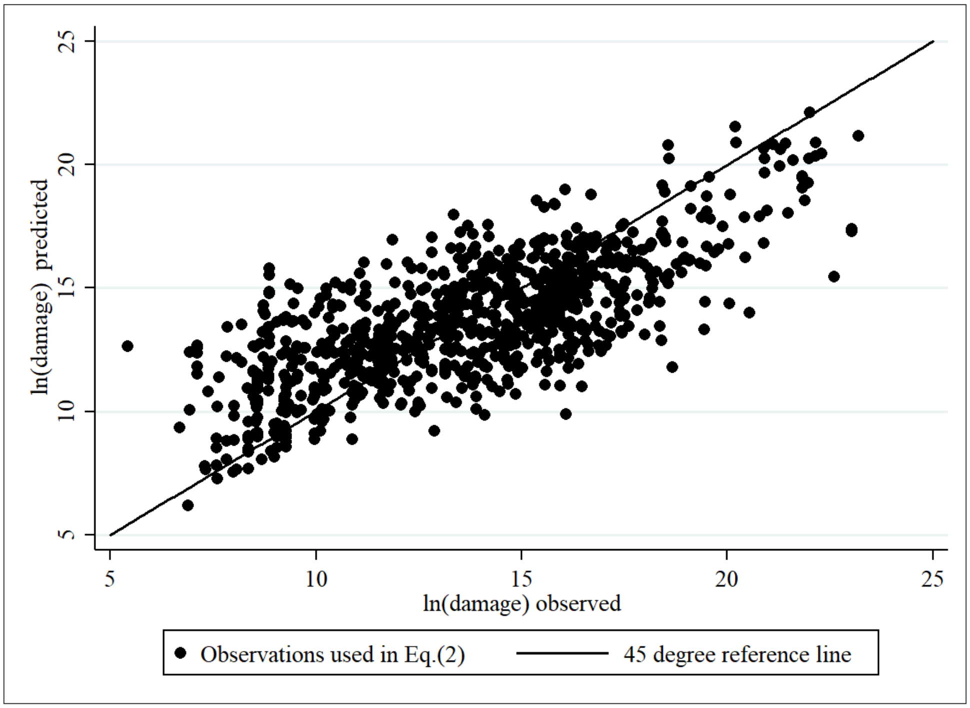

Figure 1.6: Observed vs. predicted log property damage for each observation in the conditional damage model.

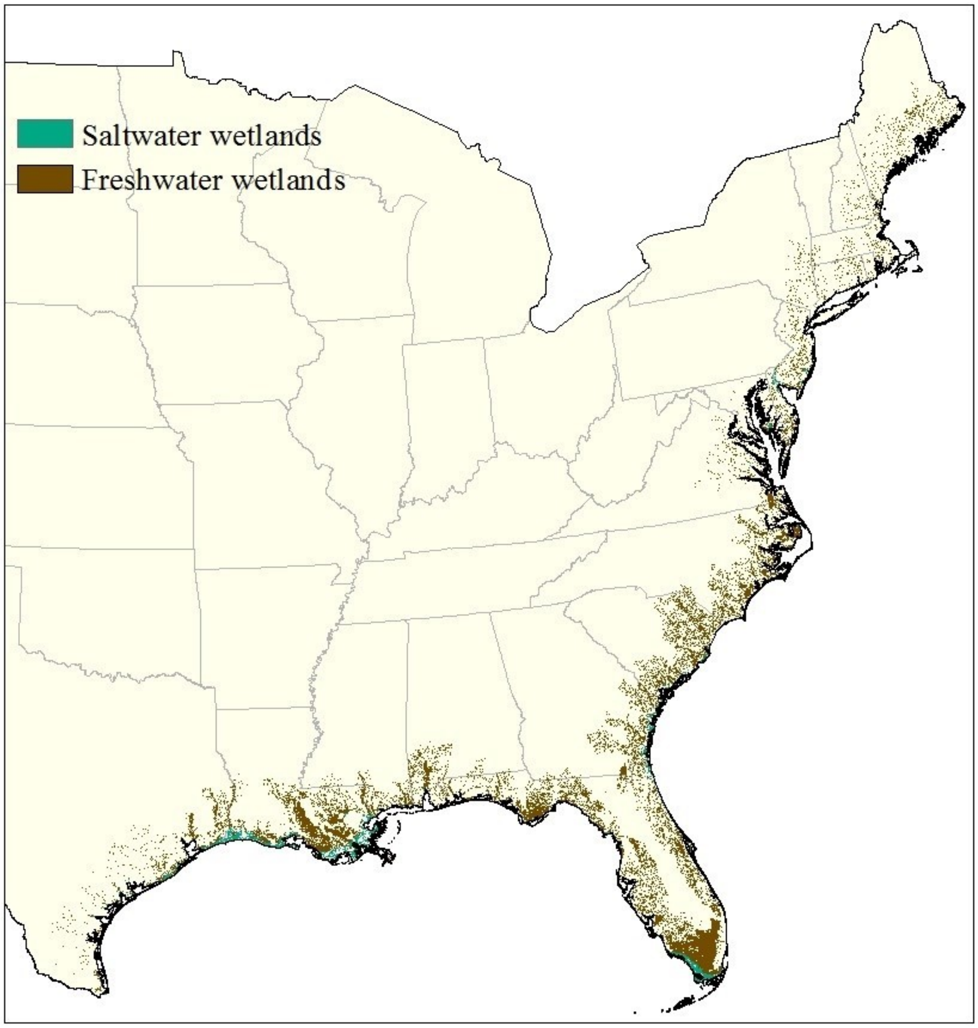

Figure 1.7: Coastal wetland coverage along the Atlantic and Gulf Coasts (2010).

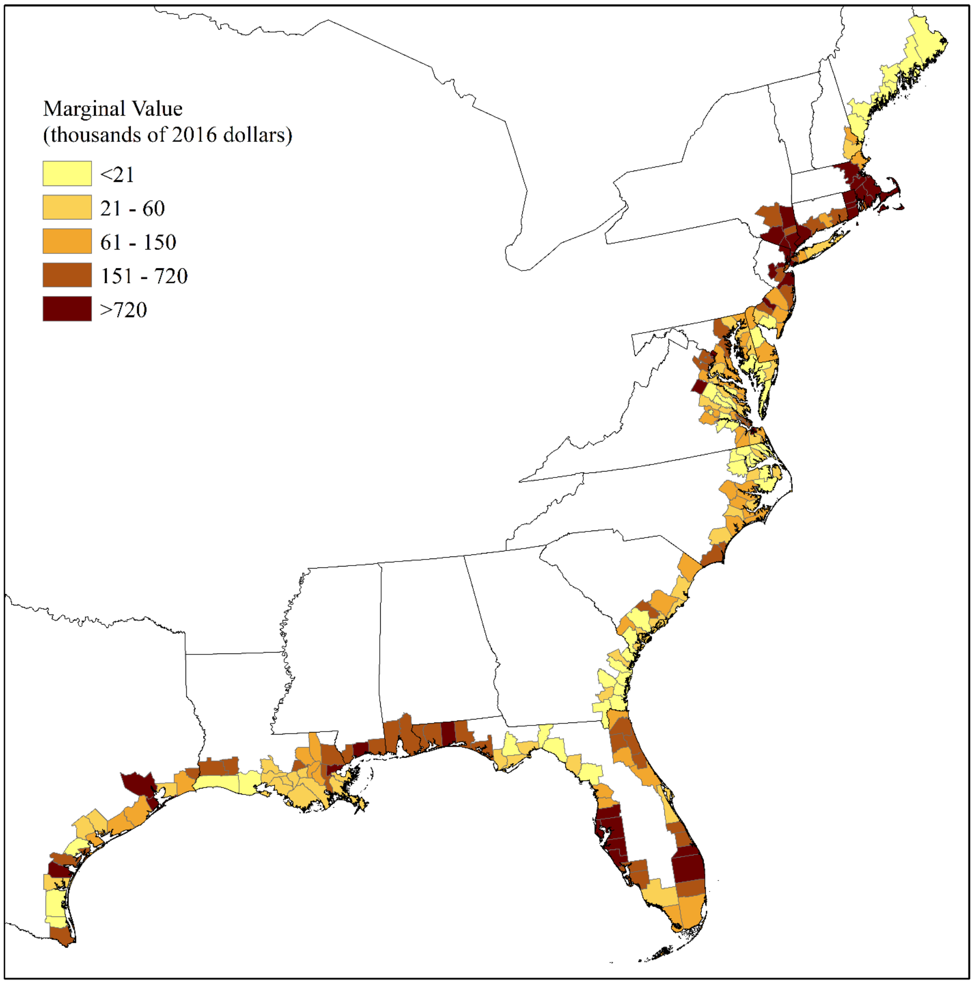

Figure 1.8: Annual county-level wetland values for storm protection services along Atlantic and Gulf Coasts.

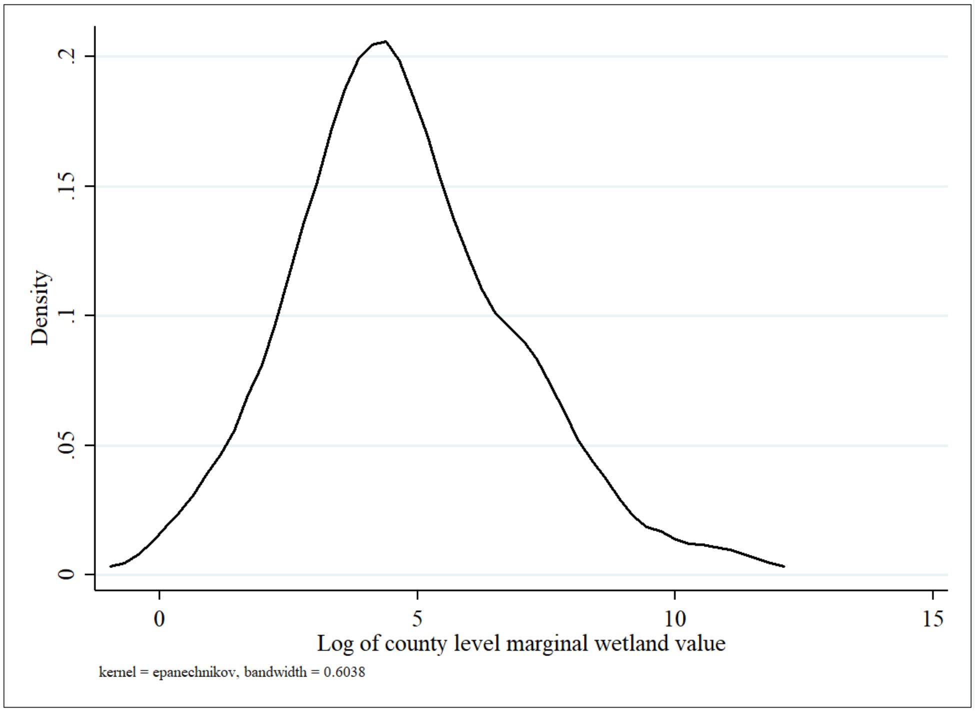

Figure 1.9: Kernel density plot of log of county level marginal wetland value.

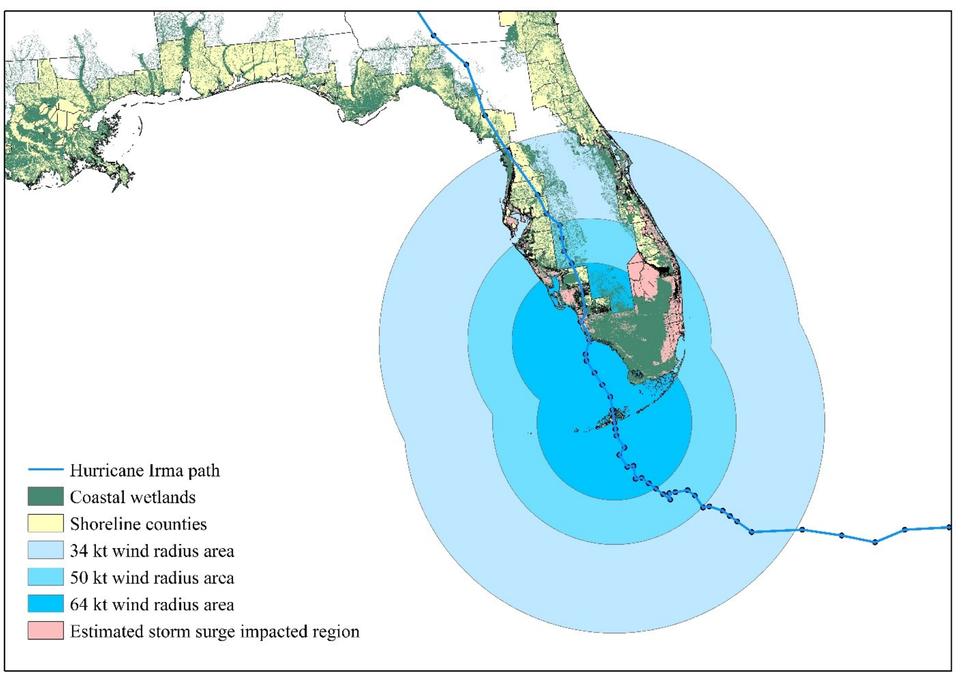

Figure 1.10: Coastal wetlands distribution and storm surge area near Hurricane Irma landfall.

1.5.3 Additional Tables

Table 1.2: Summary statistics of the conditional damage model.

Variable	Description	Units	Mean	SD	Min	Max
Property damage	County property damage during a storm.	Millions of 2016 dollars	122.75	792.22	0.00	12340.91
Wind	Maximum sustained wind speed experienced	knots	56.22	16.40	34.00	125.00
	by a county.					
Storm area	Potential storm surge area.	km^2	620.76	906.76	0.92	5178.02
Wetland	Coastal wetland coverage within the estimated	km^2	377.63	593.99	0.30	3636.25
	storm surge area of a county.		377.63	593.99	0.30	3636.25
Property at risk	Total amount of property value under the risk	Millions of 2016 dollars	5437.80	16998.40	0.77	193456.90
	of flooding during a storm.		5437.80	16998.40	0.77	193456.90
	0-1 dummy variable, equal to 1 if a county is		0.54	0.50	0	1
Right	located to the right side of the storm path and 0		0.54	0.50	0	1
	otherwise.		0.54	0.50	0	1
	0-1 dummy variable, equal to 1 if freshwater		0.66	0.47	0	1
Freshwater wetlands	wetlands are dominant within the storm surge		0.66	0.47	0	1
	area of a county and 0 otherwise.		0.66	0.47	0	1
	0-1 dummy variable, equal to 1 if saltwater		0.34	0.47	0	1
Saltwater wetlands	wetlands are dominant within the storm		0.34	0.47	0	1
	surge area of a county and 0 otherwise.		0.34	0.47	0	1
	0-1 dummy variable, equal to 1 if forested		0.41	0.49	0	1
Forested wetlands	wetlands are dominant within the storm		0.41	0.49	0	1
	surge area of a county and 0 otherwise.		0.41	0.49	0	1
	0-1 dummy variable, equal to 1 if emergent		0.59	0.49	0	1
Non-forested wetlands	and shrub wetlands are dominant within the		0.59	0.49	0	1
	storm surge area of a county and 0 otherwise.		0.59	0.49	0	1
	0-1 dummy variable, equal to 1 if a county		0.70	0.46	0	1
Tropical storms	experienced tropical storm level wind intensity		0.70	0.46	0	1
	(34-63 knots) and 0 otherwise.		0.70	0.46	0	1
	0-1 dummy variable, equal to 1 if a county		0.26	0.44	0	1
Category 1 hurricanes	experienced Category 1 level wind		0.26	0.44	0	1
	intensity (64-82 knots) and 0 otherwise.		0.26	0.44	0	1
	0-1 dummy variable, equal to 1 if a county		0.03	0.17	0	1
Category 2 hurricanes	experienced Category 2 level wind		0.03	0.17	0	1
	intensity (83-95 knots) and 0 otherwise.		0.03	0.17	0	1
	0-1 dummy variable, equal to 1 if a county		0.01	0.10	0	1
Category 3-5 hurricanes	experienced Category 3-5 level wind		0.01	0.10	0	1
	intensity ($\geq$ 96 knots) and 0 otherwise.		0.01	0.10	0	1
	0-1 dummy variable, equal to 1 if		0.81	0.40	0	1
Strict building codes	observation is in a state with above median		0.81	0.40	0	1
	building code assessment score and 0 otherwise.		0.81	0.40	0	1
	0-1 dummy variable, equal to 1 if		0.19	0.40	0	1
Less strict building codes	observation is in a state with below median		0.19	0.40	0	1
	building code assessment score and 0 otherwise.		0.19	0.40	0	1

Table 1.3: Summary statistics for property damage across different tropical cyclone classes. Sample is comprised of 2,483 county by storm observations, of which 947 observations (38% of total observations) experienced property damage (millions of 2016 dollars).

	Observation			For counties experiencing property damage				
Cyclone Class	Total	Without Damage	With Damage	Median	Mean	Min	Max	SD
Tropical Storm	1164	855	309	0.03	25.56	0.00	6845.40	389.64
C1 Hurricane	506	242	264	0.78	90.98	0.00	10497.57	913.36
C2 Hurricane	536	306	230	5.36	77.80	0.01	3189.76	302.88
C3 Hurricane	252	126	126	8.34	475.13	0.01	12340.91	1462.66
C4 Hurricane	25	7	18	3.51	364.68	0.06	3827.71	1051.08

Table 1.4: Probit model assessing effect of wetlands on reducing probability of experiencing property damage during a tropical cyclone hitting the U.S. from 1996 to 2016. $^{*}P < 0.10$, $^{**}P < 0.05$, $^{***}P < 0.01$. Robust standard errors are given in parenthesis.

	(1)
	Prob(damage)
Wetland	-0.001**
	(0.0003)
Wind	0.035***
	(0.0026)
Storm area	0.001***
	(0.0002)
Property at risk	-0.000
	(0.0000)
Right	0.492***
	(0.0554)
Constant	-2.414***
	(0.1373)
Log-likelihood	-1403.412
N	2483

Table 1.5: Regression results for alternative specifications of the conditional damage model. Standard errors (in parentheses) are clustered two-ways at the county and storm level. $^{*}P < 0.10$, $^{**}P < 0.05$, $^{***}P < 0.01$. Column 2 includes both linear and quadratic time trends, the coefficients of which are significant different from zero jointly at the 95% confidence level.

	(1) Base Model	(2) Add time trends	(3) Drop Katrina	(4) Drop Katrina & Sandy	(5) County FE
log(wetland)	-0.5756***	-0.6149***	-0.5733***	-0.6089***	-1.6945*
	(0.1840)	(0.1659)	(0.1890)	(0.1936)	(0.9116)
log(wind)	7.1885***	7.2137***	7.0594***	7.0405***	7.5881***
	(0.5653)	(0.6587)	(0.5858)	(0.6182)	(0.5715)
Right	0.8821***	0.6610*	0.8151**	0.7844**	1.0383***
	(0.3129)	(0.3668)	(0.3151)	(0.3340)	(0.3250)
log(storm area)	0.4793**	0.5448***	0.4775**	0.4772*	1.5418
	(0.2249)	(0.1980)	(0.2283)	(0.2397)	(1.0237)
log(property at risk)	0.3205***	0.2835***	0.3110***	0.3068***	0.0709
	(0.0622)	(0.0736)	(0.0622)	(0.0664)	(0.2674)
State FE	Yes	Yes	Yes	Yes	
Year FE	Yes		Yes	Yes	Yes
County FE					Yes
Time trends		Yes			
N	946	946	920	866	906
Adj. R^2	0.52	0.48	0.50	0.50	0.49

Table 1.6: Conditional damage model estimates (with the marginal effects of wetlands reported in the table). Standard errors (in parentheses) are clustered two-ways at the county level and storm level. $^{*}P < 0.10$, $^{**}P < 0.05$, $^{***}P < 0.01$.

	(1)	(2)	(3)	(4)	(5)
log(wetland)	-0.5756***				
	(0.1840)				
Tropical storms × log(wetland)		-0.5752***			
		(0.1718)			
C1 hurricanes × log(wetland)		-0.5491***			
		(0.1876)			
C2 hurricanes × log(wetland)		-0.4029**			
		(0.1724)			
C3-C5 hurricanes × log(wetland)		-0.3501*			
		(0.1873)			
Freshwater wetlands × log(wetland)			-0.5805***		
			(0.1836)		
Saltwater wetlands × log(wetland)			-0.5731***		
			(0.1863)		
Non-forested wetlands × log(wetland)				-0.5598***	
				(0.1805)	
Forested wetlands × log(wetland)				-0.5796***	
				(0.1857)	
Strict building codes × log(wetland)					-0.5044**
					(0.1979)
Less strict building codes × log(wetland)					-0.8055***
					(0.2029)
Right	0.8821***	0.8749***	0.8828***	0.8880***	0.8825***
	(0.3129)	(0.3200)	(0.3147)	(0.3183)	(0.3128)
log(wind)	7.1885***	6.4122***	7.1928***	7.1953***	7.1929***
	(0.5653)	(0.9744)	(0.5683)	(0.5668)	(0.5668)
log(storm area)	0.4793**	0.4767**	0.4811**	0.4595**	0.4558*
	(0.2249)	(0.2180)	(0.2248)	(0.2235)	(0.2293)
log(property at risk)	0.3205***	0.3135***	0.3190***	0.3194***	0.3179***
	(0.0622)	(0.0599)	(0.0638)	(0.0624)	(0.0617)
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	946	946	946	946	946
Adj. R^2	0.52	0.53	0.52	0.52	0.52

Table 1.7: Annual, 30-year and 100-year marginal value of coastal wetlands for storm protection for Atlantic and Gulf shoreline counties (thousands of 2016 dollars per km^2).

