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Hoping grey goes green: air pollution's impact on consumer automobile choices

Abstract

In this research, we examine to what extent, if any, natural environmental factors affect consumer purchase decisions regarding "green"products. We collect and combine several unique datasets to study the impact of air pollution on consumers' choices of passenger vehicles in China. Exploiting cross-city variation, we find that air pollution levels negatively affect the sales of fuel-inefficient cars on average. This relationship, though, is U-shaped over the observed air pollution levels, in that fuel-inefficient car purchases rise with air pollution beyond some threshold. Furthermore, a city's income level is a significant factor in this non-monotonic relationship, in the sense that consumers of higher-income cities are less likely to suffer this reversal. All these results are consistent with the literature's theoretical predictions of hope. The rich findings of our study yield important implications to both marketers and policy makers.

1 Introduction

Since Hardin (1968) popularized Lloyd (1833), the tragedy of the commons has been a powerful framework for how self-interested agents overuse unregulated common resources such as public land and clean air. But what if the tragedy's conception of self-interest is too narrow to capture human behavior fully? A growing body of literature in marketing and economics explores how factors such as social norms can lead individuals to behave in ways that may mitigate the tragedy of the commons. Our study considers consumers choosing "green" products.

The natural environmental conditions that consumers face may intensify individuals' attempts to single-handedly improve the environment and affect spillover-generating behavior more broadly. There is not yet a direct test of this intuition in the literature. We fill the gap by exploiting the disparate air quality of all Chinese cities and then linking this air pollution to the fuel inefficiency of cars purchased[1]. Studying China's automobile market in this context is attractive for several reasons. First, China faces serious environmental challenges, as 16 Chinese cities are among the world's 20 most polluted places (Chen et al. (2013)). For our purposes, it is especially useful that air pollution varies greatly across cities and that cities with similar incomes may have very different pollution levels. Second, cars are expensive durable goods. Consumers must consequently spend substantial resources to exercise any preference that is distinct from classically defined self-interest. Third, the fuel efficiency of a car is an easily observed and measurable green product characteristic[2].

[1]As we will discuss, the disparate air quality across Chinese cities is primarily caused by geographical and climatic factors. It is impossible that one individual's vehicle choice could materially affect the level of air quality, a fact that precludes reverse causality.

[2]In a concurrent survey study that we conducted to complement this research, 64% of Chinese consumers agree that "issues relating to the environment are very important;"82% agree that "Everyone is personally responsible for protecting the environment in their everyday life;"81% believe "if all of us, individually, made a contribution to environmental protection, it would have a significant effect;"and 57% agree that "vehicles are a significant source of air pollution."The total sample size of the survey is 160. The detailed questionnaire is available from the authors upon request. In addition, a 2008 McKinsey & Company global survey of 7751 consumers in the world's eight major economies revealed that Chi-

Because we lack information on individual consumers, we follow Berry (1994) to structurally estimate market-level demand. The model is specifically identified by the fact that air quality is largely driven by geographical and climatic factors, but identification is supplemented by our ability to observe city-level income as a proxy for economic activity. This inclusion of city income not only controls for the potential correlation between air pollution and the city's economic development but also enables us to show that this correlation is working *against* our various empirical findings.

Our results indicate a strong relationship between air pollution and a consumer's decision regarding which car to buy, in that consumers in more heavily polluted cities tend to buy less fuel-inefficient cars. This *average* trend though masks a considerably $non-monotonic$ relationship. Although relatively clean-air cities see consumers shift to greener cars when air pollution worsens, this trend stops and reverses at some level of pollution. In addition, this reversal threshold is pushed outward for richer cities, the consumers of which are evidently more willing and able to make sacrifices for the common resource of less polluted air. These findings are consistent with the theory of hope in the literature, and verify that individuals' responses to the natural environment may cumulatively mitigate the tragedy of the commons.