County	Annual	30-year	100-year				
Alabama				Okaloosa	8,028	161,493	268,584
Baldwin	177	3,552	5,908	Palm Beach	3,360	67,599	112,425
Mobile	189	3,803	6,325	Pasco	928	18,668	31,048
Connecticut				Pinellas	2,406	48,412	80,515
Fairfield	1,100	22,122	36,792	Putnam	69	1,381	2,296
Middlesex	138	2,772	4,610	Saint Johns	290	5,829	9,695
New Haven	195	3,930	6,536	Saint Lucie	383	7,711	12,825
New London	189	3,797	6,316	Santa Rosa	262	5,277	8,777
Delaware				Sarasota	763	15,355	25,538
Kent	17	351	584	Taylor	16	329	548
New Castle	70	1,403	2,334	Volusia	98	1,976	3,286
Sussex	91	1,834	3,050	Wakulla	52	1,047	1,741
District of Columbia				Walton	588	11,828	19,672
District of Columbia	3,184	64,060	106,540	**Georgia**			
Florida				Brantley	28	565	940
Bay	231	4,643	7,722	Bryan	25	507	843
Brevard	54	1,083	1,801	Camden	7	140	232
Broward	284	5,718	9,511	Charlton	16	325	541
Charlotte	305	6,132	10,199	Chatham	17	341	568
Citrus	77	1,546	2,571	Glynn	15	298	496
Clay	368	7,410	12,325	Liberty	8	160	267
Collier	38	764	1,271	McIntosh	5	107	178
Dixie	28	570	949	Wayne	3	58	97
Duval	270	5,441	9,049	**Louisiana**			
Escambia	720	14,484	24,089	Ascension	205	4,117	6,847
Flagler	156	3,142	5,226	Assumption	39	791	1,316
Franklin	36	733	1,220	Calcasieu	159	3,203	5,327
Gulf	31	615	1,022	Cameron	3	66	111
Hernando	92	1,857	3,089	Iberia	43	865	1,439
Hillsborough	987	19,847	33,009	Jefferson	392	7,889	13,120
Indian River	593	11,919	19,824	Jefferson Davis	171	3,443	5,727
Jefferson	12	242	402	Lafourche	28	573	953
Lee	321	6,452	10,731	Livingston	69	1,380	2,295
Levy	17	341	566	Orleans	1,139	22,905	38,094
Liberty	5	92	153	Plaquemines	23	454	755
Manatee	806	16,207	26,954	Saint Bernard	36	721	1,199
Martin	1,617	32,535	54,110	Saint Charles	88	1,769	2,942
Miami-Dade	138	2,776	4,616	Saint James	58	1,167	1,941
Monroe	81	1,628	2,707	Saint John the Baptist	97	1,947	3,238
Nassau	89	1,788	2,973	Saint Martin	23	457	760

Table 1.8: Annual, 30-year and 100-year marginal value of coastal wetlands for storm protection for Atlantic and Gulf shoreline counties (thousands of 2016 dollars per km^2) continued.

County	Annual	30-year	100-year				
Saint Mary	30	594	988	Jackson	161	3,232	5,376
Saint Tammany	289	5,806	9,655	**New Hampshire**			
Tangipahoa	73	1,473	2,450	Rockingham	30	600	998
Terrebonne	24	480	798	Strafford	137	2,764	4,597
Vermilion	19	383	637	**New Jersey**			
Maine				Atlantic	79	1,598	2,658
Cumberland	2	37	62	Bergen	1,699	34,173	56,834
Hancock	2	39	65	Burlington	100	2,005	3,335
Knox	2	50	83	Camden	2,164	43,525	72,388
Lincoln	3	52	86	Cape May	113	2,267	3,770
Sagadahoc	1	19	31	Cumberland	13	254	422
Waldo	8	158	263	Gloucester	157	3,156	5,249
Washington	1	14	24	Hudson	31,456	632,802	1,052,434
York	2	47	79	Middlesex	522	10,501	17,465
Maryland				Monmouth	1,858	37,375	62,160
Anne Arundel	181	3,646	6,063	Ocean	203	4,075	6,778
Baltimore	302	6,066	10,089	Salem	40	801	1,333
Calvert	98	1,963	3,265	Somerset	100,155	2,014,829	3,350,930
Caroline	29	593	987	Union	11,758	236,540	393,397
Cecil	86	1,735	2,885	New York			
Charles	32	653	1,086	Bronx	1,984	39,903	66,365
Dorchester	4	71	118	Dutchess	1,003	20,180	33,562
Harford	48	966	1,606	Kings	6,202	124,757	207,487
Kent	50	1,009	1,679	Nassau	77	1,557	2,589
Prince George’s	61	1,227	2,041	**New York**	27,139	545,955	907,997
Queen Anne’s	95	1,919	3,192	Orange	1,677	33,738	56,112
Saint Mary’s	74	1,490	2,477	Putnam	440	8,843	14,707
Somerset	6	113	188	Queens	582	11,711	19,477
Talbot	65	1,298	2,159	Richmond	166	3,340	5,556
Wicomico	16	318	529	Rockland	1,035	20,830	34,643
Worcester	31	615	1,024	Suffolk	31	620	1,031
Massachusetts				Ulster	650	13,084	21,760
Barnstable	915	18,405	30,610	Westchester	2,412	48,514	80,686
Bristol	1,118	22,487	37,399	**North Carolina**			
Dukes	2,578	51,856	86,244	Beaufort	63	1,259	2,093
Essex	137	2,752	4,577	Bertie	2	36	60
Middlesex	77,783	1,564,761	2,602,406	Brunswick	174	3,499	5,819
Nantucket	2,330	46,869	77,950	Camden	5	95	158
Norfolk	3,239	65,163	108,376	Carteret	62	1,243	2,067
Plymouth	915	18,409	30,617	Chowan	19	379	630
Suffolk	15,019	302,147	502,511	Craven	103	2,072	3,446
Mississippi				Currituck	9	179	298
Hancock	153	3,085	5,131	Dare	31	618	1,027
Harrison	800	16,098	26,773	Gates	4	71	118

Table 1.9: Annual, 30-year and 100-year marginal value of coastal wetlands for storm protection for Atlantic and Gulf shoreline counties (thousands of 2016 dollars per km^2) continued.

County	Annual	30-year	100-year				
Hertford	5	110	182	San Patricio	249	5,007	8,327
Hyde	8	160	265	Victoria	27	548	911
Jones	45	900	1,496	Willacy	14	290	483
New Hanover	454	9,140	15,202	**Virginia**			
Onslow	144	2,900	4,824	Accomack	8	155	258
Pamlico	38	757	1,259	Alexandria	40,812	821,025	1,365,475
Pasquotank	26	517	859	Arlington	8,042	161,785	269,071
Pender	51	1,030	1,713	Caroline	14	287	478
Perquimans	15	307	511	Charles City	9	183	304
Pitt	107	2,156	3,586	Chesapeake	45	909	1,511
Tyrrell	7	136	227	Chesterfield	69	1,393	2,317
Washington	32	644	1,071	Essex	22	435	724
Rhode Island				Fairfax	518	10,425	17,338
Bristol	1,033	20,775	34,551	Gloucester	35	711	1,182
Kent	2,814	56,600	94,133	Hampton	686	13,791	22,936
Newport	707	14,219	23,647	Hanover	57	1,153	1,918
Providence	4,914	98,861	164,418	Henrico	80	1,608	2,675
Washington	826	16,609	27,623	Hopewell	751	15,104	25,119
South Carolina				Isle of Wight	87	1,751	2,912
Beaufort	50	997	1,658	James City	74	1,494	2,485
Berkeley	61	1,235	2,054	King and Queen	11	221	368
Charleston	36	720	1,198	King George	52	1,050	1,746
Colleton	19	375	624	King William	19	389	648
Dorchester	170	3,427	5,700	Lancaster	124	2,491	4,142
Georgetown	34	680	1,132	Mathews	51	1,026	1,706
Hampton	80	1,603	2,666	Middlesex	120	2,421	4,027
Horry	116	2,328	3,871	New Kent	31	626	1,041
Jasper	15	303	504	Newport News	317	6,378	10,608
Texas				Norfolk	6,714	135,072	224,643
Aransas	267	5,378	8,944	Northampton	11	213	354
Brazoria	146	2,931	4,875	Northumberland	120	2,407	4,003
Calhoun	93	1,873	3,115	Poquoson	136	2,743	4,562
Cameron	470	9,462	15,736	Portsmouth	3,118	62,720	104,311
Chambers	54	1,084	1,802	Prince George	15	302	503
Galveston	1,242	24,990	41,562	Prince William	493	9,917	16,492
Harris	5,904	118,764	197,521	Richmond	16	314	523
Jackson	39	779	1,296	Spotsylvania	771	15,514	25,803
Jefferson	134	2,698	4,488	Stafford	150	3,014	5,013
Kenedy	6	123	204	Suffolk	101	2,042	3,396
Kleberg	34	693	1,152	Surry	17	333	553
Matagorda	72	1,440	2,394	Virginia Beach	116	2,326	3,869
Nueces	2,965	59,642	99,193	Westmoreland	84	1,686	2,805
Orange	224	4,515	7,508	Williamsburg	1,418	28,530	47,448
Refugio	11	217	361	York	210	4,224	7,025

Table 1.10: Summary statistics of the estimated marginal value of wetlands in storm protection for each coastal county based on the best fit gamma distribution, log-normal distribution and Weibull distribution (thousands of 2016 dollars).

Best fit wind probability distribution	R-squared	Mean MV	Median MV	SD MV	Min MV	Max MV
Gamma	0.9995	1785	91	9085	0.7	100155
Log-normal	0.9982	1727	90	8558	0.7	91551
Weibull	0.9980	1769	93	8873	0.7	96335

Chapter 1, in full, is currently being prepared for submission for publication of the material. Fanglin Sun; Richard Carson "Coastal Wetlands Reduce Property Damage during Tropical Cyclones." The dissertation author was the primary investigator and author of this material.

1.6 References

Badola, Ruchi, and Syed A. Hussain. 2005. "Valuing ecosystem functions: an empirical study on the storm protection function of Bhitarkanika mangrove ecosystem, India." *Environmental Conservation*, 32(1): 85-92.

Barbier, Edward B. 2007. "Valuing ecosystem services as productive inputs." *Economic Policy*, 22(49): 178-229.

Barbier, Edward B., Ioannis Y. Georgiou, Brian Enchelmeyer, and Denise J. Reed. 2013. "The value of wetlands in protecting southeast Louisiana from hurricane storm surges." *PloS one*, 8(3):e58715.

Barbier, Edward B., and Brian S. Enchelmeyer. 2014. "Valuing the storm surge protection service of US Gulf Coast wetlands." *Journal of Environmental Economics and Policy* 3(2): 167-185.

Boutwell, J. Luke, and John V. Westra. 2016. "The Role of Wetlands for Mitigating Economic Damage from Hurricanes." *Journal of the American Water Resources Association*, 52(6): 1472-1481.

Box, George EP, and David R. Cox. 1964. "An analysis of transformations." *Journal of the Royal Statistical Society: Series B (Methodological)*, 26(2): 211-252.

Boyle, Kevin J., Matthew J. Kotchen, and V. Kerry Smith. 2017. "Deciphering dueling analyses of clean water regulations." *Science*, 358(6359): 49-50.

C-CAP Land Cover Atlas, NOAA Office for Coastal Management; https://coast.noaa.gov/digitalcoast/tools/lca

Christiansen, T., P. L. Wiberg, and T. G. Milligan. 2000. "Flow and sediment transport on a tidal salt marsh surface." *Estuarine, Coastal and Shelf Science*, 50(3): 315-331.

Costanza, Robert, Octavio Pérez-Maqueo, M. Luisa Martinez, Paul Sutton, Sharolyn J. Anderson, and Kenneth Mulder. 2008. "The value of coastal wetlands for hurricane protection." *AMBIO*, 37(4): 241-248.

Cragg, John G. 1971. "Some statistical models for limited dependent variables with application to the demand for durable goods." *Econometrica*, 39(5): 829-844.

Danielsen, Finn, Mikael K. Sørensen, Mette F. Olwig, Vaithilingam Selvam, Faizal Parish, Neil D. Burgess, Tetsuya Hiraishi, Vagarappa M. Karunagaran, Michael S. Rasmussen, Lars B. Hansen, Alfredo Quarto, Nyoman Suryadiputra. 2005. "The Asian tsunami: a protective role for coastal vegetation." *Science*, 310(5748):643.

Das, Saudamini, and Jeffrey R. Vincent. 2009. "Mangroves protected villages and reduced death toll during Indian super cyclone." *Proceedings of the National Academy of Sciences*, 106(18):7357-7360.

Davlasheridze, Meri, Karen Fisher-Vanden, and H. Allen Klaiber. 2017. "The effects of adaptation measures on hurricane induced property losses: Which FEMA investments have the highest returns?" *Journal of environmental economics and management*, 81:93-114.

Demuth, Julie L., Mark DeMaria, and John A. Knaff. "Improvement of advanced microwave sounding unit tropical cyclone intensity and size estimation algorithms." *Journal of Applied Meteorology and Climatology*, 45(11): 1573-1581.

Dixon, Lloyd, Noreen Clancy, Seth A. Seabury, and Adrian Overton. 2006. "The National Flood Insurance Program's market penetration rate: estimates and policy implications." Santa Monica, CA: RAND Corporation.

Drossos, Constantine A., and Andreas N. Philippou. 1980. "A note on minimum distance estimates." *Annals of the Institute of Statistical Mathematics*, 32(1):121-123.

Farber, Stephen. 1987. "The value of coastal wetlands for protection of property against hurricane wind damage." *Journal of Environmental Economics and Management*, 14(2): 143-151.

Federal Register. 2017. "Discount rates for cost-effectiveness analysis of federal programs." 82 FR: 3026-3027.

Gedan, Keryn B., Matthew L. Kirwan, Eric Wolanski, Edward B. Barbier, and Brian R. Silliman. 2011. "The present and future role of coastal wetland vegetation in protecting shorelines: answering recent challenges to the paradigm." *Climatic Change*, 106(1): 7-29.

Guerry, Anne D., Stephen Polasky, Jane Lubchenco, Rebecca Chaplin-Kramer, Gretchen C. Daily, Robert Griffin, Mary Ruckelshaus, Ian J. Bateman, Anantha Duraiappah, Thomas Elmqvist, Marcus W. Feldman, Carl Folke, Jon Hoekstra, Peter M. Kareiva, Bonnie L. Keeler, Shuzhuo Li, Emily McKenzie, Zhiyun Ouyang, Belinda Reyers, Taylor H. Ricketts, Johan Rockström, Heather Tallis, and Bhaskar Vira. 2015. "Natural capital and ecosystem services informing decisions: From promise to practice." *Proceedings of the National Academy of Sciences*, 112(24): 7348-7355.

Hughes, S. A., and N. C. Nadal. 2009. "Laboratory study of combined wave overtopping and storm surge overflow of a levee." *Coastal Engineering*, 56(3): 244-259.

Insurance Institute for Business & Home Safety. 2015. "Rating the states 2015"; http://disastersafety.org/wp-content/uploads/2015/07/rating-the-states-2015-public.pdf.

Kennish, Michael J. 2001. "Coastal salt marsh systems in the US: a review of anthropogenic impacts." *Journal of Coastal Research*, 17(3): 731-748.

Klotzbach P, Gray W, Shama U, Harman L. United States landfall probability webpage, co-developed by William Gray's Tropical Meteorology Research Project at Colorado State University and the GeoGraphic Laboratory at Bridgewater State University; http://www.e-transit.org/hurricane/welcome.html.

Knapp, Kenneth R., Michael C. Kruk, David H. Levinson, Howard J. Diamond, and Charles J. Neumann. "The international best track archive for climate stewardship (IBTrACS) unifying tropical cyclone data." *Bulletin of the American Meteorological Society*, 91(3): 363-376.

Knutson, Thomas R., John L. McBride, Johnny Chan, Kerry Emanuel, Greg Holland, Chris Landsea, Isaac Held, James P. Kossin, A. K. Srivastava, and Masato Sugi. 2010. "Tropical cyclones and climate change." *Nature geoscience*, 3(3): 157-163.

Manson S, Schroeder J, Riper DV, and Ruggles S (2017) IPUMS National Historical Geographic Information System: Version 12.0 [Database]. Minneapolis: University of Minnesota. http://doi.org/10.18128/D050.V12.0.

Morris, James T., P. V. Sundareshwar, Christopher T. Nietch, Björn Kjerfve, and Donald R. Cahoon. 2002. "Responses of coastal wetlands to rising sea level." *Ecology*, 83(10): 2869-2877.

Möller, Iris, Matthias Kudella, Franziska Rupprecht, Tom Spencer, Maike Paul, Bregje K. Van Wesenbeeck, Guido Wolters, Kai Jensen, Tjeerd J. Bouma, Martin Miranda-Lange and Stefan Schimmels. 2014. "Wave attenuation over coastal salt marshes under storm surge conditions." *Nature Geoscience*, 7(10): 727-731.

Möller, Iris, Thomas Spencer, Jon R. French, D. J. Leggett, and Malcolm Dixon. 1999. "Wave transformation over salt marshes: a field and numerical modelling study from North Norfolk, England." *Estuarine, Coastal and Shelf Science*, 49(3): 411-426.

Morton, Robert A. 2002. "Factors controlling storm impacts on coastal barriers and beaches: a preliminary basis for near real-time forecasting." *Journal of Coastal Research*, 18(3): 486-501.

National Elevation Dataset (NED), United States Geological Survey (USGS); https://nationalmap.gov/elevation.html.

National Hurricane Center, "Tropical Cyclone Climatology". www.nhc.noaa.gov/climo/

NOAA National Hurricane Center, Introduction to Storm Surge; http://www.nhc.noaa.gov/surge/surge intro.pdf.

NOAA National Hurricane Center (2017) 2017 Tropical Cyclone Advisory Archive; http://www.nhc.noaa.gov/archive/2017/.

Nordhaus, William D. 2010. "The economics of hurricanes and implications of global warming." *Climate Change Economics*, 1(01):1-20.

Resio, Donald T., and Joannes J. Westerink. 2008. "Modeling the physics of storm surges." *Physics Today*, (9): 33-38.

Storm Events Database, NOAA National Centers for Environmental Information; https://www.ncdc.noaa.gov/stormevents/

US Army Corps Engineers. 2008. "US Environmental Protection Agency (2008) Compensatory mitigation for losses of aquatic resources: final rule." Fed Reg 73(70): 19594-19705.

U.S. Census Bureau, Topologically Integrated Geographic Encoding and Referencing (TIGER) Product; https://www.census.gov/geo/maps-data/data/tiger.html.

U.S. Environmental Protection Agency, (EPA), "Coastal Wetlands"; https://www.epa.gov/wetlands/coastal-wetlands

Wamsley, Ty V., Mary A. Cialone, Jane M. Smith, John H. Atkinson, and Julie D. Rosati. "The potential of wetlands in reducing storm surge." 2010. *Ocean Engineering* 37(1): 59-68.

Wooldridge, Jeffrey M. 2010. "Econometric Analysis of Cross Section and Panel Data" (MIT Press, Cambridge, MA), 2nd Ed: 692-697.

Zachry, Brian C., William J. Booth, Jamie R. Rhome, and Tarah M. Sharon. 2015. "A national view of storm surge risk and inundation." *Weather, climate, and society*, 7(2):109-117.

Chapter 2

Green Stimulus: Tax Incentives in China's Automobile Market

Abstract: In response to the global economic downturn of 2008-2009, many countries adopted "green stimulus" measures. These measures sought to achieve short-run economic recovery and long-run environmental benefits. We investigate the effects of a large-scale green stimulus measure in China involving a sales tax cut for greener vehicles. In early 2009, with less than a week's notice, the Chinese government halved the sales tax on small engine size vehicles from 10% to 5%. Using administrative data covering every car registered in China from 2006 to 2011, a difference-in-differences design is employed to estimate the impacts of the program on new vehicle sales and the environment. The program played a significant role in stimulating auto demand. Sales of eligible vehicles increased by 0.6 million cars, while sales of similar but ineligible vehicles decreased by 0.2 million cars. Under plausible counterfactuals, the policy reduced CO_2 emissions. However, as a stand alone emission control policy it was quite expensive as about 88% of the tax cut went to consumers who would have purchased a small car anyway.

2.1 Introduction

The global economic downturn of 2008-2009 caused many governments to allocate sizable portions of their national stimulus packages towards programs that also had environmental objectives. These programs are often referred to as "green stimulus" in the popular discourse (United Nations Environment Programme 2009, Barbier 2010, International Labour Organization 2011). Green stimulus measures attempt to stimulate short-run economic recovery while simultaneously advancing long-run environmental goals. These include direct investments in renewable energy and smart grids, incentive programs improving the energy efficiency of buildings and vehicles, and policies supporting water, waste and pollution management (Robins et al. 2009). South Korea led the world by committing over 80% of its total expenditure of $38 billion to green stimulus, while China took first place in terms of the overall amount of green stimulus – $220 billion (37% of its total stimulus package) – followed by the U.S. ($94 billion, 12% of its total stimulus package). The widespread promotion of a low-carbon green recovery around the world reflects common concerns over climate change, energy security and pollution.

It is often difficult to achieve multiple goals with a single policy (Tinbergen 1952), especially in the case of green stimulus where the two goals – economic recovery and environmental protection – are at least some degree contradictory. Understanding the effectiveness of green stimulus measures in achieving both of their goals is important, particularly in light of the vast sums spent on these programs. This is challenging given the lack of information on what economic outcomes would have occurred in the absence of the green stimulus programs.

We investigate the effects of a large-scale green stimulus measure in China: a major sales tax cut for greener vehicles. In early 2009, with less than a week's notice, the Chinese government cut the sales tax on small engine size vehicles (no larger than 1.6 Liter) from 10% to 5%. A year later in 2010, the tax rate was raised to 7.5%. The average savings per small car due to the tax cut was over $670, a large incentive given that the average annual income per capita in urban areas of

China was below $3,200 during this period. The tax cut was intended to achieve dual goals: to invigorate the auto industry by stimulating vehicle demand, and to reduce carbon emissions by shifting the motor vehicle fleet toward small cars. We examine the impacts of the tax cut on both new vehicle sales and carbon emissions, using administrative data covering every new car sold in China.

Stimulus programs specifically targeting the auto industry have been widely adopted by countries around the world for two reasons. First, the automobile industry is usually one of the most hard hit sectors during recessions. Demand fell sharply in major car-producing countries such as the U.S. and Japan after mid-2008.[1] Consumers tend to postpone their purchases of durable goods due to uncertainty about future economic conditions and reduced access to credit during financial crises (Bloom 2014). Second, stimulus of the auto industry is thought to have a large multiplier effect since it is strongly linked with many other sectors such as steel, rubber, and glass (Haugh et al. 2010). As such, countries fear that a collapse of their auto industry would have large impacts on the broader economy, deepening the recession.

Governments have provided various forms of support for the automobile industry based on the growth stage of the industry. Previous studies focus on stimulus policies implemented in countries with mature automobile markets where vehicle ownership is high and close to saturation. One prominent example was the "Cash-for-Clunkers" program implemented in the United States. This program attempted to boost auto demand through vehicle scrappage programs in which subsidies were offered for trading-in older vehicles and purchasing new vehicles with higher energy efficiency. Over 15 countries implemented similar programs in response to the recession (Haugh et al. 2010). Unlike developed countries, China attempted to accelerate auto demand through encouraging consumers to purchase small cars as the first car in their families. The rapid expansion of the Chinese middle class in the 2000s led to increased demand for cars. Cars went from a luxury item for wealthy consumers to an essential component of everyday life. As the

[1] See https://www.nytimes.com/2008/10/02/business/02sales.html.

vehicle fleet expanded, initial choices could significantly impact future vehicle emissions, which motivated the Chinese government to incorporate environmental goals into its stimulus policies.

The tax cut for small cars in China provides an opportunity to examine the effects of green stimulus measures in a middle income developing country context. China's policy design enables us to isolate its impact to a greater extent than previous studies. The policy was announced just six days before it was implemented, giving consumers and automakers little time to adjust their behavior ahead of time. The clear cutoffs in both time and eligibility allow us to estimate policy effects in a difference-in-differences framework by comparing vehicle sales of models with different levels of exposure to the policy before and after it began. An unexpected extension of the program near the end of its planned end date, together with the change in magnitude of the tax rate, allows us to look at whether the generosity of the tax cut mattered. The automobile market in China developed relatively late, but China is now both the largest auto manufacturing country and the largest auto market in the world. As such, China's car market is of considerable interest in its own right. The tax cut provides a good opportunity to study how consumers and suppliers in a rapidly developing market respond to fiscal stimulus initiatives.

During 2009, the first year of the policy, sales for small (eligible) cars were boosted by 16%. Sales of vehicles barely missing the program's eligibility cutoff were reduced by 19%, likely as consumers substituted towards smaller cars. Since small cars make up the largest part of the market, overall car sales went up. The policy effects were more muted during the second year. The increase in sales of small cars was about 0.6 million cars in 2009, about 12% of the total sales of small cars. This implies that over 88% of the tax cut went to consumers who would have purchased a small car anyway during the policy. The large fraction of inframarginal consumers suggest that the policy was an expensive way to stimulate demand. Of the 0.6 million increase in sales of small cars induced by the policy, approximately 32% were from consumers who changed their purchase plans from medium engine size cars to small engine size cars, and the rest were from consumers pulling forward demand from the future to the policy period.

Using these results, we investigate the extent to which the green component of the policy contributed to reducing gasoline consumption and emissions. The net impact of the policy on the environment is not clear *ex ante*. The engine size restrictions on eligibility can reduce emissions in the long run by inducing consumers to switch from ineligible models to eligible models with similar attributes. However, the program can increase emissions in the current period by inducing consumers to pull forward demand from the future. To get a comprehensive understanding of the environmental effects, we estimate emissions under two plausible counterfactual scenarios: (1) no program; and (2) an across-the-board tax reduction for all cars, holding the program's fiscal cost constant. We find that the tax cut moderately reduced carbon emissions and other environmental pollutants, but the cost of the emission reductions was very high due to the large proportion of inframarginal consumers.

A key contribution of this study is its provision of the first evidence on the effectiveness of a major green stimulus program during the Global Financial Crisis in a developing country context. Previous studies mainly focus on scrappage programs adopted in developed countries during the global recession. In particular, the "Cash-for-Clunkers" program has received much attention due to its popularity among consumers (Mian and Sufi 2012, Copeland and Kahn 2013, Li and Wei 2013, Li et al. 2013, Hoekstra et al. 2017). The program provided an average subsidy of $4,200 per order, and exhausted the fund of $3 billion within 30 days, increasing new vehicle sales by about 0.37 million (Li et al. 2013). The surge in auto purchases induced by the program was largely offset by a sharp drop in purchases in subsequent months. Compared to the "Cash-for-Clunkers" program, the tax incentives provided by the Chinese program were much smaller in absolute terms, about $670 per car, but we estimate that it increased sales by 0.6 million in 2009. Our results suggest that Chinese consumers were more sensitive to vehicle price changes, likely due to a much lower average annual income. Another contribution is our examination of the Chinese auto market, which is young, rapidly growing and large, and still barely explored by the literature. Lessons learned here may be instructive to other emerging car markets.

Our study adds to the emerging literature studying the impacts of different emission control practices targeting motor vehicles in China. A series of policies have been designed: tightening new vehicle fuel economy standards (Oliver 2009), limiting car purchases (Li 2017), restricting driving (Chen et al. 2013, Viard and Fu 2015), and changing vehicle consumption and fuel taxes (Xiao and Ju 2014), among many others. However, these policies did not specifically target small engine size vehicles. The one exception is a recent study by Chen et al. (2017) that investigates the effects of an alternative policy instrument targeted at energy efficient vehicles – a five-year flat rate subsidy program (about $430 per car) implemented after the policy studied here, with much more complicated eligibility rules that not only considered engine size, but also other features such as fuel economy, curb mass, transmission type, and emission standard levels. The green stimulus measure studied in this paper differs from these policies because it was designed with the primary goal of stimulating vehicle demand and averting industry downturn. Furthermore, as with most fiscal stimulus policies, the tax cut was temporary, while other green policies were designed for a much longer time horizon. Due to its short-term nature, the policy pulled forward a substantial portion of demand from the future, potentially offsetting part of the emission reduction because these are largely first time car buyers.

Our rich dataset allow us to explore the heterogeneous effects of the policy across cities with different levels of economic development and automakers with different exposure to the policy. Unlike subsidies for energy efficient products, which have often been criticized for disproportionately benefiting the wealthy (Allcott et al. 2015, Borenstein and Davis 2016, Davis and Knittel 2016), we find this tax cut policy had stronger effects in stimulating demand for eligible cars in less developed regions of China.

2.2 Policy Background

China's passenger vehicle market has recorded strong growth in production and sales since China joined the World Trade Organization in 2001 (see Fig. 2.1).[2] In order to improve technology and expand production capacity, the Chinese government has gradually eased barriers to market access and encouraged foreign manufacturers to invest in the Chinese auto market through joint ventures with local partners. By the end of 2008, 34 domestic auto manufacturers had been established in China, consisting of 75 vehicle subsidiary companies (about 30% are joint ventures) and 78 brands.[3] On the demand side, rapid economic growth has made cars affordable for a growing fraction of Chinese families. The boom in the Chinese auto industry has been mainly driven by the domestic market since both exports and imports are at relatively low levels (less than 5% of production and sales in 2008). As such, the number of vehicles produced in China annually more or less equals the number of vehicles sold there.

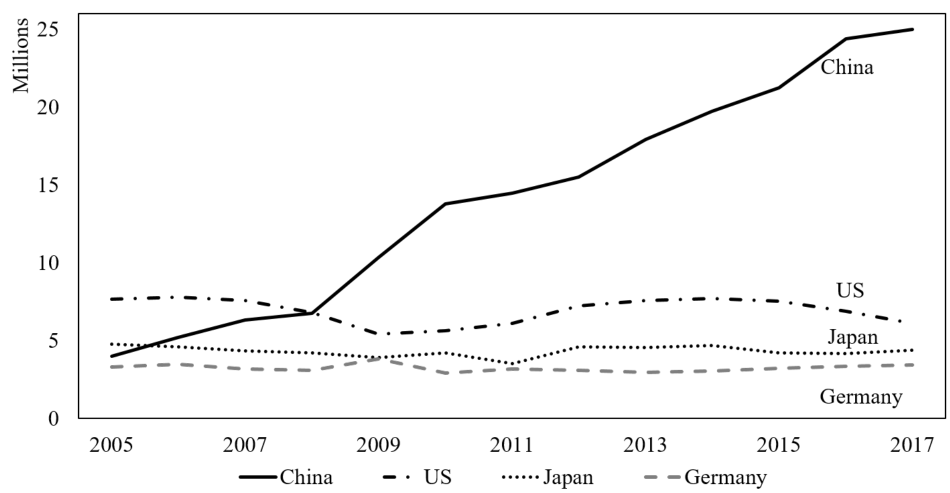

Figure 2.1: Passenger Vehicle Sales in Major Auto Markets (2005-2017).Note: Data collected from the International Organization of Motor Vehicle Manufacturers, www.oica.net.

[2]Passenger vehicles consists of vehicles designed for carrying passengers with less than ten seats. They made up 70% of total auto sales in China in 2008. This study focus on analyzing this market since it is the relevant one for the tax cut. Definitions of vehicle categorizations and market share data come from the International Organization of Motor Vehicle Manufacturers website, www.oica.net.

[3]During the substantial growth of the Chinese auto industry, many mergers, acquisitions, and changes in brand names happened in the industry, and the numbers reported here are based on the authors' counts from the 2008 vehicle registration data together with information from each automaker's Wikipedia page.

The double-digit year-to-year growth in Chinese auto sales dipped below 6% in 2008, its slowest during the 2000s, when the global financial crisis severely hit the auto industry in other countries. The negative impacts were even more serious in the United States – demand dropped sharply in 2008, by 26% compared to the previous year.[4] Leading auto manufacturing companies such as General Motors and Chrysler were on the verge of bankruptcy and sought bailouts at the end of 2008.[5] After witnessing the collapse of the auto industry in mature markets, in early 2009, the Chinese government quickly came up with stimulus measures, halving the vehicle sales tax for small cars in an effort to avert a sharper slowdown in domestic demand.

All cars sold in China had been subject to a 10% vehicle sales tax since 2001.[6] On January 14, 2009, the State Council of China announced, in a bid to boost the domestic car demand and to facilitate emission cuts, that the vehicle sales tax would be cut to 5% for cars with engine sizes no larger than 1.6 liters (L) during the period January 20 to December 31, 2009.[7] After that date the tax rate was expected to return to its normal 10%. However, the State Administration of Taxation (SAT) decided to extend the policy for an extra year, but raised the tax rate from 5% to 7.5% in 2010 (See Fig. 2.2). The tax rate went back to 10% after 2011. During the tax cut, 11 million cars out of the 17 million cars sold from 2009 to 2010 met the requirements for the tax reduction, about 60% of the total market. With the average price of eligible vehicles sold during the policy being about 115,000 RMB (about $17,000), the average tax savings for each eligible vehicle are about 4,900 RMB in 2009 and 2,450 RMB in 2010 (about $720 and $360 in 2009 and 2010).

[4]See https://www.nytimes.com/2008/10/02/business/02sales.html.

[5]See https://www.nytimes.com/2008/12/09/business/09auto.html.

[6]Consumers are required to pay the sales tax to local vehicle registration departments within 60 days of the purchase date. In most cases, consumers pay the tax through dealers to avoid the time consuming processes of registration. To calculate the amount of vehicle sales tax, the 17% value added tax should be excluded from the transaction price. Thus, the formula can be expressed as Vehicle Sales Tax $= \frac{\text{Vehicle Transaction Price}}{(1+17\%)} * 10\%$. See http://www.gov.cn/banshi/2005-08/19/content_24868.htm.

[7]Details of policy descriptions are available through www.chinatax.gov.cn. The tax cut for small cars was also considered as one of the major economic measures included in the energy conservation and emission reduction plan in 2009, available through http://www.gov.cn/zwgk/2009-07/31/content_1380418.htm.

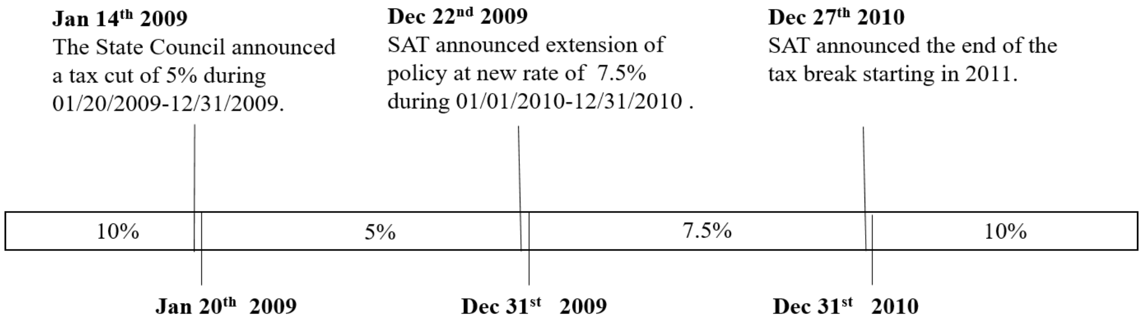

Figure 2.2: Tax Cut Policy Time Line. Vehicle sales tax rate is indicated by the percentages.

Several features of this policy make it particular conducive for our empirical analysis. First, the policy was announced less than a week before it was launched, creating a real shock to the automobile market in China. The possibility of a sales tax reduction targeting small engine size vehicles was first mentioned in online news published in December 2008, when the China Passenger Car Association submitted a report to the central government of China, discussing a series of suggestions to develop the domestic auto market.[8] However, neither the market nor the report established a clear definition of small cars. Furthermore, it was unclear whether the central government would support the suggestion, when the policy would be implemented, or the magnitude of the tax reductions. Thus, with all these uncertainties, our estimated policy effects are not expected to be dampened by auto makers and consumers adjusting their original production or purchase plans before the policy was introduced.

Another nice feature of the policy is that it has a clear and simple eligibility rule based on an important attribute of the car: engine size. This is a key factor that influences the performance and energy consumption of a vehicle. Generally, vehicles with larger engines consume more fuel, holding other characteristics constant. The Chinese government's intent was to encourage consumers to purchase smaller and more energy efficient vehicles by designing the tax incentives based on engine size. The policy is likely to be more beneficial for auto makers with large share of existing models eligible for the tax cut since it would be very costly for auto makers to adjust the

[8] See http://auto.gasgoo.com/News/2008/12/061044154415.shtml.

engine size of an existing car model or to expand production capacity in the short run, especially during the initial year of the policy.[9]

2.3 Data

We create a novel and comprehensive dataset of the Chinese automobile market by merging together several datasets, including administrative vehicle registration records, vehicle model characteristics, and city-level socioeconomic conditions.

The administrative vehicle registration data was collected from local Vehicle Management Offices in each city, containing monthly records on every new vehicle registered in China from 2006 to 2011. The complete set of registration records includes data from 41,305,947 vehicles, together with major vehicle attributes such as engine size, transmission type, segment, curb weight, and vehicle dimensions. Information on engine size is crucial for our empirical analysis because it enables us to separately identify vehicles of the same model but different engine sizes. In this analysis, we define a "vehicle model" at the model by engine size level (e.g., a 1.6 L Corolla and a 1.8 L Corolla are considered as two vehicle models).

Each vehicle is registered at the trim level with a unique product ID.[10] Using the product ID, we merge the registration data with the Vehicle Fuel Consumption Database from the Ministry of Industry and Information Technology of China to get the average fuel economy for each model and subsequently merge it with data collected from Haicheji.com, a major vehicle trading website that provides information on the manufacturer suggested price and other features for each model.[11]

[9] Any change in the design of main vehicle features including engines requires a lengthy application and approval process (Ministry of Industry and Information Technology of China, www.miit.gov.cn).

[10] All vehicles produced in China are required to have a product ID which is an identification code designed based on the National Standard GB 9417-88 Motor Vehicles-type and Model Designation.

[11] The Vehicle Fuel Consumption Database is available through http://chaxun.miit.gov.cn/asopCmsSearch/. We also collect vehicle information from other primary online vehicle trading websites including Quanna, Sohu, Autohome to cross check the data from Haicheji and to fill in some missing information from Haicheji.

Moreover, we control for the gasoline expenditure for each vehicle model in the empirical analysis since fuel cost is an important factor determining vehicle choices. The monthly retail gasoline prices in each city was collected from the gasoline price adjustment announcements by the National Development and Reform Commission of China.[12] The average gasoline price in China followed an increasing trend during the study period, with much less volatility compared to the U.S. retail gasoline price and the Brent crude oil spot price (see Fig. 2.10).

Lastly, to investigate the extent to which the policy had heterogeneous effects across cities with different socio-economic conditions, we use city level demographic data from the China City Statistical Year Book and Provincial Statistical Year Book during the study period.

Table 2.1 provides summary statistics for the final sample. It includes 3,352,429 city-month-model-level observations, covering 39,815,318 vehicles, about 96% of all new passenger vehicles sold across 361 cities in China between 2006 to 2011.[13] We focus on vehicle models with engine size no larger 2.5 L as the excluded vehicle models are dominated by luxury sedans, large SUVs, or MPVs, which only make up about 2% of the total market share but highly skew the price distribution (the average price of models with engine size above 2.5 L is about 506,000 RMB, over four times higher than that of eligible models during the study period). Though including these vehicles does not significantly change our estimation results (see Section 8).

The policy may change the market composition by encouraging consumers to switch to eligible cars. Fig. 2.3 shows the market share by engine size one year before and after the policy was implemented (see Fig. 2.11 for data of other years). Market share of vehicles eligible for the tax cut increased from 55% in 2008 to 64% one year after the policy was implemented. Among eligible vehicle models, 1.6 L vehicles were the most popular ones, making up over half of sales

[12]Retail gasoline prices in China are strictly regulated by the central government. From 2006 to 2011, The National Development and Reform Commission of China (NDRC) had adjusted the gasoline prices in different provinces 21 times. Retail gasoline prices schedules are available through http://www.ndrc.gov.cn/.

[13]The rest 4% (about 1.5 million cars) of the total number of cars sold in China during the study period are excluded due to having reporting errors in registered locations (27,941 vehicles), missing price data (555,784 vehicles could not be matched with vehicle information data from Haicheji), or missing fuel economy data (511 vehicles), or having engine sizes above 2.5 L (906,393 vehicles).

Table 2.1: Summary Statistics of Vehicle and City Characteristics

	Mean	SD	Min	Max
Panel 1: Passenger Vehicles Sold in China (2006-2011)				
Monthly sales by city-model	11.88	35.47	1.00	4635.00
Engine size (L)	1.73	0.40	0.00	2.50
Fuel economy ($L/100km$)	7.93	1.43	0.00	13.50
Curb Weight (1000kg)	1.31	0.26	0.60	2.30
Volume (m^3)	11.78	1.92	6.45	18.66
Horsepower (hp)	119.93	33.95	15.00	262.00
MSRP (1000RMB)	170.17	107.37	25.72	879.87
Fuel cost ($RMB/100km$)	51.88	11.87	0	132.09
Share of Vehicle Segments				
Sedan	0.80	0.40	0.00	1.00
SUV	0.13	0.34	0.00	1.00
MPV	0.07	0.25	0.00	1.00
Share of Vehicle Brand by Country				
China	0.38	0.48	0.00	1.00
Japan	0.25	0.43	0.00	1.00
Europe	0.21	0.41	0.00	1.00
US	0.10	0.30	0.00	1.00
Korea	0.07	0.25	0.00	1.00
Panel 2: City Socio-economic Conditions (2008)				
GDP per capita (1000RMB)	23.45	18.29	3.60	106.86
Salary (1000RMB)	24.79	6.90	11.71	56.56
Population density ($person/km^2$)	357.13	315.70	0.28	2454.31
Share of eligible vehicles	0.57	0.10	0.26	0.84

This table describes the summary statistics for the city-month-model level data of passengers vehicles sold in China from 2006 to 2011. The total number of observations is 3,352,429, including 39,815,318 vehicles. Fuel cost refers to the estimated gasoline expenditure of driving 100km for each vehicle model.

of eligible cars in 2009. Detailed comparisons of vehicle features across eligible and ineligible models are discussed in Section 3.

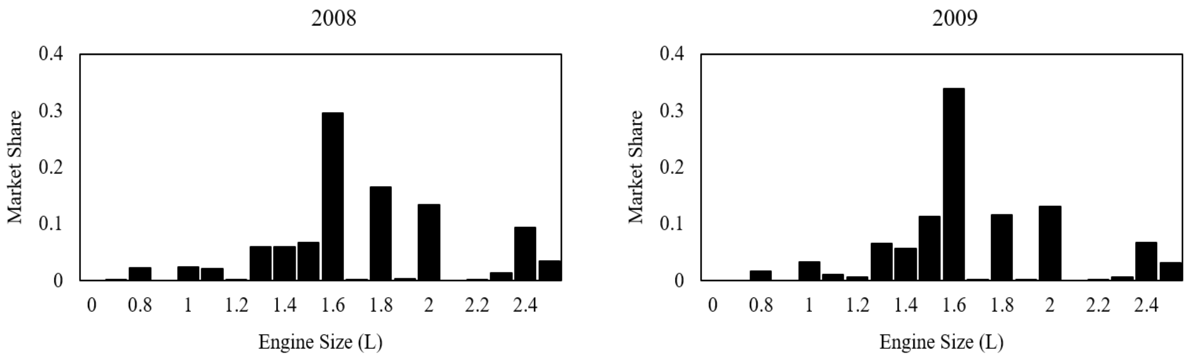

Figure 2.3: Market Share of New Vehicle Sales by Engine Size Group (2008-2009)

2.4 Empirical Model

2.4.1 Research Design

To estimate the policy effects on sales, our empirical strategy exploits across-model variation in exposure to the tax cut. All newly purchased vehicles are categorized into three groups based on engine size: small, medium and large vehicles. Table 2.8 presents major characteristics of vehicle models by engine size sold during 2006 to 2011. The small vehicle category includes models qualifying for the tax cut (engine size less than or equal to 1.6 L), which are directly influenced by the policy. The medium vehicles consist of models that are not eligible for the policy but with an engine size very close to the regulation cut off (engine size equal to 1.7 L or 1.8 L).[14] We refer to this group of vehicles as the switcher group as many vehicle models in this category are comparable in price and vehicle characteristics, such as horse power, weight and interior space. Thus consumers at the margin are likely to trade off in some vehicle features such as horse power and switch to smaller engine cars. We consider the small and medium groups as

[14]Only two models have a 1.7 L engine size and they are grouped into medium vehicles.

treatment groups and the large engine size group, consisting models with engine size above 1.8 L, as control group. Sales of large vehicle models are less likely to be influenced by the policy since the gap in prices and attributes of these vehicles are likely too big for consumers to substitute to small engine cars.

1.8 L is a reasonable cutoff dividing the medium and large vehicle groups as there is much overlap in price, segment type, and other vehicle features across the small and medium groups, but much less with the large group. First, price is one of the most important factors in vehicle purchase decisions. This is especially the case during the study period when the auto loan and financing system was not well developed in China and about 90% of new vehicle purchases were purchased with cash (Huang and Hecker 2015). Many of the 1.8 L models are priced roughly in the range of eligible models, especially 1.6 L models (Table 2.8). 1.9-2.0 L vehicles, however, are much more expensive, with the average price over 70% higher than that of 1.6 L models (251,000 RMB vs 147,000 RMB).

Second, 1.9-2.0 L vehicles also tend to be much larger, heavier and more powerful compared to eligible vehicles. In terms of segment types, over 85% of cars with 1.7-1.8 L engine size are classified as microcompact, subcompact or compact sedans, which are the primary segment types (96%) of eligible vehicles. 1.9-2.0 L vehicles, on the other hand, mainly consist of intermediate sedans, SUVs, and MPVs, while microcompact, subcompact or compact sedans take less than 12%. Moreover, the average horsepower of 1.9-2.0 L models is 35% higher than that of 1.6 L models. It is therefore relatively less likely that consumers who planned to buy 1.9-2.0 L models would be willing to switch to small cars during the policy.

Once the policy is implemented, we expect to see an upsurge in sales of small engine size cars. The increase might be induced by consumer behavior on two margins – vehicle choices (switching effect) or purchase timing (pull forward effect), with different implications for emission control. Fig. 2.4 illustrates the main potential policy impacts on consumer behavior. First, the switching effect refers to consumers who would have purchased a medium car but switch to an eligible car since the policy lowers the relative price of small engine size vehicles (Fig. 2.4, arrow 1). The switching effect is expected to be stronger when consumers originally plan to purchase vehicles with engine size slightly above the policy requirement but having other attributes similar to the eligible vehicle models. Consumers in this group contribute to carbon control through purchasing a more energy-efficient vehicle.