To our knowledge, this is the first study in the marketing literature to directly test and quantify the relationships of natural environmental factors on consumer purchase behavior. In so doing, we effectively test the relevance of Kotler (2011) and his Marketing 3.0 emphasis on social responsibilities. Previous studies extensively address how consumer choice is influenced by relatively micro factors (e.g., product features, advertising, and word of mouth), assuming consumers occupy the same macro environment. Our study, however, advocates the importance of recognizing the macro environment and tailoring marketing approaches accordingly. For instance, our results imply that firms' marketing

nese consumers are very "green," ranking no. 1 in the categories of "using energy-efficient appliances" and "driving less/using public transportation more" (Bonini et al. (2008)).

strategies should vary across markets with regard to income and air pollution.

2 Data

In this study, we collected and combined several unique datasets at the city level. The city is the proper level to analyze our question[3]. Although there is substantial income dispersion across cities, there is much less dispersion within Chinese cities than in US cities.

City-level automobile sales We obtained monthly automobile sales data in China at the city level from the nation's central administration of motor vehicles. Though our dataset spans only 4 months (January-April 2010), the cross-sectional coverage is exhaustive, both in terms of cities (273) and vehicle models (257)[4]. The 257 distinct models come from 63 brands and include virtually all gasoline-powered car models sold in China during the sample period. Moreover, we are able to observe the sales of not only distinct models but also of different transmissions (automatic vs. manual) within a model. Because transmission type is a key determinant of a car's performance and fuel efficiency, data from these 426 transmissions are used throughout the data analysis.

Car characteristics The sales data are supplemented with transmission characteristics from xcar.com.cn, one of the most authoritative and popular web portals on car information in China. The collected characteristics are again fairly exhaustive. Among the collected characteristics, fuel consumption (L/100 km) is the standard measurement of a transmission's fuel inefficiency[5].

City characteristics Our foremost city characteristic is air pollution, which has an

[3] A "city"in China is more like a Metropolitan Statistical Area (MSA) than a city or town in the USA.

[4] There are four direct-controlled municipalities (Beijing, Tianjin, Shanghai, and Chongqing). The remaining 269 cities belong to 22 provinces and five autonomous regions (Guangxi, Inner Mongolia, Ningxia, Tibet, and Xinjiang). Our data do not cover China's two special administrative regions (Hong Kong and Macau) and the territories governed by the Republic of China (R.O.C.), commonly known as Taiwan.

[5] A complete list of the characteristics collected is available from the authors upon request.

objective measurement: the Air Quality Index (AQI). In China, AQI is determined by six atmospheric pollutants: sulfur dioxide (SO_2), nitrogen dioxide (NO_2), suspended particulates smaller than 10 μm in aerodynamic diameter (PM_{10}, suspended particulates smaller than 2.5 μm in aerodynamic diameter ($MP_{2.5}$), carbon monoxide (CO), and ozone (O_3). Although the measurement of each pollutant is scientifically sophisticated, the resulting AQI is a single number, in which a higher value indicates worse air quality.

In China, municipal governments are required to post the current AQI on their websites daily[6]. Because some city governments do not make historical AQI information available, we collected the historical AQI information from January to April 2010 from only 209 cities. These omitted cities were geographically dispersed across 20 provinces/autonomous regions. Chi-squared tests could not reject that the omitted cities had the same mean population, development, air pollution level, and auto sales as the included cities (National Bureau of Statistics of the People's Republic of China 2010). We conclude that the 209 cities are representative of all Chinese cities.

We use the combined data of the 209 cities in our empirical analysis. Table 1 reports the summary statistics of this sample on sales of car and car transmissions, car fuel inefficiency, city monthly AQI, and city income. Figure 1 plots each city's mean fuel inefficiency of cars purchased in the sample against that city's mean AQI with linear and quadratic trend lines. Even though in the figure the fuel inefficiency is aggregated across all car models sold in a city and all transmission-level variation in the data is ignored, the figure visualizes a non-monotonic relationship, prompting us to go beyond a linear model specification in our empirical investigation.

[6]In the complementary survey study, 85% of Chinese consumers understand the meaning of AQI and 77% pay attention to the AQI reports and updates.