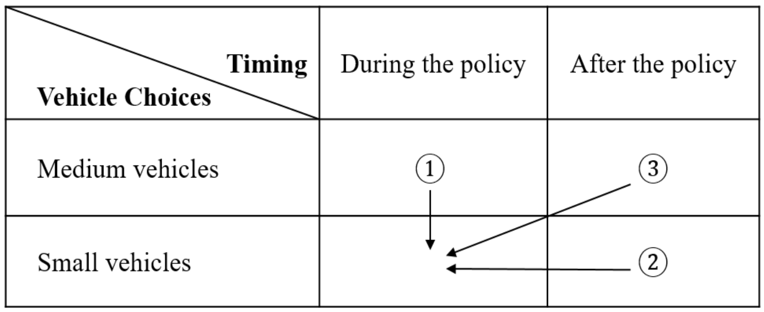

Figure 2.4: Potential Policy Impacts on Consumer Behavior. Rows represent the original vehicle choices and columns represent the timing. Arrows indicate the expected direction of the policy effects.

Second, the pull forward effect means that consumers who would have purchased a new car in the near future may bring forward their purchase to take the advantage of the policy. These include consumers who planned to buy a small car in the future (Fig. 2.4, arrow 2) or consumers who planned to buy a medium car in the future (Fig. 2.4, arrow 3). The former consumers would increase emissions, and the amount depends on the extent to which the policy stimulates demand from the future. The latter consumers adjust both their vehicle choices and purchase timing because of the policy, thus the impacts on emissions are ambiguous.

There might be another channel within the pull forward effects. The policy may induce consumers who never wanted to buy a car to make a purchase during the policy period. We believe this group of people is small because very few people in China use loans to buy cars during our study period. Given the price of a vehicle relative to the average income, the 5% tax reduction is expected to mainly influence consumers who are close buying a new car and have saved most of the money to make the purchase. After the policy is announced, they are then able to come up with the cash or credit needed to purchase a new vehicle. In any case, if this group is large, then we underestimate the effects on emissions.

We see suggestive evidence of the switching effect and pull forward effect by looking at the monthly sales of new vehicles falling into the three categories described above (Fig. 2.5). The logarithm of sales of vehicles in the three categories followed parallel trends before the policy was announced, which provides supporting evidence that the large vehicles group is a valid control group to vehicles in the other two categories. We do not observe a drop in sales of eligible models in the months right before the policy went into force, which suggests that consumers did not anticipate the tax cut, in which case they likely would have delayed their purchases by a few months. The sales of all cars were following a growing trend from 2006 to 2011, but a sudden jump in monthly sales of small engine size vehicles is visible immediately after the tax policy took force in January 2009. On the other hand, sales of large cars remain relatively stable over time.

Fig. 2.5 also provides evidences of the pulling forward effects. Absent the policy, annual sales of all vehicles peak in the month before the Chinese New Year.[15] During the policy period, peak sales of ineligible cars still occurred in January, but for small cars the peak is observed in December instead. This is due to the fact that the policy was expected to end in December and many consumers pulled forward their demand to take advantage of the discount.

[15] The Chinese New Year follows the lunar calendar, and most of the time it happens around February, so the peaks are usually in January.

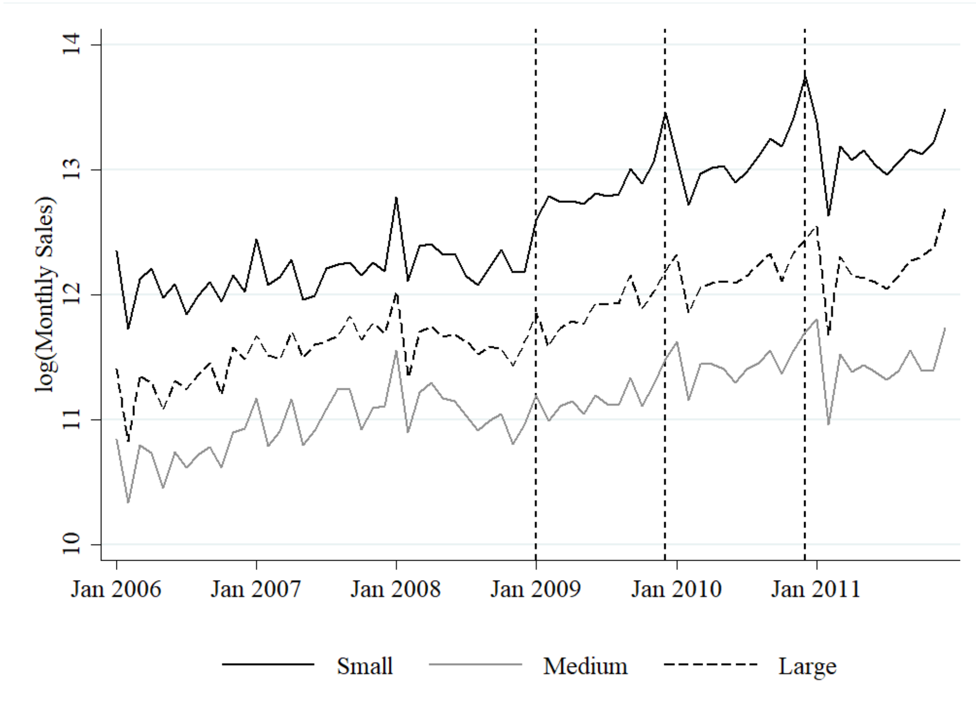

Figure 2.5: Monthly New Vehicle Sales by Engine Size Group (2006-2011). Vertical dashed lines indicate the start and end of the two year tax cut, and the announcement of the extension of the program with adjusted tax rate happened in December 2010.

2.4.2 Econometric Model

In the empirical analysis, we first estimate the switching effect and pull forward effect on new vehicle sales, then in Section 6, we further decompose the pull forward effect with some additional assumptions to estimate the impacts of policy on emissions.

To analyze the effects of the policy on new vehicle sales, we use a difference-in-difference framework, comparing sales of vehicle models with different levels of exposure to the policy before and after the policy was implemented. The regression model can be expressed as follow:

$$\begin{aligned} ln(Q_{mct}) =& \beta_1(Small_m \times Tax_t) + \beta_2(Medium_m \times Tax_t) \\ & + \beta_3 ln(FuelCost_{mct}) + \alpha_{cm} + \lambda_{ct} + \varepsilon_{mct}, \end{aligned} \tag{2.1}$$

where Q_{mct} is the monthly sales for a certain car model m in city c of year-month t. $Small_m$ and

$Medium_m$ are dummy variables for small and medium engine size vehicles. The omitted category consists of large vehicles with an engine size above 1.8 L. Tax_t is an indicator for the period during which the policy was in place, equal to 1 after Jan 2009 and 0 otherwise.

α_{cm} is a city-model fixed effect which not only captures time invariant model-specific attributes but also allows each city to have a unique preference for a specific vehicle model due to, for example, the city's geography (larger engine size vehicles might be more popular in cities located in mountainous areas), population density, or whether an automaker is located in the city. Furthermore, China is a large country covering various climatic zones. Thus, to control for the seasonality of vehicle sales in each city, a city-year-month fixed effect, λ_{ct}, is included.

We also control for the expected fuel costs, $ln(FuelCost_{mct})$, of each vehicle model, which play an important role in determining consumers' vehicle choices (Li et al. 2009; Klier and Linn 2010). An increase in gasoline price could reduce new car sales of less fuel efficient models, thus reducing sales of models with larger engine size. $ln(FuelCost_{mct})$ is the logarithm of the gasoline expenditure required to drive 100 km for each model, which is constructed based on monthly retail gasoline prices in different cities and the fuel use intensity of each vehicle model.

Based on the assumption that unobserved demand and supply shocks during the policy period are the same across the three groups, β_1 and β_2 estimate the average equilibrium effect of the tax cut on sales of small and medium vehicles, respectively. We believe that, from a policy design perspective, the equilibrium effect is the relevant estimate for analyzing the tax cut program. Based on an additional assumption that only consumers who planned to purchase vehicles with engine size barely above the policy cutoff would be willing to switch to small cars due to the policy, β_2 identifies the switching effect on sales (Fig. 2.4, 1), and $\beta_1 - \beta_2$ identifies the pull forward effect.

Next, in order to study how the policy effects evolve over time throughout the policy period, we employ a flexible difference-in-differences model that estimates a separate policy effect in each month. The regression model can be expressed as follows:

$$\begin{aligned} ln(Q_{mct}) = & \sum_{0}^{K} \beta_1^k (Small_m \times 1(t=k) + \sum_{0}^{K} \beta_2^k (Medium_m \times 1(t=k)) \\ & + \beta_3 ln(FuelCost_{mct}) + \alpha_m + \lambda_t + \varepsilon_{mct}, \end{aligned} \quad (2.2)$$

where k refers to each month between 2009-2011, and β_1^k and β_2^k are the coefficients of primary interest that capture the monthly policy effects on small and medium vehicles. This allows us to explore in more depth the intertemporal substitution effects of the policy.

2.5 Results

2.5.1 Effects on Sales

Table 2.2 presents our main regression results over different time horizons. Since the one-year tax cut in 2009 was unexpectedly extended to the end of 2010, but with a different rate, we first examine the effects of the first year of the tax cut (Model 1); next, we extend the sample to investigate the average effect on new vehicle sales during 2009 and 2010 and compare the effects during these two years (Columns 2 and 3). Across all three models, standard errors are clustered two-ways at the automaker and city level to allow the error terms to be correlated across models and over time within an automaker and within a city.

The results of Model 1 suggest that the 5% tax cut in 2009 increased sales of small cars by around 17% (about 160 small cars per city per month), while reducing sales of medium cars by 22% (about 36 medium cars per city per month).[16] The estimation results are robust across various specifications – controlling for vehicle segment sales trends, vehicle model age, or other national or local policies that might affect sales of different engine size groups (detailed

[16]The exact percentage value of the average effect on sales of small and medium cars was calculated by 100[exp(0.158)-1]≈17 and 100[exp(0.195)-1]≈22, respectively.]

discussions in Section 8).

When we extend the sample to 2010 (Model 2), the average policy effect on sales of small cars is no longer statistically different from zero. The increase in sales of small cars was mainly driven by the first year of the policy (Model 3). This could be explained through two channels. First, with the expectation that the tax reduction would end in December 2009, consumers who intended to purchase small cars or medium cars in 2010 may have pulled forward their demand and made the purchase in 2009. Second, the tax rate was raised from 5% to 7.5% in 2010, which may have been less attractive.

The coefficient estimate for fuel costs, $ln(FuelCost_{mct})$, is negative, as expected, but it is not significantly different from zero across all specifications. It is likely that the across vehicle model variations of fuel cost are largely absorbed by the model-year-month fixed effects since gasoline prices are adjusted at the same time by the same amount across the nation and the differences of gasoline price across cities is relatively small.

2.5.2 Effects on the Timing of Purchase

Fig. 2.6 and Fig. 2.7 plots the estimated policy effects on new car sales in each month after the tax cut was implemented using the average monthly sales before 2009 as the baseline (Fig. 2.6 plots the estimation parameters and Fig. 2.7 transforms the parameters to number of cars). The first year of the tax cut resulted in a significant increase in small engine car sales every month. The increase was the weakest in January, the first month when the policy implemented. This is probably because the policy began in late January (January 20) and it took a while for consumers to learn about it before the sales really took off in February. From February to December of 2009, the policy results in a U-shape trend in the effect on eligible car sales. This is consistent with the intuition that, at the beginning, consumers are excited about the new policy, while their enthusiasm cools down later on. However, consumers rush to make their purchases when approaching the end of the policy period, in expectation of a higher tax rate to follow.

Table 2.2: Average Policy Effects on Sales of Small and Medium Vehicles.

	(1) 2006–2009	(2) 2006–2010	(3) 2006–2010
Small $\times$ Tax	0.158**	0.096	
	(0.066)	(0.073)	
Medium $\times$ Tax	-0.195*	-0.237**	
	(0.100)	(0.108)	
Small$\times$ Tax2009			0.128*
			(0.072)
Small$\times$ Tax2010			0.060
			(0.079)
Medium$\times$ Tax2009			-0.204*
			(0.110)
Medium$\times$ Tax2010			-0.273**
			(0.115)
City-Model FEs	Yes	Yes	Yes
City-Year-Month FEs	Yes	Yes	Yes
Fuel Costs	Yes	Yes	Yes
N	1,843,687	2,559,697	2,559,697
Number of vehicles	20,304,815	29,979,661	29,979,661
adj. R^2	0.71	0.72	0.72

Standard errors in parentheses are clustered two-ways at the automaker and city level. Column 1 includes passenger vehicles sold between 2006 and 2009 while Column 2 and 3 extend the sample to include passenger vehicles sold in 2010 as well.* $p < 0.10$, ** $p < 0.05$,*** $p < .01$.

In the first quarter of 2010, sales of eligible cars significantly dropped. This might due to the fact that the policy was expected to end – many consumers who planned to buy cars in these months already made the purchase in 2009. Like the first year, the policy created another small car sales spike in the last month of the policy (December 2010).

On the other hand, the policy decreased sales of medium cars during the policy, and the reduction continued to exist even after the policy ended for at least 12 months. There are several possible explanations for this long term change in medium car sales. First, the policy shifted people's preferences towards small cars as more people realized the benefits in terms of fuel costs and convenience for parking or due to peer effects and so on. Second, in the long run, automakers can adjust their production agenda by cutting medium car production and reallocating their capital and labor towards producing more small cars or introducing new models with small engines. Furthermore, near the end of the two-year tax cut, the Chinese government launched a long term subsidy program (3,000 RMB/vehicle, about $440/vehicle) targeting certain car models with small engines starting from June 2010. This long run policy support for small vehicles might encourage more automakers to switch away from producing medium vehicles. This is likely to be the reason for decreasing sales of medium vehicle in 2011.

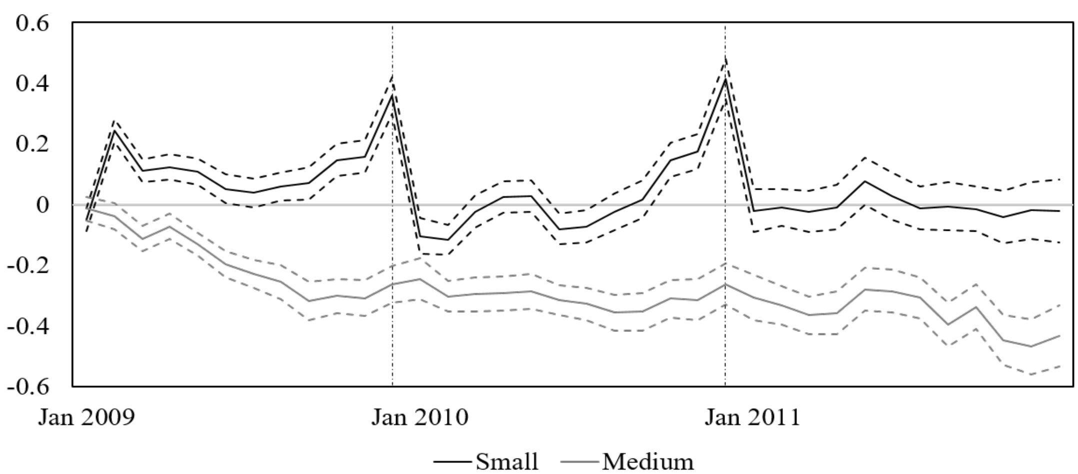

Figure 2.6: Sales Effect Parameter Estimates (with 95% C.I.). The plots show parameter estimates, β_1^k and β_2^k, in Eq. 2.2. The average monthly sales before 2009 is the baseline. Standard errors are clustered at the province-engine size level.

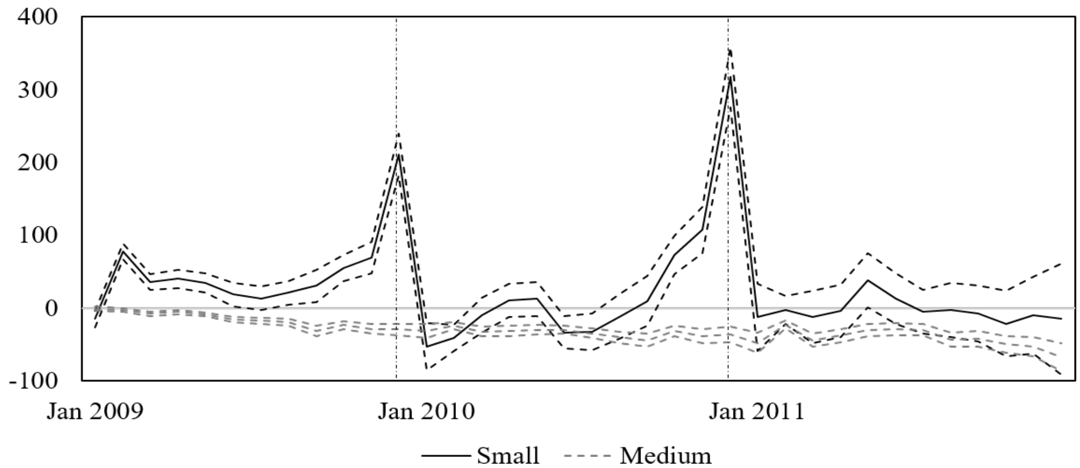

Figure 2.7: Sales Effect (in Thousands, with 95% C.I.). Policy effect on vehicle sales from January 2009 to December 2011. The estimates are based on parameter estimates in Eq. 2.2. The 95% confidence intervals are estimated using the Delta Method.

2.5.3 Effects on Carbon Emissions

This section evaluates how green the "green stimulus" measure was and whether the tax cut reached its environmental goal of reducing carbon emissions during the first year of the policy. We compare the observed emission outcomes with two plausible counterfactual outcomes: first, what would have happened to emissions in the absence of the program; second, what would have happened to emissions if the policy had been designed without the green component, i.e., if the Chinese government had only cared about stimulating automobile demand and implemented an across-the-board tax cut for all cars, holding constant the loss in tax revenue.

Counterfactual Scenario 1

As discussed in Section 4.1, the tax cut might affect vehicle sales through three main channels (illustrated in Fig. 2.4), each of which has a different impact on emissions. Group 1 (Fig. 2.4, 1) is expected to contribute to emission reduction in the long run by switching to more fuel-efficient cars. The reduction can be approximated by the following equation:

$$Emission_1 = (\overline{E}_{small} - \overline{E}_{medium}) \times VKT \times Lifespan \times Q_1, \tag{2.3}$$

where $\overline{E}_{small} - \overline{E}_{medium}$ is the difference in emissions between small and medium cars, VKT is annual vehicle kilometers traveled, $Lifespan$ is the average lifespan of a car, and Q_1 is the number of switchers.

Group 2 (Fig. 2.4, ②) is expected to increase emissions because consumers of this group previously commuted either by walking, biking or public transit. The increase in emissions depends on how far from the future the policy pulls forward demand for small cars and the average emission gap between small cars and public transportation over the pull forward period:

$$Emission_2 = (\overline{E}_{small} \times VKT - \overline{E}_{public}) \times \text{Time pulled forward} \times Q_2. \tag{2.4}$$

The emission effect of Group 3, is more complicated. On one hand, this group might contribute to emission reductions by switching to more energy efficient vehicles. On the other hand, it might increase emissions through intertemporal substitution. As a consequence, the net emission effect of Group 3 is unclear ex-ante, and can be estimated as

$$\begin{aligned} Emission_3 =& (\overline{E}_{small} \times VKT - \overline{E}_{public}) \times \text{Time pulled forward} \times Q_3 \\ &+ (\overline{E}_{small} - \overline{E}_{medium}) \times VKT \times Lifespan \times Q_3. \end{aligned} \tag{2.5}$$

The policy effect on emissions can be estimated by adding up the above three components. We are implicitly assuming that all the increase in sales of small cars induced by the policy are from the first car owners, i.e., these consumers would have used public transit absent the policy. This is a reasonable assumption because the car ownership in China during the study period was very low.[17]

[17]If the tax cut induces some car owners to purchase new small cars (they can either sell their old cars or keep

Table 2.3: Parameters for Emission Estimation

Parameter	Unit	Value
Average fuel economy of small cars	L/100km	7.15
Average fuel economy of 1.6L cars	L/100km	7.59
Average fuel economy of medium cars	L/100km	8.26
VKT	km/year	16900
Lifespan	year	10
$\overline{E}_{public}$	Metric ton CO_2/passenger/year	0.0013

How far from the future did the policy pull forward vehicle demand? To answer this question, recall that the tax cut could increase sales of small vehicles through consumers who planned to buy medium cars but switch to small cars, and consumers who planned to buy small or medium cars in the future who pull forward demand and make the purchase earlier. To estimate the pull forward window, we follow a similar procedure to that of Li et al. (2013) and Hoeskstra et al. (2017), who estimate the pull forward time for the Cash-for-Clunker program. We first estimate the total increase in the number of small cars during the policy. Then, we expand the time window sequentially to include more months after the policy and search for the month in which the total number of small car sales increased during the policy is offset by the decrease in small and medium car sales after the policy up to that point. This is based on the assumption that total sales of new vehicles in absence of the policy would be the same as the observed total sales. This assumption is reasonable since we cannot reject that the aggregate sales effect equals zero during 2011 (see Fig. 2.8). To formally estimate the pull forward window, we let γ be the maximum number of months from which the tax cut can pull forward demand, and estimate γ such that the following equation is satisfied:

both), then the change in emissions depends on the differences in fuel economy between the old and the new cars and how often the consumer drive them. Since new cars are more energy efficient due to improvements in fuel economy standards over time, the current analysis is likely to overestimate emissions. On the other hand, this might be offset by the higher VKT of new purchased cars due to the rebound effect (Small and Dender 2007). In any case, this group of consumers is likely to take only a small portion of the total increase in eligible cars since very few people own more than one car during the study period. According to the Chinese Household Financial Survey (see http://www.chfsdata.org/), of Chinese households with at least one vehicle in 2011, 89.64% own one vehicle, 8.18% own two vehicles, and 2.18% own three or more vehicles (these statistics are very different to those of the United States, where 37.6% of households own one vehicle, 41.3% own two vehicles, and 21.1% own three or more).

$$\underbrace{\int_{t=Jan2009}^{t=Dec2009} \Delta Q_t^s dt}_{\substack{\text{Sales effect on small cars}\\ \text{during the policy}}} + \underbrace{\int_{t=Jan2009}^{t=Dec2009} \Delta Q_{1t} dt}_{\substack{\text{Switcher effect}\\ \text{during the policy}}} + \underbrace{\int_{t=Jan2010}^{t=\gamma} \Delta Q_{2t} dt}_{\substack{\text{Pull forward effect}\\ \text{of small cars}}} + \underbrace{\int_{t=Jan2010}^{t=\gamma} \Delta Q_{3t} dt}_{\substack{\text{Pull forward effect}\\ \text{of medium cars}}} = 0 \quad (2.6)$$

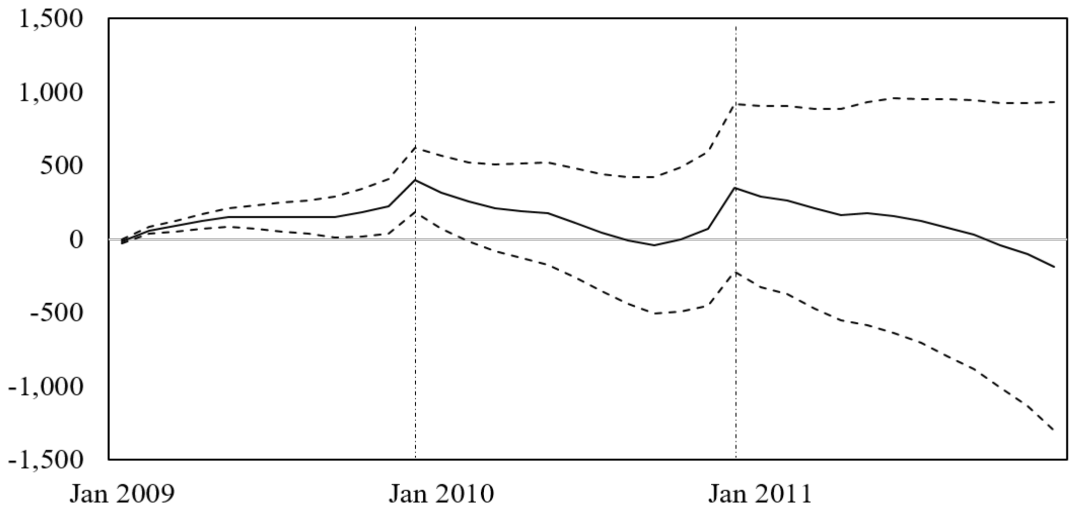

Figure 2.8: Aggregate Sales Effect (in Thousands, with 95% C.I.). Policy effect on aggregate vehicle sales from January 2009 to December 2011. The estimates are based on parameter estimates in Eq.2.2. The 95% confidence intervals are estimated using the Delta Method.

Based on the point estimates of Eq. 2.2, we find that the tax cut increased small car sales by about 600,000 during 2009, from which 190,000 (32%) come from the switcher effect. The rest of the increase is from pulling forward of either small cars or medium cars from the moths after the policy ended. γ is estimated to be 8 months, suggesting that the pull forward window is January to August 2010. The pull forward effect on small car sales and medium car sales is estimated to be 160,000 and 250,000, respectively. The policy is effective in inducing people to buy small cars. On the other hand, Fig. 2.7 suggests that the pull forward effect dominates approaching to the end of the policy (October to December 2010), and the effect is the strongest in December. While these effects are large, baseline small car sales are also large. The overall increase in small cars contributes only 12% of the total sales of small cars during 2009, implying that over 88% of the tax cut went to consumers who would have purchased a small car anyway.

The large fraction of inframarginal consumers suggest that the policy is not cost effective.

Table 2.3 presents the parameters used to estimate Eqs 4-6. The average emissions of small and medium cars are estimated based on their average fuel economy and the common conversion factor that burning 1 L of gasoline emits 0.0023 metric tons of CO_2. When calculating Eq. 2.3, to be conservative, we use the average fuel economy of 1.6 L cars (7.59 L/100km) as the average fuel economy of small cars since the substitution effects between medium and 1.6 L cars are stronger as they share similar characteristics (Section 6). Furthermore, we assume that the annual VKT is 16900 km (about 46 km/day), following Huo *et. al.* (2012). The regulated scrappage mileage for passenger vehicles is 600,000 km in China, however, most cars are scrapped long before reaching that mileage. Instead, we make the conservative assumption that the average lifespan of a car is 10 years, leading to a lifetime VKT for passenger cars of 169,000 km.[18] We also provide emission estimates under alternative cases where VKT and lifespan follow the estimation by the US Department of Transportation, National Highway Traffic Safety Administration that passenger cars should last roughly 20 years and travel a lifetime mileage of 126,665 miles (328,061 km).[19]

The average annual emissions from the public transit system per person, $\overline{E}_{public}$, are likely to be close to zero. This is because the number of consumers switching from public transit to cars due to the policy only make up a small portion of the total passengers served by the public transit system. Thus, they are unlikely to have a substantial influence on public transportation supply and related emissions. In this analysis, we assume that public transportation emits 0.00013 metric tons of CO_2 per passenger per year. This number is calculated based on an evaluation of a major bus and taxi company in Shenzhen (Shenzhen Green & Low-Carbon Development Foundation 2014).[20]

We consider three cases regarding how long consumers pull forward their demand in Eqs 5-6. As discussed in Section 5, the pull forward window is about 8 months after the first year

[18] Regulations on vehicle scrappage are accessible through the website of the Ministry of Commerce of China: http://www.mofcom.gov.cn/article/b/d/201301/20130100003957.shtml.

[19] https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/809952.

[20] The report is accessible through https://ets-china.org/.

of the policy ended, and the decrease in small and medium car sales after the policy could have been pulled forward to any month during the policy. Fig. 2.7 shows that demand is most likely to be pulled forward from the immediate months after the policy and the intertemporal substitution is likely to decay over time. Thus the average number of months pulled forward would likely range from a lower bound of 1 month to an upper bound of 8 months. The results from these two cases are likely to bound the true effects on carbon emissions. We also provide an emission estimation for the case where the average number of months pulled forward is assumed to be 4 months, which we think is closer to the reality.

Table 2.4 presents estimates for the change in CO_2 emissions due to the policy under different scenarios. The results suggest that the policy actually reduced emissions by between 0.4 and 2.2 million tons, equivalent to the annual emissions of about 70,000 to 380,000 people in China during the study period.[21] This is also equivalent to about 2 to 9 days worth of residential gasoline consumption in China.[22] Even though the reduction amount is not very large in magnitude, the stimulus policy did not, in fact, lead to a net increase in carbon emissions.

From January 2009 to August 2010, the sales tax revenue collected from newly sold small and medium cars was estimated to be 74 billion RMB based on the average price of small and medium cars (137,170 and 208,710 RMB). Absent the tax cut, total tax collected is estimated to be around 108 billion RMB, suggesting that the Chinese government spent around 34 billion RMB (about 5 billion USD) for this green stimulus program. The fiscal cost of CO_2 reduction is at least 2300 \$/ton. This is very large compared to the social cost of carbon estimated by the EPA (105 \$/metric ton of CO_2).[23] However, since the policy also provided stimulus benefits during the financial crisis, simply comparing the cost of the emissions reduction with other environmental policies that were only targeted at emission control, does not tell the full story. In Section 7.2, we

[21] China's CO_2 emissions per capita were estimated to be 5.72 metric tons in 2008. Data is available through https://data.worldbank.org/.

[22] Residential gasoline consumption in China is about 110 million L per day, emitting about 250 thousand metric tons of CO_2. Residential gasoline consumption is collected from the 2017 China Energy Statistic Year Book and the corresponding emission is estimated based on a factor of 0.0023 metric tons per liter of gasoline.

[23] See https://19january2017snapshot.epa.gov/climatechange/social-cost-carbon_.html.

discuss some evidence of other stimulus effects such as increasing employment in automakers with more exposures to the policy.

Counterfactual Scenario 2

In the second scenario, we estimate vehicle sales and related emissions if the government had ignored the green component of the stimulus policy and implemented a 5% tax cut for all cars, keeping the amount of stimulus budget constant.

We conduct a back-of-the-envelope calculation of the counterfactual sales based on several plausible assumptions. First, we only focus on the pull forward effects induced by the policy and assume zero cross product substitution when the government reduces the sales tax from 10% to 5% for all cars. This is likely to provide a lower bound on emissions since the across-the-board tax cut is likely to induce consumers to switch to larger engine size vehicles.

In Section 5.3, we estimated that the 5% tax cut pulled forward the purchase of about 155,000 small vehicles from the following 8 months after the policy ended. This is a 3.7% increase in sales due to only the pull forward channel.[24] We assume that the pull forward effects of medium and large cars experience the same pull forward effects as small cars under the true policy, i.e., the across-the-board tax cut would increase sales of all cars by 3.7% due to intertemporal substitution.

Based on the above assumptions, we find that the stimulus budget can support an across-the-board tax cut for 9 months. Based on the counterfactual sales of small, medium and large cars during the policy, we estimate the related CO_2 emissions under different pull forward periods in Table 2.4.

[24] 155150/4182847=0.037, where 4,182,847 is the total sales of small cars in 2009 absent the tax cut.

Table 2.4: Emission Results

	Scenario 1	Scenario2
	$E_{true} - E_{scenario1}$	$E_{true} - E_{scenario2}$
Panel 1: Lifetime VKT=169000 km		
Case 1: Time pull forward=1 month	-1,045	-1,086
Case 2: Time pull forward=4 month	-765	-927
Case 3: Time pull forward=8 month	-393	-717
Panel 2: Lifetime VKT=328061 km		
Case 4: Time pull forward=1 month	-2,164	-2216
Case 5: Time pull forward=4 month	-1,802	-2011
Case 6: Time pull forward=8 month	-1,351	-1769

Note: $E_{true} - E_{scenario1}$ reports the net emissions induced by the true policy compared with emission outcomes under Scenario 1. $E_{true} - E_{scenario2}$ reports the net emissions induced by the true policy compared with emission outcomes under Scenario 2.

2.5.4 Heterogeneity

In this section, we exploit our rich dataset to investigate differential policy effects across eligible models and cities.

Heterogeneity Across Vehicle Models

Estimation results in the previous section suggest that the 5% tax cut in 2009 substantially increased sales of small cars, however, the effects might vary across different eligible models. Which group of small cars benefit the most from the tax cut? We expect a larger increase in sales as the engine size of a vehicle model gets closer to the eligibility cut off. There are two reasons for this hypothesis. First, consumers who planned to buy small cars in the absence of the policy might switch to cars that have bigger engines, but are still eligible for the policy. Second, consumers who planned to buy medium cars in absence of the policy are more likely to switch to eligible cars with similar attributes. As a consequence, sales of 1.6 L cars would increase due to consumers switching from either smaller or larger engine size groups. To test this hypothesis, we categorize eligible cars into three groups based on their engine size and estimate policy effects for each group. Estimation results in Table 2.5 reveal that the sales increase for 1.6 L vehicle models is larger than other eligible models.

Table 2.5: Heterogeneous Policy Effects Across Eligible Vehicles

	(1)
0-1.3× Tax	0.000
	(0.078)
1.4-1.5× Tax	0.214*
	(0.117)
1.6× Tax	0.238***
	(0.089)
Medium× Tax	-0.194*
	(0.099)
City-Model FEs	Yes
City-Year-Month FEs	Yes
Fuel Costs	Yes
N	1,780,123
Number of vehicles	19,694,297
adj. R^2	0.71

* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Heterogeneity Across Cities

We explore the distributional effects of the tax cut across cities with different socioeconomic conditions in Table 2.6. Environmentally oriented tax incentives including for hybrid and electrical vehicles and adoption of solar panels have long been criticized for subsidizing the wealthy at the cost of all taxpayers (Allcott et al. 2015, Borenstein and Davis 2016). Which income group benefits the most from this tax incentive program is an important but challenging question to answer. Unfortunately, we do not have access to data on the socioeconomic characteristics of program recipients. We instead address this issue by exploring the level of economic wellbeing of different cities.

In Columns 1-2 of Table 2.6, we use GDP per capita and share of urban population to measure the level of economic development in different cities. The estimation results suggest that cities with lower GDP per capita and that are less urbanized have larger increases in sales of small cars due to the policy; on the other hand, richer cities have larger switcher effects. There are two possible reasons. First, richer cities often have higher population density, more existing cars, more congestion, and limited parking space, making switching to small cars potentially more attractive. Second, the policy effect on sales may also depend on the existing market for small and medium cars. Richer cities may experience smaller increase in small car sales because existing small car shares might already be high, leaving less people to potentially purchase small cars. In less developed cities, the switcher effects may be small because fewer consumers planned to purchase medium cars. We additionally consider using population density and existing shares of small cars in Columns 3-4, and the results are again consistent with our expectations. The results suggest that the tax savings were not necessarily regressive, but targeted proportionally more of the benefits to less developed cities.

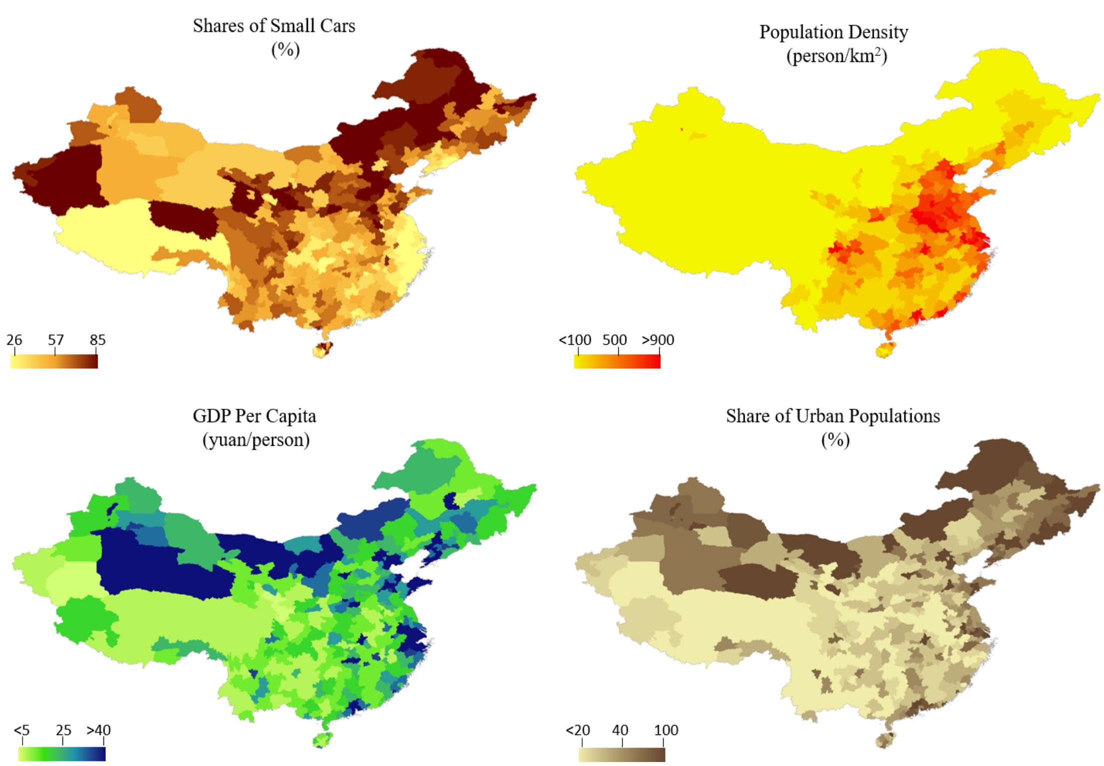

Figure 2.9: City Characteristics

Table 2.6: Heterogeneous Policy Effects Across Cities

	(1) GDP	(2) Urban	(3) Density	(4) Small Car Share
Small × Tax	0.216***	0.198***	0.217***	0.087
	(0.060)	(0.064)	(0.060)	(0.074)
Small × Tax × High GDP	-0.090**			
	(0.043)			
Small × Tax × Urban		-0.068**		
		(0.032)		
Small × Tax × High Density			-0.092**	
			(0.044)	
Small × Tax × High Small Car Share				0.147***
				(0.034)
Medium × Tax	-0.110	-0.126	-0.106	-0.234**
	(0.070)	(0.086)	(0.075)	(0.117)
Medium × Tax × High GDP	-0.134**			
	(0.057)			
Medium × Tax × Urban		-0.125***		
		(0.032)		
Medium × Tax × High Density			-0.142**	
			(0.055)	
Medium × Tax × High Small Car Share				0.084*
				(0.047)
N	1,780,123	1,780,123	1,780,123	1780123
Number of vehicles	19,694,297	19,694,297	19,694,297	19,694,297
adj. R^2	0.71	0.71	0.71	0.71

Standard errors in parentheses are clustered two-ways at the automaker and city level. Column 1-4 examine whether the policy effects various depending on GDP per capita, share of urban population,population density, and market share of small car during the pre-policy period. * $p < 0.10$, ** $p < 0.05$,*** $p < .01$.

2.6 Robustness Checks

Table 2.7 reports regression estimates from four alternative specifications. Column 1 shows results of our base specification of Eq.2.1. In order to control for the national-wide decline/increase of a certain vehicle segment (sedans, SUVs, MPVs, and light trucks) over time (for example, the increasing popularity of SUVs), we control linear and quadratic segment time trend in Model 2. Moreover, different vehicle models are introduced to the market at different times, and the popularity of a vehicle model might be correlated with the time it exists in the market. To control for such sales pattern of each model, we introduce model age and age squared in Model 3. So far, all models we present in the paper use samples excluding vehicle models with engine size over 2.5 L for reasons discussed in Section 3. In Model 4 and Model 5, we check whether the estimation results are sensitive to relaxing or removing the engine size restrictions. In Model 4, we run the base model with extended samples consisting all vehicle models within engine size no larger than 3 L. Furthermore, in Model 5, we completely remove the restrictions on engine size and include all vehicle models. The estimation results are largely stable across different specifications.

To verify that a single city is not driving the tax cut results, we run the base model regressions excluding each city in turn. The coefficient on β_1 varies from 0.157 (SE=0.066) to 0.161 (SE=0.066) and the coefficient on β_2 varies from -0.196 (SE=0.100) to -0.193 (SE=0.099).

2.7 Conclusion

We examine the effectiveness of a large-scale fiscal policy in China targeted at stimulating auto demand while at the same time incorporating the green objective of inducing consumers to buy energy efficient vehicles. A difference-in-differences design is employed to investigate the impacts of the tax cut on stimulating new vehicle purchases over different time horizons as well as its impacts on emissions.

Table 2.7: Alternative Specifications.

	(1)	(2)	(3)	(4)	(5)
	Base	Segment	Model	Extended Sample	
	Model	Trend	Age	0 - 3 L	All Vehicles
Small× Tax	0.1582**	0.1462**	0.1434**	0.1825***	0.1887***
	(0.0665)	(0.0699)	(0.0687)	(0.0654)	(0.0651)
Medium× Tax	-0.1954*	-0.1933*	-0.2206**	-0.1703*	-0.1637*
	(0.0999)	(0.1072)	(0.1065)	(0.0978)	(0.0973)
Segment Trend		Yes			
Model Age			Yes		
N	1,843,687	1,843,687	1,843,687	1,945,872	1,980,279
Number of vehicles	20,304,815	20,304,815	20,304,815	20,699,542	20,801,890
adj. R^2	0.71	0.71	0.71	0.71	0.71

All models consist passenger vehicles sold in 200 and control for fuel costs, City-Model FEs and City-Year-Month FEs. Standard errors in parentheses are clustered two-ways at the automaker and city level. Column 1-3 restrict samples to vehicles with engine size less than or equal to 2.5 L. Column 4 extends the sample to include vehicle models with engine size no larger than 3 L, and Column 5 completely removes the restrictions on engine size to includes all vehicle models. * $p < 0.10$, ** $p < 0.05$,*** $p < .01$.

The tax cut played a significant role in stimulating auto demand, boosting sales of eligible vehicles while reducing sales of similar but ineligible vehicles. It induced a substantial amount of intertemporal substitution – about 70% of the increase in sales observed during the policy was pulled forward from the following eight months. Unlike subsidies for greener products such as solar panels, hybrid or electrical vehicles that have often been criticized as regressive, the tax cut had stronger effects in stimulating demand for eligible cars in less developed regions of China.

Overall, the policy reduced CO_2 emissions compared to what would have happened absent of policy, though it was expensive from the perspective of a pure environmental policy. This is because the program was not successful in targeting marginal consumers – most buyers under the program would have bought a new vehicle anyway. In practice, however, the policy should not be viewed as a pure environmental policy – China would likely have chosen to stimulate demand in any case. Rather, it should be viewed as a means of mitigating some of the negative environmental consequences of stimulus, and should be compared to alternative stimulus packages with different or no green measures. Compared to an alternative counterfactual scenario of stimulus with no green element, in which the government implements an across-the-board tax cut with the same fiscal cost, net emission savings would have been larger by about 20%.

Our findings thus show that green stimulus is capable of achieving “win-win” outcomes by reducing emissions despite increasing the number of cars. A remaining question is whether other environmental measures could have been chosen that would have reduced emissions even further. While green stimulus is a relatively new phenomenon and few comparable policies have been implemented, our results provide several insights that should be considered in the future. To improve the targeting of marginal rather than inframarginal consumers, it might be desirable to tighten the eligibility requirements by combining engine size rules with other features such as fuel economy. For example, the tax cut could be greater for small cars with higher fuel economy. Also, our findings suggest important distributional effects. By allowing the policy to vary at the local level, rather than having a uniform national policy, it might be possible to more finely target places with greater economic or environmental needs.

We provide the first evidence on the effectiveness of a major green stimulus program during the Global Financial Crisis in a developing country context. With climate change, treaties targeted at reducing emissions are a key and increasingly prominent issue in international politics, and many developing countries are among the largest polluters. Most international treaties include a significant fiscal policy element and, moreover, allow for different contingencies such as recessions. Understanding how such policies should be designed will remain an important task.

2.8 Appendix

2.8.1 Additional Figures and Tables

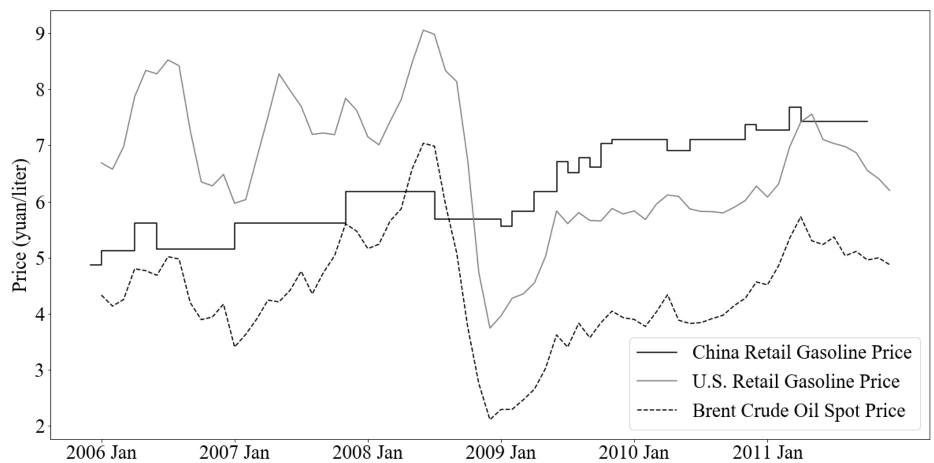

Figure 2.10: Average Monthly Gasoline Price (2006-2011). Prices are in 2017 yuan. Monthly data of U.S. retail gasoline prices and Brent crude oil spot prices are collected from U.S. Energy Information Administration.