Table 1: Summary statistics

	Avg monthly sales by city	Avg monthly sales by transmission	Car fuel inefficiency (L/100 km)	Avg monthly city AQI	City income (CNY/year)
# Obs	209	426	426	209	209
Mean	2878	1412	8.48	67.59	32695
S. D.	4656	1811	1.72	14.88	7720
Min	139	77	4.9	27.14	18604
Max	46857	13303	14.7	121.5	71875

3 Identification and model

3.1 The identification strategy

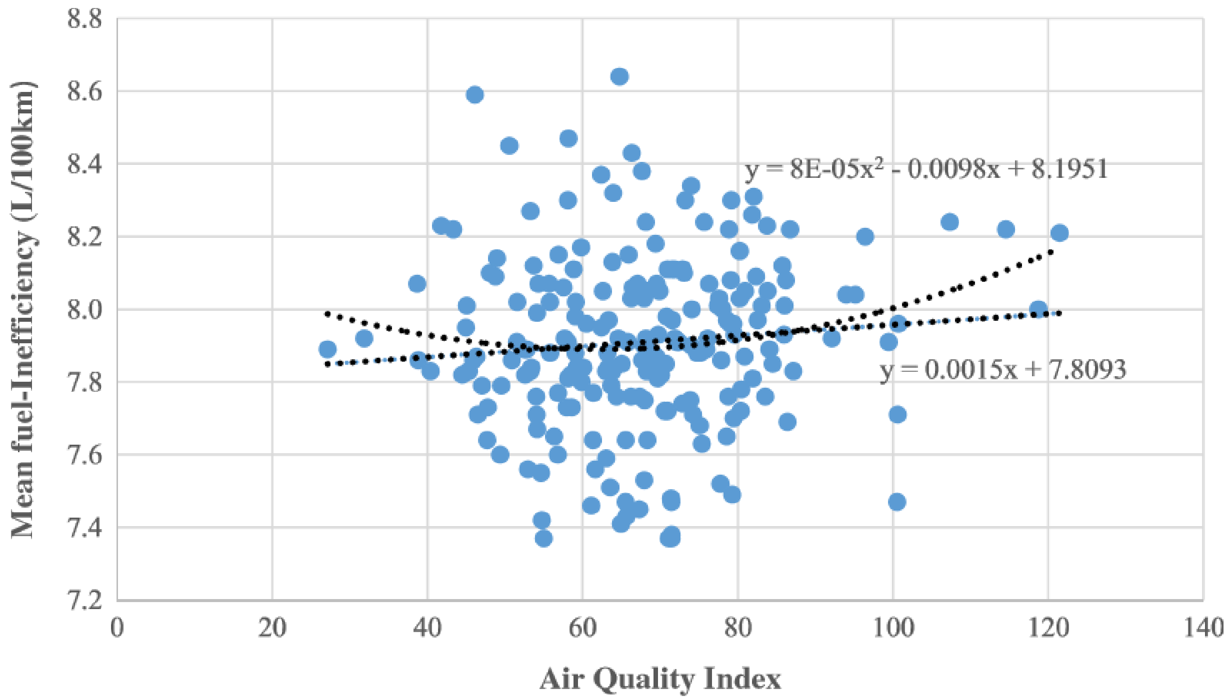
Identifying the natural environment's impact on purchases is challenging. Our empirical strategy takes advantage of a unique feature of our data, i.e., the tremendous variation of air quality across cities. In our data, the average monthly city AQI during the sample period is 65, indicating an acceptable although not excellent air quality in China. The 10th and 90th percentiles are 52 and 86, so the range is substantial[7].

Importantly, the cross-sectional variation of air quality is primarily caused by exogenous geographical and consequent climatic factors. China's vast size and latitudinal breadth ensure substantial diversity on this margin. Relevant geographical features range from alluvial plains to grasslands to hills and mountain ranges. China also exhibits notable climate diversity, ranging from tropical in the far south to subarctic in the far north to alpine in the higher elevations of the Tibetan Plateau. All these factors interact to determine a city's air quality.

A city's economic development may also affect its air quality. Fortunately, the variation in economic development level across cities is substantial and largely orthogonal to geographical features. Areas along the coastline are generally richer than interior areas, but both rich and poor cities are scattered across China. For example, Xinjiang, a north-

[7]These monthly averages mask the fact that air pollution varies within and across days and therefore substantially understate a city's air pollution at its worst time on its worst day.