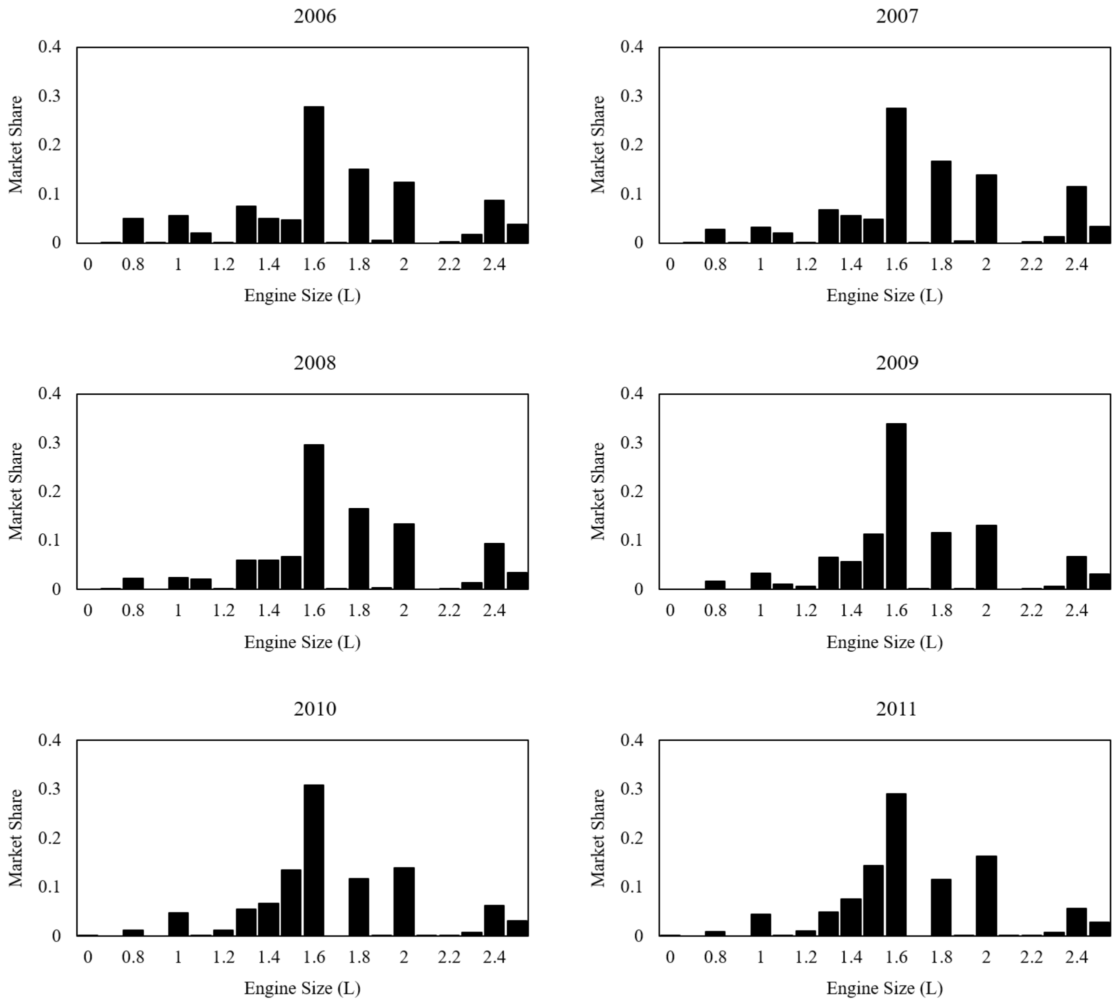

Figure 2.11: Market Share of New Vehicle Sales by Engine Size Group (2006-2011)

Table 2.8: Vehicle Model Characteristics by Engine Size

Group	**Engine Size** (L)	**MSRP** (1000RMB)	**Fuel Econ.** (L/100km)	**HP** (hp)	**Weight** (1000kg)	**Volume** (m^3)	**Segment**			**Brand Origin**					**Best-selling Models**
							Sedan	SUV	MPV	China	Japan	Europe	US	Korea	
	≤1.0	54.99	5.76	56.80	0.87	8.35	0.97	0.00	0.03	0.80	0.11	0.00	0.09	0.00	FAW Xiali, Chery QQ, BYD F0
Small	1.1-1.3	74.33	6.78	84.16	1.01	9.70	0.93	0.04	0.03	0.67	0.22	0.00	0.09	0.02	Geely Gleagle CK, Suzuki Antelope, Chevrolet Sail
	1.4-1.5	101.80	6.93	102.83	1.14	10.81	0.95	0.00	0.05	0.46	0.18	0.16	0.11	0.08	BYD F3, VW Polo, Chevrolet Lova
	1.6	147.12	7.54	108.25	1.23	11.32	0.98	0.01	0.01	0.12	0.23	0.34	0.14	0.16	Hyundai Elantra, Buick Excelle, VW Jetta
Medium	1.7-1.8	205.67	8.09	132.14	1.35	12.00	0.94	0.04	0.03	0.15	0.19	0.44	0.21	0.02	VW Santana, Ford Focus, VW Passat
	1.9-2.0	251.40	8.66	146.12	1.49	12.95	0.69	0.28	0.03	0.15	0.37	0.25	0.08	0.15	Honda Accord, Mazda 6, Toyota Camry
Large	2.1-2.4	314.90	9.73	162.35	1.63	13.96	0.59	0.31	0.10	0.17	0.53	0.09	0.20	0.01	Toyota Camry, Buick LaCrosse, Honda Accord
	2.5	360.65	9.63	182.26	1.63	13.32	0.79	0.11	0.09	0.08	0.66	0.14	0.12	0.00	Toyota Reiz, Nissan Teana, Toyota Crown

Notes: This tables presents the average value (weighted by annual sales) of major characteristics of vehicle models by engine size in 2006-2011. Data presented in the table covers all 2,621 vehicle models in our sample, of which 1211 models are eligible for the tax cut, 323 models are classified as medium vehicles, and 1,087 models are classified as large vehicles.

Chapter 2, in full, is currently being prepared for submission for publication of the material. Fanglin Sun; Rudai Yang; Dong Yuan "Green Stimulus: Tax Incentives in China's Automobile Market." The dissertation author was the primary investigator and author of this material.

2.9 References

Allcott, Hunt, Christopher Knittel, and Dmitry Taubinsky. 2015. "Tagging and Targeting of Energy Efficiency Subsidies." American Economic Review 105 (5): 187-91.

Barbier, Edward. 2010. "How is the Global Green New Deal Going?" *Nature* 464 (7290): 832.

Bloom, Nicholas. 2014. "Fluctuations in uncertainty." *Journal of Economic Perspectives* 28 (2): 153-176.

Borenstein, Severin, and Lucas W. Davis. 2016. "The Distributional Effects of US Clean Energy Tax Credits." *Tax Policy and the Economy* 30 (1): 191-234.

Chen, Yuyu, Ginger Zhe Jin, Naresh Kumar, and Guang Shi. 2013. "The Promise of Beijing: Evaluating the Impact of the 2008 Olympic Games on Air Quality." *Journal of Environmental Economics and Management* 66 (3): 424-443.

Chen, Chia-Wen, Wei-Min Hu, and Christopher R. Knittel. 2017. "Subsidizing Fuel Efficient Cars: Evidence from China's Automobile Industry." No. w23045. National Bureau of Economic Research.

Copeland, Adam, and James Kahn. 2013. "The Production Impact of "Cash-for-Clunkers": Implications for Stabilization Policy." *Economic Inquiry* 51 (1): 288-303.

Davis, Lucas W., and Christopher R. Knittel. 2016. "Are Fuel Economy Standards Regressive?" No. w22925. National Bureau of Economic Research.

Haugh, David, Annabelle Mourougane, and Olivier Chatal. 2010. "The Automobile Industry in and Beyond the Crisis." *OECD Economics Department Working Papers*, No. 745, OECD Publishing, Paris.

Hoekstra, Mark, Steven L. Puller, and Jeremy West. 2017. "Cash for Corollas: When Stimulus Reduces Spending." *American Economic Journal: Applied Economics* 9 (3): 1-35.

Huang, John and Macro Hecker. 2016. "2015 China Auto Finance Report." Deloitte China Automotive Service. https://www2.deloitte.com/cn/en/pages/manufacturing/articles/auto-finance-white-paper-2015.html.

Huo, Hong, Qiang Zhang, Kebin He, Zhiliang Yao, and Michael Wang. 2012. “Vehicle-use Intensity in China: Current Status and Future Trend.” *Energy Policy* 43: 6-16.

International Labour Organization. 2011. “Green Stimulus Measures.” European Commission and the International Labour Organization joint discussion paper series No.15. https://www.ilo.org/global/lang–en/index.htm

Klier, Thomas, and Joshua Linn. 2010. “The Price of Gasoline and New Vehicle Fuel Economy: Evidence from Monthly Sales Data.” *American Economic Journal: Economic Policy* 2 (3): 134-153.

Li, Shanjun, Christopher Timmins, and Roger H. Von Haefen. 2009. “How do Gasoline Prices Affect Fleet Fuel Economy?” *American Economic Journal: Economic Policy* 1 (2): 113-137.

Li, Shanjun, Joshua Linn, and Elisheba Spiller. 2013. “Evaluating “Cash-for-Clunkers”: Program Effects on Auto Sales and the Environment.” *Journal of Environmental Economics and Management* 65 (2): 175-193.

Li, Shanjun. 2017. “Better Lucky Than Rich? Welfare Analysis of Automobile Licence Allocations in Beijing and Shanghai.” *The Review of Economic Studies* 85 (4): 2389-2428.

Li, Shanjun, and Chao D. Wei. 2013. “Green Stimulus: A Dynamic Discrete Analysis of Vehicle Scrappage Programs.” Working paper.

Mian, Atif, and Amir Sufi. 2012. “The Effects of Fiscal Stimulus: Evidence from the 2009 Cash for Clunkers Program.” *The Quarterly Journal of Economics* 127 (3): 1107-1142.

Oliver, Hongyan H., et al. 2009. ”China’s Fuel Economy Standards for Passenger Vehicles: Rationale, Policy Process, and Impacts.” *Energy Policy* 37 (11): 4720-4729.

Robins, Nick, Robert Clover, and D. Saravanan. 2010. “Delivering the Green Stimulus.” *HSBC Global Research, New York*.

Robins, Nick, Robert Clover, and Charanjit Singh. 2009. “A Climate for Recovery: The Colour of Stimulus Goes Green.” HSBC Global Research 25: 1-45.

Small, Kenneth A., and Kurt Van Dender. 2007. “Fuel efficiency and motor vehicle travel: the declining rebound effect.” *The Energy Journal*: 25-51.

Tang, Rachel. 2009. “The Rise of China’s Auto Industry and Its Impact on the US Motor Vehicle Industry.” *Federal Publications*: 688.

Tinbergen, Jan. 1952. “On the Theory of Economic Policy.”

United Nations Environment Programme. 2009. “Global Green New Deal: An Update for the G20 Pittsburgh Summit.” http://wedocs.unep.org/handle/20.500.11822/7736.

Viard, V. Brian, and Shihe Fu. 2015. ”The Effect of Beijing’s Driving Restrictions on Pollution and Economic Activity.” *Journal of Public Economics* 125: 98-115.

Xiao, Junji, and Heng Ju. 2014. “Market Equilibrium and the Environmental Effects of Tax Adjustments in China’s Automobile Industry.” *Review of Economics and Statistics* 96 (2): 306-317.

Chapter 3

Extreme Temperatures and Time Use in China

Abstract: How do the poor in developing countries respond to extreme temperatures? Using individual-level panel data over two decades and relying on plausibly exogenous variation in weather, we estimate how extreme temperatures affect time use in China. Extreme temperatures reduce time spent working, and this effect is largest for female farmers. Hot days reduce time spent by women on outdoor chores, but there are no compensatory increases by men. Finally, hot days dramatically reduce time spent on childcare, reflecting large effects on home production. Taken together, our results suggest time use is an important margin of response to extreme temperatures.

3.1 Introduction

Despite a growing interest amongst economists and social scientists in the effects of extreme temperatures, evidence remains concentrated in developed countries. The relative scarcity of evidence in developing countries limits our understanding of the economic damages from rising temperatures in two important ways (Greenstone and Jack, 2015; Jack, 2017). First, damage functions in developing countries may differ because of income differences, non-linearity in dose-response functions (Hsiang *et al.* 2019), and differences in the availability and adoption of adaptation technologies (Graff-Zivin and Neidell 2014). Second, responses in home production and informal labor markets may be substantially more important in developing countries.

In this paper, we use individual-level panel data from nine major provinces in China to estimate the causal effect of extreme temperatures on time use. This unique data set was constructed by confidential matching of gridded weather data with a geolocated panel of households tracked over two decades, from 1989 to 2011. To recover the causal effects of extreme temperatures, we use random daily variation in weather faced by individuals over time, conditional on individual and space-time fixed effects. We report three principal findings. First, extreme temperatures negatively affect time spent working, but there is substantial heterogeneity on dimensions of research and policy interest. Effects are larger amongst farmers, particularly female farmers. Second, extreme heat reduces time spent by women on household chores, with no compensatory increases by men. Finally, time spent on childcare falls by almost 30% for every additional day with an average temperature above 80°F, but this effect is only present in households without cooling technologies.

Our research makes several contributions to the literature. First, we add to a small body of evidence on the effect of extreme temperatures on poor populations in developing countries.[1] Within this literature, to the best of our knowledge, we are the first to examine how heat affects allocation of the time budget, which is especially important in households with small cash budgets.[2] Second, this paper is among the first to study optimizing time-use responses to an exogenous shock using panel data.[3] Previous work in this space has relied on using repeated

[1]For a non-exhaustive list, see Burgess et al. (2017); Geruso and Spears (2018) on mortality, Colmer (2018); Santangelo (2016) on labor reallocation, Fishman, Carrillo and Russ (2019); Garg, Jagnani and Taraz (2018) on human capital, Chen and Yang (2017); Zhang et al. (2018) on industrial output and Masuda et al. (2019); Somanathan et al. (2015) on labor productivity. For a broader review, see Heal and Park (2016).

[2]See Graff-Zivin and Neidell (2014) for the effects of temperature on time-use in the United States.

[3]Krueger and Mueller (2012) use a panel to examine time-use responses to endogenous reemployment. Cherchye,

cross-sections (Garg, Jagnani and Taraz, 2018; Graff-Zivin and Neidell, 2014). By instead using a panel, we are able to rule out time-varying sample selection correlated with the treatment of interest. Third, our estimated weather effects provide a lower bound on the magnitudes of climate effects. Lemoine (2018) shows that the effect of climate on costly adaptive actions, like changes in time allocation, can be approximated by the sum of responses to forecast and realized weather. For agents with plausibly low cost of time-use change, like farmers, forecasts are less important and our estimates approach the effect of long-run climate changes. Finally, we investigate the heterogenous effects of temperature by gender: our finding that women's time use is more sensitive to extreme temperatures than men's has important implications for the distribution of damages from extreme temperatures.

3.2 Data

Data on Time Use: We obtain time-use data from the China Health and Nutrition Survey (CHNS), an ongoing large-scale longitudinal survey. It is conducted by the Carolina Population Center at the University of North Carolina at Chapel Hill and the National Institute for Nutrition and Health at the Chinese Center for Disease Control and Prevention. The baseline data was collected in 1989 and nine subsequent surveys have been implemented every two to four years since. The survey uses a multistage, random-clustered sampling process to draw a sample from nine provinces and six large cities, covering about 7,200 households with over 30,000 individuals.[4]

The CHNS is valuable for our empirical analysis for two reasons. First, though the CHNS instruments were mainly designed to investigate the health and nutrition status of Chinese families, one section of the survey collects data on individuals' time allocation to working, household chores, childcare and other activities. Most of the questions relating to time allocation to a specific

De Rock and Vermeulen (2012) study household labor supply using panel time-use data, with identifying variation from the number and age of children.

[4]Detailed descriptions of the survey design and sample profiles are available through *https://www.cpc.unc.edu/projects/china* and Popkin et al. (2010).

activity are framed as, for instance, "during the past week, for how many hours did you work" or "during the past week, how much time (minutes) did you spend per day, on average, to prepare and cook food for your household."[5] Our analysis focuses on data collected from nine rounds of the CHNS, conducted from 1989 to 2011. When analyzing temperature impacts on time spent on childcare, household chores and working, we use data from survey years 1989-2011, 1997-2011, and 1991-2011, respectively, depending on the availability of the questions on time use. Importantly, each interview date is known, which allows us to link the interview date with weather data to capture how individuals' time use responds to short-run weather variation. In Appendix Tables 3.1, 3.2, and 3.3 we provide descriptive statistics on the datasets used to estimate the effects on work, household chores and childcare respectively.

Second, CHNS covers a large sample size from different climate zones which allows us to obtain greater spatial variation in temperature exposure. There is substantial spatial variation in weather conditions in China (see Appendix Figure 3.6). Our sample covers 13,769 individuals from nine provinces: Heilongjiang, Liaoning, Shandong, Henan, Jiangsu, Hubei, Human, Guangxi, and Guizhou, which are highlighted in Appendix Figure 3.6.[6]

Weather Data: Weather data, including temperature, precipitation, and relative humidity at the daily level are collected from the ERA-Interim archive, which is a global atmospheric reanalysis dataset constructed by the European Centre for Medium-Term Weather Forecasting (Dee et al., 2011). This dataset provides consistent estimates of weather conditions from 1979 to the present. Our analysis uses ERA-Interim weather data on a 0.125 x 0.125 degree latitude-longitude grid from 1989 to 2011. For each county, we construct the daily average temperature, daily total rainfall, and daily mean relative humidity by averaging over all weather grid points within the county boundaries. There is reasonable agreement in the environmental economics

[5] While the survey question is somewhat ambiguous on whether respondents interpret the question as the previous calendar week or the past seven days, research in survey methods suggests that most respondents interpret such questions as the "past seven days" (Gryczynski et al., 2015). As a robustness check, we also consider the previous calendar week. The results are qualitatively similar.

[6] Three large cities, Beijing, Shanghai, and Chongqing, are excluded from our samples because CHNS sampled them only in 2011.

literature that use of such reanalysis data is the preferred way to consistently estimate marginal effects of weather (Auffhammer et al., 2013; Schlenker and Lobell, 2010). Appendix Figure 3.7 shows the spatial distribution of temperature in the nine provinces covered by the CHNS survey during the study period.

Linked Temperature-Time Use Data: The county-level household locations recorded by the CHNS are confidential. To merge the weather data to the CHNS data, we submitted our county-level weather data and a data linkage request to the Carolina Population Center at the University of North Carolina (CPC). CPC in turn provided us the matched dataset with anonymized county identifiers with one caveat: to prevent backward induction of county identities, CHNS introduced small random errors in our weather variables. Since this is classical measurement error and small by construction, the resulting attenuation bias is minimal. In Appendix Table 3.4, we compare descriptive statistics from our original weather data and the linked CPC data; they are strongly similar.

3.3 Research Design

To investigate how temperature influences individuals' time-allocation decisions, we flexibly estimate the effect ofweather theweek prior to the interviewon time use during the same time frame following the approach laid out in Deschênes and Greenstone (2011) and Hsiang (2016):

$$ActivityTime_{icpwmy} = \sum_{k=1}^{K} \beta_k Tempbin^k_{cpwmy} + \delta Z_{cpwmy} + \xi X_{icpy} + \alpha_i + \lambda_{ym} + \gamma_{pm} + \varepsilon_{icpwmy}$$

where $ActivityTime_{icpwmy}$ is the number of hours allocated to a given activity for individual i, in county c of province p, during week w in month m of year y. The variable $Tempbin^k_{cpwmy}$

measures the number of days in the bin that an individual is exposed to during week w in month m of year y. To construct $Tempbin^k_{cpwmy}$, we first group the average daily temperature of the county where the individual lives into 13 temperature bins, with the hottest bin covering temperatures above 80°F, the coldest bin covering temperature below 25°F, and 5°F temperature increments in-between. Second, we count the number of days experienced by the individual living in county c of each temperature bin k during week w in month m of year y. The 56-60°F temperature bin is omitted. The coefficient β_k can be interpreted as the marginal effect of shifting a day from the reference bin (56-60°F) to bin k (for example, above 80°F).

Individual fixed effects are represented by α_i and capture all time-invariant observable and unobservable individual attributes that affect time allocation decisions. The λ_{ym} are year-month fixed effects to control for nationwide trends in time spent on working, household chores and childcare. Since people living in different climate zones might, for example, harvest crops at a different time, our model also includes province-month fixed effects, γ_{pm}, to control for seasonal trends.

Z_{cpwmy} includes county-level weather controls that might be correlated with temperature, including precipitation, humidity, and sunset time. To allow flexible relationships between precipitation and time allocation, we create 11 precipitation bins with 0.1 inches per bin. We also control for quadratic polynomials in average relative humidity and average sunset time during week wmy.

X_{icpy} includes individual-level controls that may be related to time allocation preferences. This includes linear and quadratic terms for age, employment status, years of education, annual net household income of individual i, and the ownership of cooling technologies, fridges and washing machines. Some of these variables are likely endogenous and the corresponding coefficients cannot be interpreted causally. These controls are included to improve precision.

Our parameters of interest, β_k, reflect behavioral responses to short-run temperature variations. The identifying assumption is exogeneity of daily average temperature with respect to time-varying unobservable determinants of time use, conditional on a battery of fixed effects and other weather variables. Intuitively, the identifying variation in temperature comes from unusual or unseasonable weather not captured by these controls. Standard errors are clustered at the county level.

3.4 Results

In this section we document how poor communities in China adjust their time use in response to extreme temperatures. We report three principal findings: (1) extreme temperatures reduce overall time spent working, and this effect is most pronounced for agricultural work; (2) extreme heat particularly reduces time spent by women on household chores; and (3) time spent on childcare is sensitive to extreme heat, but this effect is only present in households without cooling technologies like fans and air-conditioners. Finally, we discuss a number of checks on the robustness of our results.

Time Spent Working: In Figure 3.1, we show the results by temperature bin on the overall time spent working across all adults in our sample. As noted in Section 3.3, we interpret each coefficient as the marginal effect of one day in a given week being moved from the omitted bin (60°F-65°F, normalized to zero) to the given bin. Figure 3.1 shows that extreme temperatures on both the hot and cold ends of the temperature distribution reduce overall time spent working. During a given week, an extra day below 25°F reduces time spent working by 1.8 hours, while an extra day above 80°F reduces time spent working by 1.2 hours. These two coefficient estimates are 4.5% and 3% of the sample mean, respectively.