Figure 1: Observed mean fuel inefficiencies vs. city AQI



ern inner autonomous region bordering Mongolia and Kazakhstan, has China's richest and poorest cities, Karamay and Hotan. The 20 richest (poorest) cities belong to seven (11) different provinces.

A city's economic development can presumably derive from varying sources. Some cities rely heavily on "clean" production processes (e.g., the primary product of Ordos, one of China's richest cities, is wool). Other cities depend on natural resources with substantial negative environmental impact (e.g., Taiyuan, another of China's richest cities, is a center of coal production). Economic development may also have varying effects in cities that do not rely on natural resource extraction. Production expansions in Shanghai and Dongguan, China's respective financial and manufacturing capitals, have very different implications for the environment.

Despite this arguably exogenous variation, the potential endogeneity of air pollution and income prompted our collection of city-level income data. The correlation of income with our city-level air pollution is $\rho = 0.2$, suggesting a modest endogeneity concern. In our empirical investigation, we exclude and then include income in our empirics to reveal by comparison the consequences of any such correlation[8].

3.2 Model specification

Given the large number of cities and car models, our demand estimation could become parametrically cumbersome; we therefore turn to the industrial organization literature with respect to differentiated products. The now well-established logit framework popularized by Berry (1994) enables the analyst to concisely control for population and the depth of product offering.

We assume that each consumer makes a relatively straightforward discrete choice among possible car brand/model/transmission. Formally, consumer i in city c has conditional indirect utility V for buying car brand/model/transmission j in month m, given by

$$V_{i,j,c,m} = \theta_j + \phi_c + \mu_m + f(F_j, A_c, Y_c) + \xi_{j,c,m} + \epsilon_{i,j,c,m} \quad (1)$$

where θ_j represents a set of binary indicators, one for each car brand/model/transmission[9]. Similarly, ϕ_c and μ_m respectively denote dummy variables for each city and month. The variables A_c and Y_c represent the monthly averages of AQI and city income during our sample period, respectively. F_j denotes the fuel consumption of transmission j, i.e., fuel inefficiency, measured by the number of liters of gas consumed to drive 100 km. F_j, A_c, and Y_c influence consumer i's utility through the function $f(\cdot)$, which we will discuss in detail below. $\xi_{j,c,m}$ refers to the mean valuation of characteristics that all agents (consumers and

[8] The Chinese government forbids the free movement of people across cities, which ensures that higher-income households moving to less polluted cities are not driving our results.

[9] We henceforth use "brand/model/transmission" and "transmission" interchangeably.

marketers) in the market, but not the researcher, observe. Finally, $\epsilon_{i,j,c,m}$ is consumer i's idiosyncratic error term. This specification then implies that mean consumer utility will be

$$\delta_{j,c,m} = \theta_j + \phi_c + \mu_m + f(F_j, A_c, Y_c) + \xi_{j,c,m} \tag{2}$$

During our sample period, automobile manufacturers applied a universal pricing strategy in the Chinese market. Thus, even though these price data are unavailable to us, consumer preferences regarding price will be absorbed by our binary indicators for each transmission. These same transmission fixed effects also absorb any consumer preference regarding green characteristics, ensuring that our identification comes entirely from differences in sales across cities.

Next, we discuss the specification of $f(\cdot)$, or how F_j, A_c, and Y_c enter consumer i's utility. Our empirical investigation focuses on how the marginal utility for fuel inefficiency changes with air pollution: $\frac{\partial^2 \delta_{j,c,m}}{\partial F_j \partial A_c}$. We are also interested in how this second partial derivative changes with air quality ($\frac{\partial^3 \delta_{j,c,m}}{\partial F_j \partial A_c^2}$) and with city income ($\frac{\partial^3 \delta_{j,c,m}}{\partial F_j \partial A_c \partial Y_c}$). The former prediction can be addressed by including second degree polynomial terms in $f(F_j, A_c, Y_c)$, while the latter ones can be addressed by including higher degree polynomial terms. Rather than specify an ad hoc collection of interaction terms, we employ full quadratic (second degree) and cubic (third degree) polynomials. Because fuel inefficiency levels in isolation have already been captured by the transmission indicators and both the air and income levels of cities have been captured by city binary variables, specifications with second and third degree polynomials respectively become:

$$\delta_{j,c,m} = \theta_j + \phi_c + \mu_m + \alpha_1 F_j A_c + \alpha_2 F_j Y_c + \xi_{j,c,m} \tag{2a}$$

$$\delta_{j,c,m} = \theta_j + \phi_c + \mu_m + \alpha_1 F_j A_c + \alpha_2 F_j Y_c + \beta_1 F_j A_c^2 + \beta_2 F_j^2 A_c + \beta_3 F_j^2 Y_c + \beta_4 F_j Y_c^2 + \beta_5 F_j A_c Y_c + \xi_{j,c,m} \quad (2b)$$

The second degree polynomial's estimates reveal the average impact of air quality and city income on consumer preferences for fuel inefficiency in cars. The third degree polynomial's estimates reveal how those impacts change with air quality and income.

Consumers also have the option of not purchasing any car. Denoting this outside option as transmission $j = 0$, we normalize mean utility $\delta_{0,c,m}$ to zero so that $V_{i,0,c,m} = \epsilon_{i,0,c,m}$. Thus, we allow the mean utility from the outside option to vary from month to month.

$\epsilon_{i,j,c,m}$ in Eq. (1) represents unobserved idiosyncratic variation in the preference of consumer i. The simplest case assumes that $\epsilon_{i,j,c,m}$ is an identically and independently distributed extreme value, resulting in a simple logit that serves as the baseline model of our study. Let Pop_c denote city c's potential market size (i.e., the set of all consumers who might purchase a car). We then denote a transmission's purchase probability within a city, or unconditional market share, as $s_{j,c,m} = q_{j,c,m}/Pop_c$, and the probability of no purchase as $s_{0,c,m} = (Pop_c - \Sigma q_{j,c,m})/Pop_c$. Following Berry (1994), this simple logit model has the convenient transformation as:

$$\ln(s_{j,c,m}) - \ln(s_{0,c,m}) = \theta_j + \phi_c + \mu_m + f(F_j, A_c, S_c) + \xi_{j,c,m} \quad (3)$$

In our preferred specification, however, we assume that $\epsilon_{i,j,c,m}$ is distributed according to the generalized extreme value (GEV) model of McFadden (1978) that generates a nested logit allowing for consumers to be more likely to substitute from one transmission to another (inside options) than to the option of no purchase (outside option). This form of segmentation mitigates mismeasurement of market size and has been useful in prior research (e.g., Berry and Waldfogel (1999); Einav (2007)). Letting q denote quantity sold, this nested logit framework is operationalized by including information on a choice's city-month market share, or *conditional* market share, as traditionally defined ($\tilde{s}_{j,c,m} = q_{j,c,m}/\Sigma_{k \in B_{c,m}} q_{k,c,m}$), in which $B_{c,m}$ defines the full set of city-month markets. More specifically, following Berry (1994), the nested logit model has the convenient transformation as:

$$\ln(s_{j,c,m}) - \ln(s_{0,c,m}) = \sigma \ln(\tilde{s}_{j,c,m}) + \theta_j + \phi_c + \mu_m + f(F_j, A_c, S_c) + \xi_{j,c,m} \tag{4}$$

In this nested logit specification, the importance of segmentation between the inside options and the outside option is captured by the unit interval parameter σ, the coefficient on $\ln(\tilde{s}_{j,c,m})$. If $\sigma = 0$, such segmentation is unimportant and the model reduces to the simple logit. As $\sigma \to 1$, this segmentation becomes complete, and the total demand for the product becomes perfectly inelastic.

3.3 Instruments in the nested logit model

Given our application's lack of endogeneity bias from prices, the need for instrumental variables (IVs) is motivated by the correlation between the transmission's unobservable ξ and the transmission's $\ln(\tilde{s})$ in the nested logit model. Following the relevant literature introduced by Berry (1994), we leverage the assumption of exogenous product characteristics to construct instruments that capture the fierce-ness of a transmission's competitive environment. That is, we instrument for the city-month market share, $\ln(\tilde{s})$, by using the product characteristics of rival transmissions in the market. Such IVs are made valid by their exclusion from the mean consumer utility, and their power comes from the fact that the competitive environment will directly affect a transmission's market share. The short length of our sample ensures that no firm had the opportunity to introduce a new product in response to a competing product that had especially favorable unobservable characteristics.