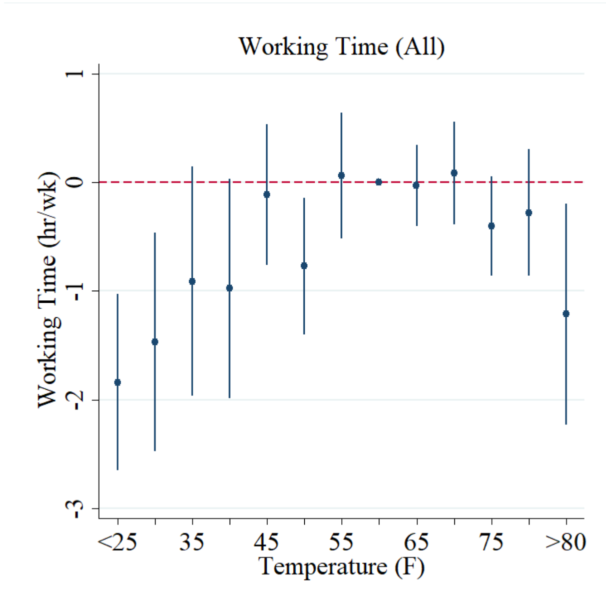

Figure 3.1: Effects of Temperature on Working Time. This figure plots coefficient estimates for individuals' working time adjustment in response to different temperature bins corresponding to specification in Column (1) of Table 3.5. Vertical lines represent 95% confidence intervals. The temperature bin 60°F-65°F is the omitted category.

However, this result across the full sample of adults masks substantial heterogeneity. In Figure 3.2 we explore this heterogeneity. Comparing Panel (A) to Panel (B), we find that the effects of extreme temperatures are larger for farmers than non-farmers. Within the sample of farmers, the effects are larger for women than for men. We formally test for this difference in Appendix Table 3.5. An extra day above 80°F in a given week decreases time spent working by female farmers by 1.94 hours, and the difference relative to male farmers is statistically significant at the one percent level.

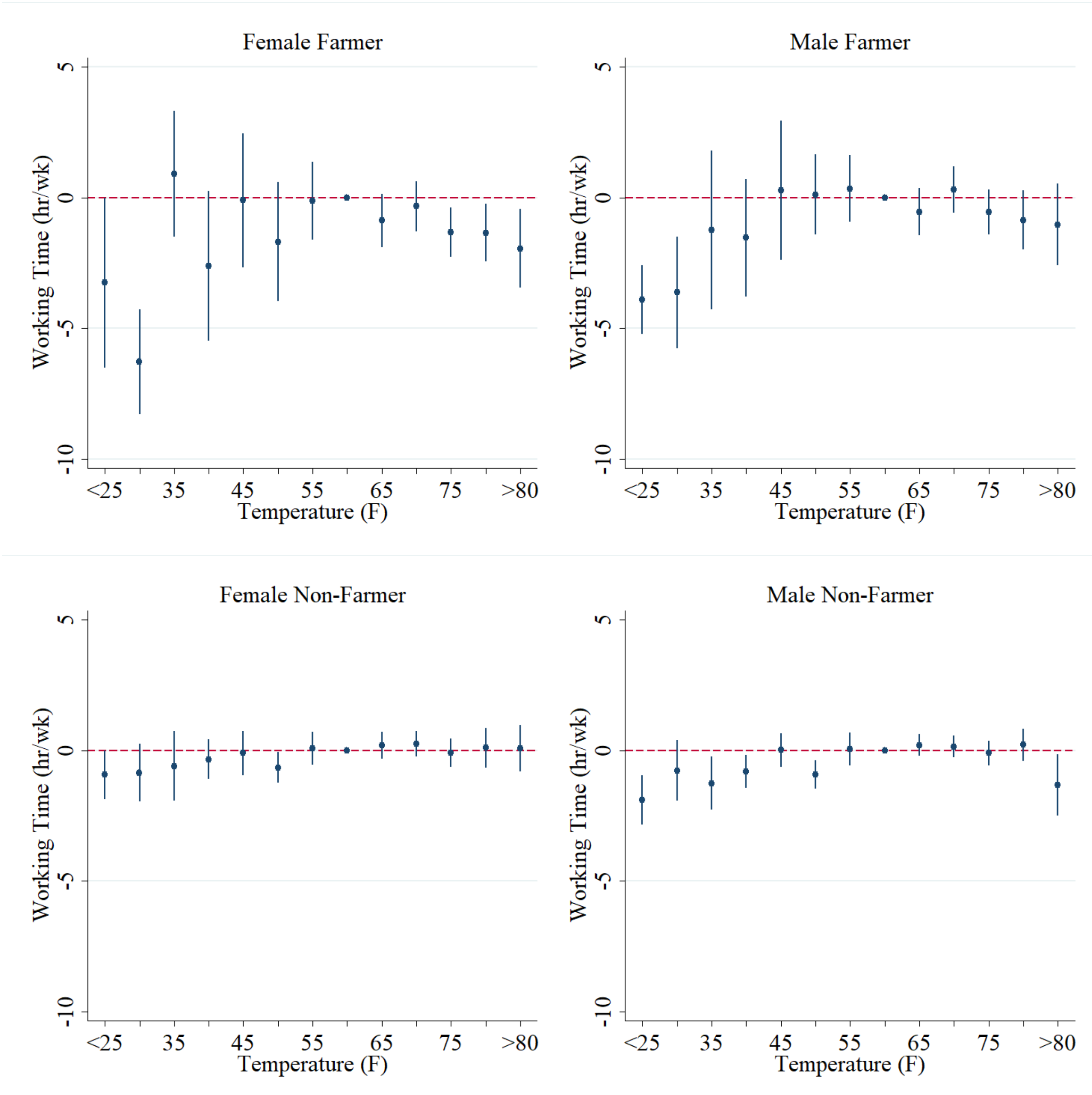

Figure 3.2: Effects of Temperature on Working Time: By Occupation and Gender. All four graphs correspond to the same regression in Column (2) of Table 3.5. Vertical lines represent 95% confidence intervals. The temperature bin 60°F-65°F is the omitted category.

Time Spent on Household Chores: In Figure 3.3, we estimate the effects of extreme temperatures on time spent on household chores by gender (Panel A) and by location of household chores (Panel B). The interpretation of coefficients is the same as before. We find that an additional extremely hot day reduces time spent on household chores for women but the same hot day has no discernible effect on men. Testing formally for this difference in Appendix Table 3.6, we find that in response to another day above 80°F during the week, relative to the omitted bin, women spent about 0.4 hours less on chores. Importantly, we note that in response to reduced time on household chores by women, there is no corresponding increase in time spent on household chores by men, suggesting that extreme heat results in not just lower market work as documented above, but also lower home production. As expected, in Panel (B), we note that most of the reduction in time spent on home production comes from outdoor tasks as opposed to indoor tasks.

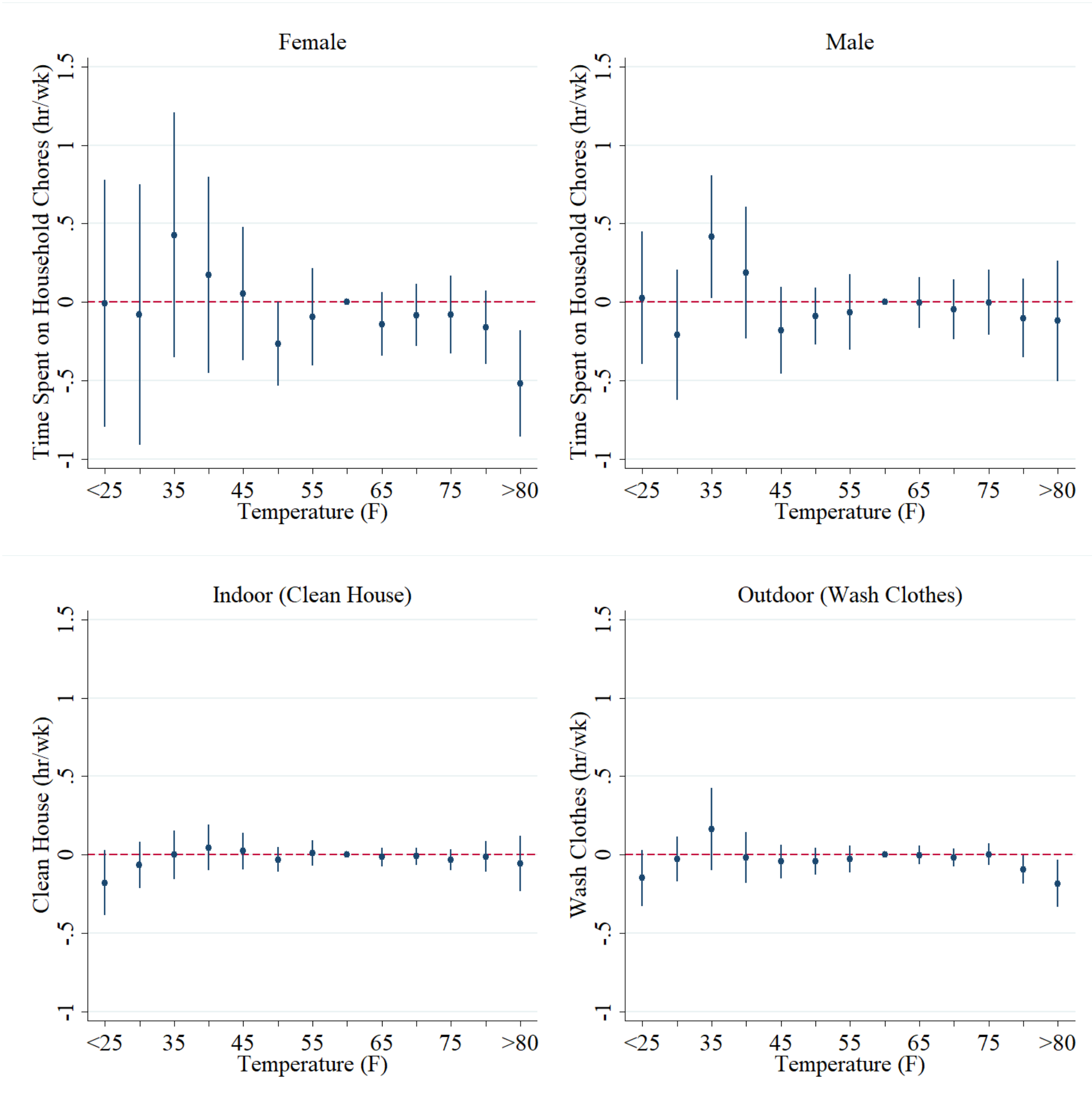

Figure 3.3: Effects of Temperature on Time Spent on Household Chores. The top panel plots the relationship between temperature and time allocated to household chores by gender, corresponding to specification in Column (1) of Table 3.6. The bottom panel plots the relationship between temperature and time allocation on indoor tasks (cleaning house) and outdoor tasks (washing clothes), corresponding to the specification in Column (2) and Column (3) of Table 3.6, respectively. Vertical lines represent 95% confidence intervals. The temperature bin 60°F-65°F is the omitted category.

Time Spent on Childcare: Next, we examine the effects of extreme temperatures on childcare. In Figure 3.4 we estimate this effect separately for households with and without cooling technologies. For households without some form of cooling technology (ACs or fans), one additional day with a mean temperature above 80°F, instead of between 56°F and 60°F, reduces time spent on child care by over 4 hours each week (see Appendix Table 3.7). Measured against the baseline mean of 14.24 hours, this estimate corresponds to a 29% effect. Remarkably, this entire effect disappears when we consider households that have adopted some form of cooling technology, suggesting that in this setting, adaptation decisions of households may disproportionately favor investments in infants and young children.

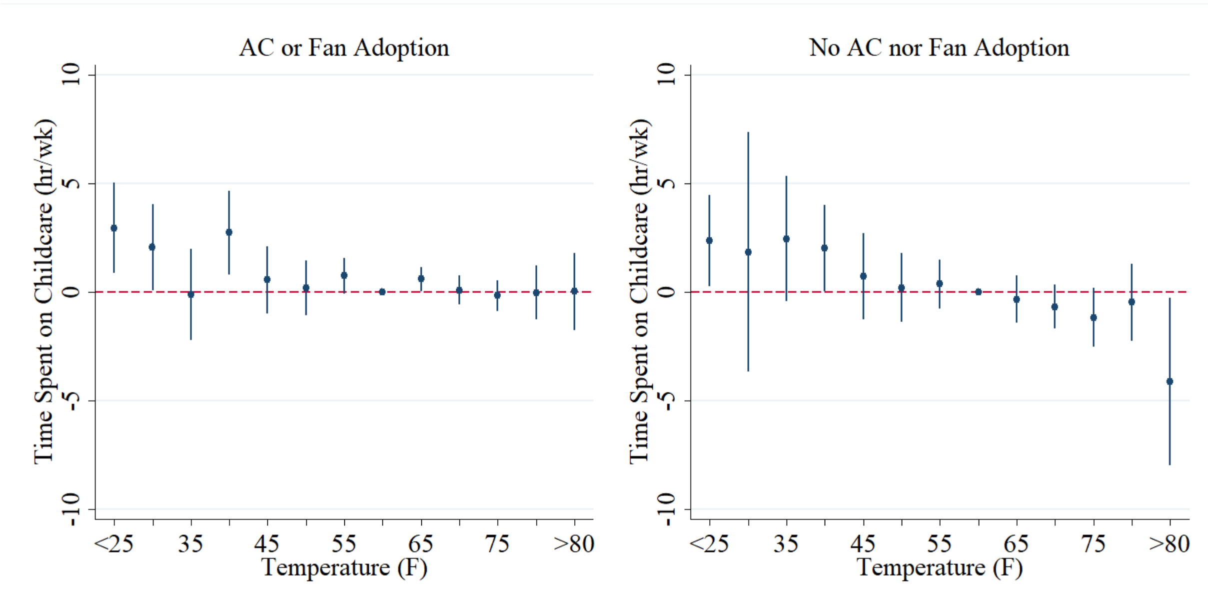

Figure 3.4: Effects of Temperature on Childcare by AC/Fan Adoption. This figure plots the relationship between temperature and time allocated to taking care of children under 6 years old, corresponding to the specification in Column (1) of Table 3.7. Vertical lines represent 95% confidence intervals. The temperature bin 60°F-65°F is the omitted category.

Robustness Checks: In Figure 3.5 (and correspondingly in Appendix Table 3.8) we report robustness checks for our model of work time. Results are robust to the using a degree-day specification, using a poisson regression, limiting our sample to a balanced panel of individuals, and including province×year×month fixed effects.

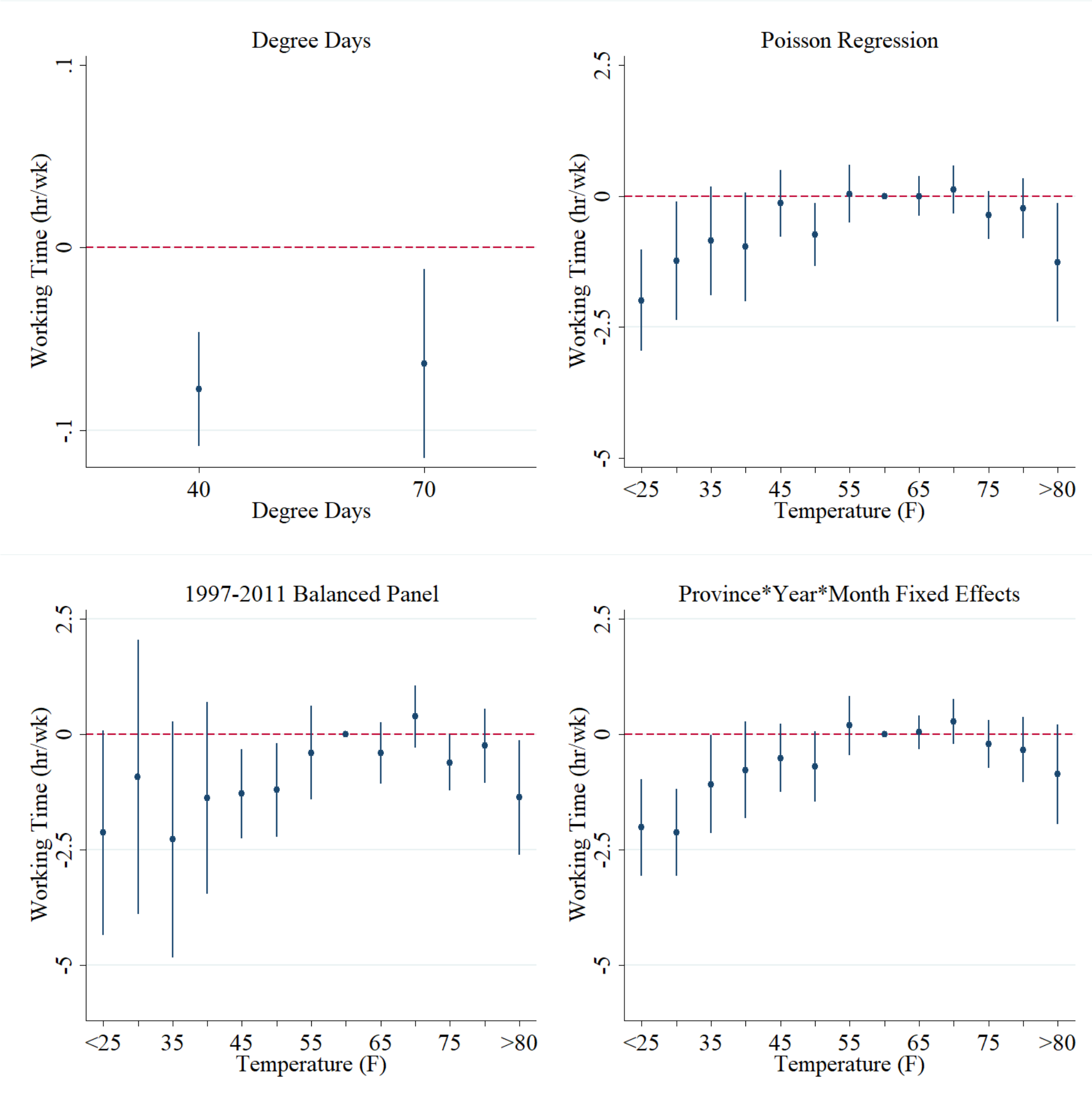

Figure 3.5: Robustness Checks. These four graphs presents coefficient estimates for different temperature bins corresponding to alternative specifications in Column (1)-(4) of Table 3.8. In the degree days specification, we use 40°F and 70°F when calculating the heating and cooling degree days. Vertical lines represent 95% confidence intervals. The temperature bin 60°F-65°F is the omitted category.

3.5 Conclusion

The vulnerability of marginal populations to extreme weather poses a particular risk for global anti-poverty goals (Barrett, Garg and McBride 2016). In this paper, we use individual panel time-use data over two decades to study how different groups respond along different margins to extreme temperatures. In particular, we show that extreme temperatures reduce time spent working, but that these effects are largest for female agricultural workers. Moreover, hot days with a daily mean temperature above80°F reduce women's time spent on household chores (with no compensatory increase from men) and households' time on childcare, suggesting considerable reductions in home production.

Our research has important implications for climate research and policy. First, it suggests that broadening the outcomes studied may be vital in developing countries. For the rural poor in the developing world, adjustments to time use may be important, particularly as adjustments on other margins may be constrained or impossible. Some time-use adjustments, like childcare, can have important long-run implications. Second, the distribution of effects can differ substantially across important socio-demographic lines like gender. This suggests that effects may be non-uniform even within households. More research into the distribution of extreme weather effects is surely needed.

3.6 Appendix

3.6.1 Additional Figures

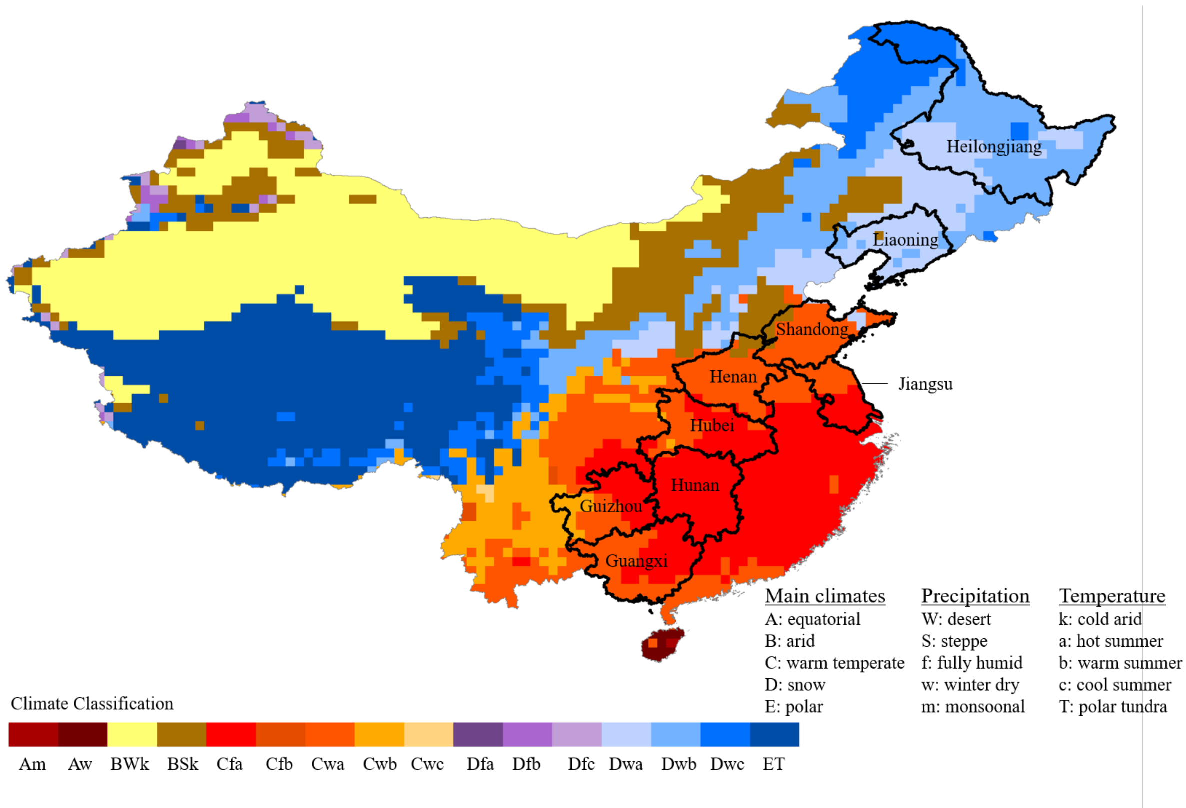

Figure 3.6: China's Climate Zones. This maps presents climate zones across the mainland of China. Administrative boundaries of the nine provinces covered in the emipiral analysis are highlighted in black. Climate zones are classified based on the Köppen-Geiger climate classification, available through http://koeppen-geiger.vu-wien.ac.at/shifts.htm.

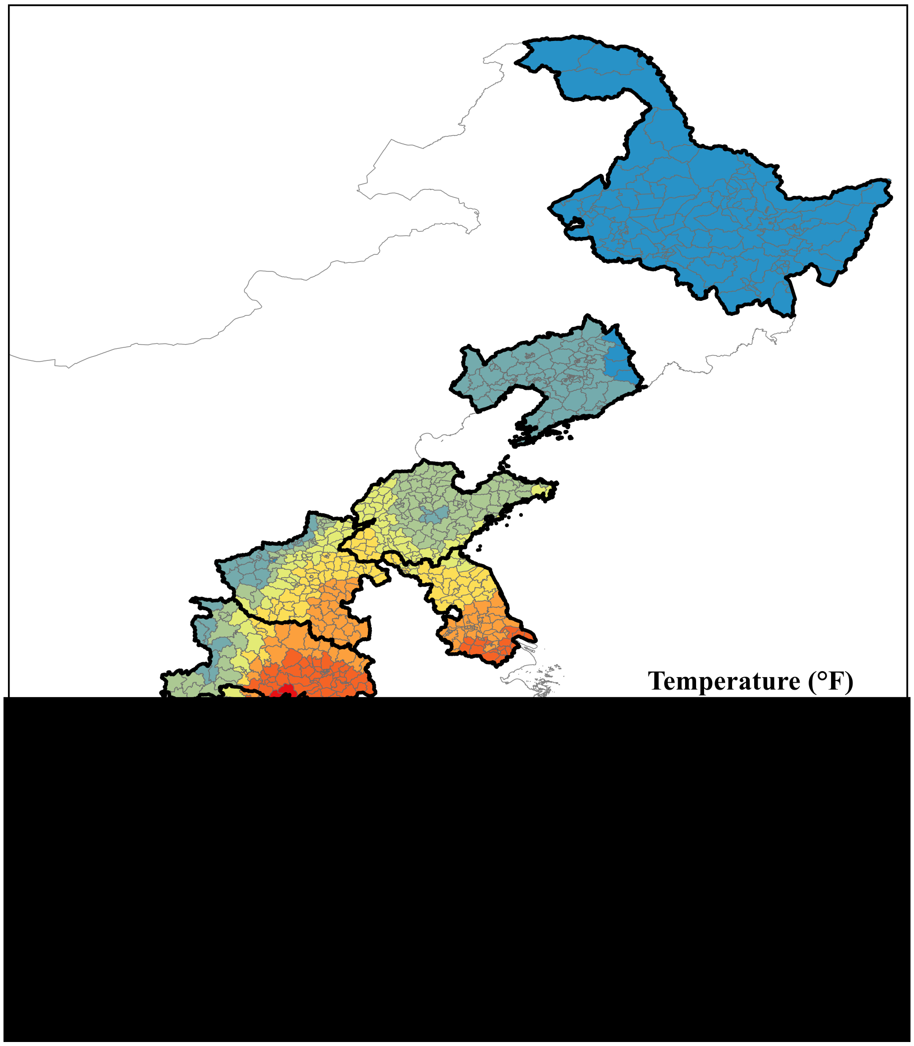

Figure 3.7: Average Daily Temperature by County. Average daily temperature in Fahrenheit in all counties of the nine provinces covered by the CHNS survey during the study period (1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009, and 2011). Temperatures are categorized into eight groups based on quantiles.

3.6.2 Additional Tables

Table 3.1: Summary Statistics (Working Time)

	mean	sd	min	max
Working Time (hr/wk)	40.41	19.26	0.00	156.00
Female	0.42	0.49	0.00	1.00
Age	42.76	11.69	18.00	84.20
Year of Education	8.56	3.83	0.00	18.00
Net Household Income (1,000 yuan/yr)	27.06	35.80	-564.00	900.60
Employment Status	0.99	0.07	0.00	1.00
AC/Fan Ownership	0.83	0.37	0.00	1.00
Washing Machine Ownership	0.71	0.45	0.00	1.00
Fridge Ownership	0.56	0.50	0.00	1.00
Farmer	0.33	0.47	0.00	1.00
Average Humidity (%)	93.14	3.30	79.11	99.45
Average Sunset Time (hr)	18.05	0.65	15.65	19.63
N	26269			

Based on sample of 26,269 individuals during survey year 1991 to 2011 when data on working time is available. Individual characteristics are from CHNS and weather variables are from the ERA-Interim archive. Our estimation results are robust to dropping the top 1% of the observations in terms of working time.

Table 3.2: Summary Statistics (Time Spent on Household Chores)

	mean	sd	min	max
Household Chores (hr/wk)	12.34	11.63	0.00	134.40
Clean House (hr/wk)	1.89	2.60	0.00	115.50
Wash Clothes (hr/wk)	2.40	3.10	0.00	107.33
Purchase Food (hr/wk)	2.39	3.46	0.00	116.32
Cook (hr/wk)	5.66	6.39	0.00	105.12
Female	0.55	0.50	0.00	1.00
Age	49.23	15.10	18.00	100.80
Year of Education	7.05	4.25	0.00	18.00
Net Household Income (1,000 yuan/yr)	25.59	33.40	-564.00	900.60
Employment Status	0.63	0.48	0.00	1.00
AC/Fan Ownership	0.80	0.40	0.00	1.00
Washing Machine Ownership	0.65	0.48	0.00	1.00
Fridge Ownership	0.54	0.50	0.00	1.00
Average Humidity (%)	93.33	3.32	79.11	99.45
Average Sunset Time (hr)	18.06	0.65	15.65	19.63
N	40826			

Based on sample of 40,826 individuals during survey year 1997 to 2011 when data on household chores is available. Household chores include four tasks – cleaning house, washing clothes, purchasing food and cooking. Individual characteristics are from CHNS and weather variables are from the ERA-Interim archive. Our estimation results are robust to dropping the top 1% of the observations in terms of time spent on household chores.

Table 3.3: Summary Statistics (Time Spent on Childcare)

	mean	sd	min	max
Childcare (hr/wk)	14.24	20.80	0.00	148.00
Age	39.93	14.45	18.20	85.10
Year of Education	6.58	4.07	0.00	18.00
Net Household Income (1,000 yuan/yr)	19.19	28.86	-26.60	383.37
Employment Status	0.75	0.43	0.00	1.00
AC/Fan Ownership	0.80	0.40	0.00	1.00
Washing Machine Ownership	0.58	0.49	0.00	1.00
Fridge Ownership	0.39	0.49	0.00	1.00
Average Humidity (%)	93.30	3.34	79.11	99.29
Average Sunset Time (hr)	18.11	0.63	15.82	19.63
N	5936			

Based on sample of 5,936 individuals during survey year 1989 to 2011 when data on childcare is available. Time spent on childcare is defined as time spent on taking care of children under six years old. Individual characteristics are from CHNS and weather variables are from the ERA-Interim archive. Our estimation results are robust to dropping the top 1% of the observations in terms of time spent on child care.

Table 3.4: Summary Statistics of Weather Variables

	mean	sd	min	max
Panel 1: Weather Variables Provided to CHNS				
Temperature (°F)	55.08843	20.41572	-27.90515	96.18461
Precipitation (inch)	2.78724	6.45893	0.00000	233.15747
Humidity (%)	92.90370	5.31594	60.47364	99.94583
Sunset Time (hr)	18.34055	0.94822	15.33463	20.02283
Panel 2: Noise Added to Weather Variables				
Temperature Noise (°F)	0.00118	0.33946	-1.79692	1.81050
Precipitation Noise (inch)	0.00039	0.22174	-1.79915	1.86726
Humidity Noise (%)	0.00065	0.22686	-1.64472	1.64568
Sunset Time Noise (hr)	-0.00005	0.04877	-0.29068	0.28398
Panel 3: New Weather Variables With Noise Added by CHNS				
Temperature_New (°F)	55.08960	20.41914	-27.68640	95.78651
Precipitation_New (inch)	2.78763	6.46340	-1.56230	233.17691
Humidity_New(%)	92.90436	5.32079	60.28096	101.09986
Sunset Time_New (hr)	18.34050	0.94960	15.13215	20.07031
Number of Linked County-Date Observations	322,176			

Observations included in this table are daily weather conditions of counties that could be linked to the CHNS dataset during survey year 1989 to 2011.

Table 3.5: Time Spent on Working

	(1) Work (All)	(2) Work by Individual Characteristics
<25	-1.841***	-1.899***
	(0.405)	(0.474)
25-30	-1.469***	-0.784
	(0.502)	(0.579)
31-35	-0.911*	-1.262**
	(0.527)	(0.504)
36-40	-0.977*	-0.816**
	(0.505)	(0.312)
41-45	-0.115	0.004
	(0.322)	(0.326)
46-50	-0.770**	-0.936***
	(0.314)	(0.269)
51-55	0.063	0.037
	(0.288)	(0.312)
61-65	-0.032	0.189
	(0.186)	(0.207)
66-70	0.085	0.138
	(0.236)	(0.207)
71-75	-0.401*	-0.102
	(0.227)	(0.237)
76-80	-0.277	0.204
	(0.291)	(0.308)
>80	-1.214**	-1.331**
	(0.508)	(0.588)
female × farmer		-1.530
		(2.437)
<25 × female		0.965***
		(0.199)
25-30 × female		-0.075
		(0.429)
31-35 × female		0.654
		(0.488)
36-40 × female		0.467
		(0.372)
41-45 × female		-0.111
		(0.413)
46-50 × female		0.276
		(0.322)
51-55 × female		0.039
		(0.340)
61-65 × female		0.005
		(0.252)

Table 3.5 Time Spent on Working (Continued)

	(1) Work (All)	(2) Work by Individual Characteristics
66-70 × female		0.110
		(0.215)
71-75 × female		0.002
		(0.242)
76-80 × female		-0.114
		(0.258)
>80 × female		1.400***
		(0.514)
<25 × farmer		-2.010***
		(0.439)
25-30 × farmer		-2.839**
		(1.190)
31-35 × farmer		0.015
		(1.527)
36-40 × farmer		-0.721
		(1.093)
41-45 × farmer		0.268
		(1.309)
46-50 × farmer		1.052
		(0.722)
51-55 × farmer		0.306
		(0.648)
61-65 × farmer		-0.733
		(0.530)
66-70 × farmer		0.170
		(0.419)
71-75 × farmer		-0.451
		(0.505)
76-80 × farmer		-1.071*
		(0.613)
>80 × farmer		0.299
		(0.683)
<25 × female × farmer		-0.316
		(1.834)
25-30 × female × farmer		-2.579**
		(1.165)
31-35 × female × farmer		1.505
		(1.415)
36-40 × female × farmer		-1.547*
		(0.798)
41-45 × female × farmer		-0.272
		(1.029)
46-50 × female × farmer		-2.081**

Table 3.5 Time Spent on Working (Continued)

	(1)	(2)
	Work (All)	Work by Individual Characteristics
		(0.962)
51-55 × female × farmer		-0.514
		(0.661)
61-65 × female × farmer		-0.338
		(0.467)
66-70 × female × farmer		-0.757*
		(0.435)
71-75 × female × farmer		-0.780
		(0.484)
76-80 × female × farmer		-0.364
		(0.376)
>80 × female × farmer		-2.314***
		(0.677)
farmer		-13.583***
		(2.343)
N	26269	26269
adj. R^2	0.33	0.38

All specifications control for (1) county-level weather conditions including precipitation, linear and quadratic terms of relative humidity level and sunset time; (2) individual-level time-varying characteristics including linear and quadratic terms for age, years of education, annual net household income, employment status, and ownership of fans or AC, fridges and washing machines; (3) individual fixed effects, year-month fixed effects, and province-month fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$. Standard errors are clustered at the county level.

Table 3.6: Time Spent on Household Chores

	(1) HHChore by Gender	(2) CleanHouse	(3) WashClothes
$<$25	0.026	-0.178*	-0.149
	(0.210)	(0.103)	(0.090)
25-30	-0.209	-0.065	-0.029
	(0.207)	(0.074)	(0.071)
31-35	0.416**	-0.001	0.162
	(0.196)	(0.078)	(0.131)
36-40	0.188	0.045	-0.016
	(0.210)	(0.072)	(0.081)
41-45	-0.180	0.024	-0.042
	(0.138)	(0.057)	(0.053)
46-50	-0.090	-0.030	-0.042
	(0.091)	(0.038)	(0.043)
51-55	-0.064	0.009	-0.028
	(0.120)	(0.040)	(0.044)
61-65	-0.002	-0.015	-0.001
	(0.081)	(0.029)	(0.030)
66-70	-0.045	-0.009	-0.019
	(0.095)	(0.027)	(0.029)
71-75	-0.001	-0.031	0.003
	(0.105)	(0.033)	(0.034)
76-80	-0.102	-0.012	-0.095**
	(0.126)	(0.049)	(0.045)
$>$80	-0.120	-0.055	-0.183**
	(0.192)	(0.087)	(0.075)
$<$25 $\times$ female	-0.035		
	(0.458)		
25-30 $\times$ female	0.129		
	(0.534)		
31-35 $\times$ female	0.012		
	(0.387)		
36-40 $\times$ female	-0.015		
	(0.399)		
41-45 $\times$ female	0.235		
	(0.231)		
46-50 $\times$ female	-0.176		
	(0.150)		
51-55 $\times$ female	-0.031		
	(0.166)		
61-65 $\times$ female	-0.137		
	(0.133)		
66-70 $\times$ female	-0.038		
	(0.105)		

Table 3.6 Time Spent on Household Chores (Continued)

	(1)	(2)	(3)
	HHChore by Gender	CleanHouse	WashClothes
71-75 $\times$ female	-0.079		
	(0.136)		
76-80 $\times$ female	-0.059		
	(0.117)		
$>$80 $\times$ female	-0.400**		
	(0.169)		
N	40826	24993	23410
adj. R^2	0.47	0.17	0.10

All specifications control for (1) county-level weather conditions including precipitation, linear and quadratic terms of relative humidity level and sunset time; (2) individual-level time-varying characteristics including linear and quadratic terms for age, years of education, annual net household income, employment status, and ownership of fans or AC, fridges and washing machines; (3) individual fixed effects, year-month fixed effects, and province-month fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$. Standard errors are clustered at the county level.

Table 3.7: Time Spent on Childcare

	(1) Childcare by AC/Fan Adoption
<25	2.366**
	(1.051)
25-30	1.839
	(2.748)
31-35	2.457*
	(1.432)
36-40	2.026**
	(0.990)
41-45	0.731
	(0.991)
46-50	0.202
	(0.785)
51-55	0.367
	(0.559)
61-65	-0.329
	(0.551)
66-70	-0.672
	(0.501)
71-75	-1.168*
	(0.676)
76-80	-0.470
	(0.887)
>80	-4.134**
	(1.924)
<25 × AC/Fan	0.584
	(0.441)
25-30 × AC/Fan	0.211
	(2.401)
31-35 × AC/Fan	-2.569
	(1.778)
36-40 × AC/Fan	0.709
	(0.900)
41-45 × AC/Fan	-0.181
	(1.197)
46-50 × AC/Fan	-0.015
	(0.987)
51-55 × AC/Fan	0.375
	(0.798)
61-65 × AC/Fan	0.931
	(0.606)
66-70 × AC/Fan	0.751
	(0.465)

Table 3.7 Time Spent on Childcare (Continued)

	(1)
	Childcare by AC/Fan Adoption
71-75 × AC/Fan	1.001
	(0.757)
76-80 × AC/Fan	0.430
	(0.721)
>80 × AC/Fan	4.154**
	(1.772)
AC/Fan	-3.451
	(2.821)
N	5936
adj. R^2	0.32

All specifications control for (1) county-level weather conditions including precipitation, linear and quadratic terms of relative humidity level and sunset time; (2) individual-level time-varying characteristics including linear and quadratic terms for age, years of education, annual net household income, employment status, and ownership of fans or AC, fridges and washing machines; (3) individual fixed effects, year-month fixed effects, and province-month fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$. Standard errors are clustered at the county level.

Table 3.8: Robustness Check

	(1) Degree Days	(2) Poisson	(3) Balanced Panel 1997-2011	(4) Province*Year*Month
DD40	-0.078***			
	(0.015)			
DD70	-0.064**			
	(0.026)			
<25		-1.989***	-2.130*	-2.017***
		(0.496)	(1.087)	(0.523)
25-30		-1.237**	-0.925	-2.122***
		(0.579)	(1.457)	(0.467)
31-35		-0.857	-2.277*	-1.083**
		(0.529)	(1.253)	(0.528)
36-40		-0.969*	-1.374	-0.772
		(0.530)	(1.022)	(0.521)
41-45		-0.142	-1.289**	-0.512
		(0.326)	(0.473)	(0.366)
46-50		-0.738**	-1.206**	-0.699*
		(0.310)	(0.497)	(0.378)
51-55		0.039	-0.400	0.188
		(0.281)	(0.501)	(0.319)
61-65		-0.001	-0.409	0.047
		(0.191)	(0.326)	(0.182)
66-70		0.123	0.385	0.272
		(0.236)	(0.330)	(0.240)
71-75		-0.358	-0.610*	-0.214
		(0.234)	(0.302)	(0.259)
76-80		-0.236	-0.247	-0.337
		(0.295)	(0.396)	(0.353)
>80		-1.263**	-1.368**	-0.868
		(0.575)	(0.609)	(0.535)
N	26269	26161	8920	26264
adj. R^2	0.33		0.33	0.35

All specifications control for (1) county-level weather conditions including precipitation, linear and quadratic terms of relative humidity level and sunset time; (2) individual-level time-varying characteristics including linear and quadratic terms for age, years of education, annual net household income, employment status, ownership of fans or AC, fridges and washing machines; (3) individual fixed effects. Column (1)-(3) include year-month fixed effects and province-month fixed effects, while Column (4) controls for province-month fixed effects instead. Pseudo R^2 of the Poisson regression in Column (3) is 0.33. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Chapter 3, in full, is currently being prepared for submission for publication of the material. Teevrat Garg; Matthew Gibson; Fanglin Sun "Extreme Temperatures and Time-Use in China." The dissertation author was one of three co-authors of this material.

3.7 References

Auffhammer, Maximilian, Solomon M. Hsiang, Wolfram Schlenker, and Adam Sobel. 2013. "Using weather data and climate model output in economic analyses of climate change." *Review of Environmental Economics and Policy*, 7(2): 181-198.

Barrett, Christopher B., Teevrat Garg, and Linden McBride. 2016. "Well-being dynamics and poverty traps." *Annual Review of Resource Economics*, 8(1): 303-327.

Burgess, Robin, Olivier Deschenes, Dave Donaldson, and Michael Greenstone. 2017. "Weather, climate change and death in India." *University of Chicago*.

Chen, Xiaoguang, and Lu Yang. 2017. "Temperature and industrial output: firm-level evidence from China." *Journal of Environmental Economics and Management*.

Cherchye, Laurens, Bram De Rock, and Frederic Vermeulen. 2012. "Married with children: A collective labor supply model with detailed time use and intrahousehold expenditure information" *American Economic Review*, 102(7): 3377–3405.

Colmer, Jonathan. 2018. "Weather, labor reallocation and industrial production: evidence from India."

Dee, Dick P., S. M. Uppala, A. J. Simmons, Paul Berrisford, P. Poli, S. Kobayashi, U. Andrae, M. A. Balmaseda G. Balsamo P. Bauer P. Bechtold A. C. M. Beljaars L. van de Berg J. Bidlot N. Bormann C. Delsol R. Dragani M. Fuentes A. J. Geer L. Haimberger S. B. Healy H. Hersbach E. V. Hólm L. Isaksen P. Kållberg M. Köhler M. Matricardi A. P. McNally B. M. Monge-Sanz J.-J. Morcrette B.-K. Park C. Peubey P. de Rosnay C. Tavolato J.-N. Thépaut F. Vitart. 2011. "The ERA-Interim reanalysis: Configuration and performance of the data assimilation system." *Quarterly Journal of the royal meteorological society* 137(656): 553-597.

Deschênes, Olivier, and Michael Greenstone. "Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US." 2011. *American Economic Journal: Applied Economics*, 3(4): 152-85.

Fishman, Ram, Paul Carrillo, and Jason Russ. 2019. "Long-term impacts of exposure to high temperatures on human capital and economic productivity." *Journal of Environmental Economics and Management*, 93: 221–238.

Garg, Teevrat, Maulik Jagnani, and Vis Taraz. 2018. "Temperature and human capital in India."

Geruso, Michael, and Dean Spears. 2018. "Heat, Humidity, and Infant Mortality in the Developing World." National Bureau of Economic Research.

Graff Zivin, Joshua, and Matthew Neidell. 2014. "Temperature and the allocation of time: Implications for climate change." *Journal of Labor Economics*, 32(1): 1-26.

Greenstone, Michael, and B Kelsey Jack. 2015. "Envirodevonomics: A research agenda for an emerging field." *Journal of Economic Literature*, 53(1): 5–42.

Gryczynski, Jan, Courtney Nordeck, Shannon Gwin Mitchell, Kevin E. O'Grady, Jennifer McNeely, Li-Tzy Wu, and Robert P. Schwartz. 2015. "Reference periods in retrospective behavioral self-report: A qualitative investigation." *The American journal on addictions*, 24(8): 744-747.

Heal, Geoffrey, and Jisung Park. 2016. "Reflections – temperature stress and the direct impact of climate change: a review of an emerging literature." *Review of Environmental Economics and Policy*, 10(2): 347–362.

Hsiang, Solomon. 2016. "Climate econometrics." *Annual Review of Resource Economics* 8: 43-75.

Hsiang, Solomon, Paulina Oliva, and Reed Walker. 2019. "The distribution of environmental damages." *Review of Environmental Economics and Policy*, 13(1): 83-103.

Jack, B Kelsey. 2017. "Environmental economics in developing countries: An introduction to the special issue." *Journal of Environmental Economics and Management*, 86(C): 1–7.

Krueger, Alan B, and Andreas I Mueller. 2012. "Time use, emotional well-being, and unemployment: Evidence from longitudinal data." *American Economic Review*, 102(3): 594–99.

Lemoine, Derek. 2018. "Estimating the Consequences of Climate Change from Variation in Weather." NBER Working Paper w25008.

Masuda, Yuta J., Brianna Castro, Ike Aggraeni, Nicholas H. Wolff, Kristie Ebi, Teevrat Garg, Edward T. Game, Jennifer Krenz, and June Spector. 2019. "How are healthy, working populations affected by increasing temperatures in the tropics? Implications for climate change adaptation policies." *Global Environmental Change*, 56: 29-40.

Santangelo, Gabriella. 2016. "Firms and farms: The impact of agricultural productivity on the local indian economy." *Unpublished Manuscript*.

Schlenker, Wolfram, and David B. Lobell. 2010. "Robust negative impacts of climate change on African agriculture." *Environmental Research Letters*, 5(1): 014010.

Somanathan, E., Rohini Somanathan, Anant Sudarshan, and Meenu Tewari. 2015. "The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing." Indian Statistical Institute, New Delhi, India.

Zhang, Peng, Olivier Deschenes, Kyle Meng, and Junjie Zhang. 2018. "Temperature effects on productivity and factor reallocation: Evidence from a half million Chinese manufacturing plants." *Journal of Environmental Economics and Management*, 88: 1–17.