Specifically, we use means of products' variables for transmissions in the same city and month as our potential instrumental variables for $\ln(\tilde{s})$. Many firm brands are sold by the same ultimate manufacturer (group), and we construct some IVs accordingly. Preliminary analysis indicated that IVs based on car weight, size (passenger capacity), and ratio of horsepower to weight were especially powerful. We then used these variables to construct IVs that exploit potential portfolio effects so that "competing"transmissions are divided into other transmissions that are sold by the same firm and transmissions that are sold by other firms. For example, two IVs for one transmission's city-month market share are the average weights of all other transmissions sold by the firm and of all transmissions sold by other firms. We added to these two IVs a third IV based on other competing transmissions that shared the transmission's group. Overall, we use nine IVs (mean weight, mean size, and mean horsepower-to-weight ratio for each of the three IV types) to accommodate our inclusion of $\ln(\tilde{s})$ as a regressor in the nested logit specification[10].

4 Results

We estimate both the simple logit model and the nested logit model. The first is our baseline model, in which the lack of any endogenous regressors permits the use of OLS. The second is our preferred specification and requires 2SLS. In our estimations, standard errors are robust to arbitrary heteroskedasticity.

A key identification assumption for our estimation is that the level of unobserved economic development of a city is orthogonal to its air quality. We have discussed its plausibility in our context, but concerns may remain that air pollution is proxying for economic development and that it is this spurious correlation that drives our results. We have addressed the concern in our model by collecting and using each city's income

[10]These instruments have sufficient power. Using $\ln(\tilde{s})$ as the dependent variable, a comparison of goodness-of-fit measures with and without the set of IVs yields an F-stat of 151.61, well above the 99% confidence threshold of 2.41.

information. First, by explicitly including the information in the model, we are able to control for the potential endogeneity issue. Moreover, by comparing models without and with the inclusion of income, we are able to illuminate the validity of the identification assumption and any implications of its violation. Thus, we first estimate a variant of both our models in which income is omitted and then estimate our full models that do include income information.

Table 2 displays OLS and 2SLS estimates that omit income. Columns (1) and (3) are the second degree polynomial specification under the two cases, so the estimated coefficient on the air×fuel interaction (α_1) denotes the *average* impact of increasing air pollution on the mean consumer's marginal utility for fuel inefficiency. Our result shows that higher air pollution is associated with a lower preference for fuel-inefficient cars. Economists and marketing researchers have identified various altruistic considerations that may drive consumers' pro-environmental behaviors (e.g., Goldstein et al. (2008)). One interpretation of the result is that when the environmental imperatives (e.g., substantial air pollution) become greater, these altruistic forces are more easily triggered (Mazar and Zhong (2010)). As a result, consumers are more likely to avoid environ-mentally unfriendly products, such as fuel-inefficient vehicles.

Table 2: Logit and nested-logit estimates, second and third degree, income excluded

	A: Simple logit		B: Nested logit	
	(1) w/ second degree polynomials	(2) w/ third degree polynomials	(3) w/ second degree polynomials	(4) w/ third degree polynomials
$Air_c \times fuel_k (\alpha_1)$	-2.08**	-27.66***	-.74**	-8.94**
	(.76)	(7.44)	(.26)	(2.44)
${Air_c}^2 \times fuel_k (\beta_1)$	-	38.54***	-	10.82**
		(2.99)		(1.07)
$Air_c \times {fuel_k}^2 (\beta_2)$	-	-172.37***	-	-42.86**
		(32.89)		(11.12)
$ln(\tilde{s}_{j,c,m})(\sigma)$	-	-	.72***	.72***
			(.01)	(.01)

In neither case is the estimate of α_1 large or precise, especially given the sample size, thereby suggesting that the simple linear relationship is unable to adequately capture the underlying relationship. The inside-outside segmentation parameter σ, in contrast, is estimated with extraordinary precision, justifying our preference for the nested logit model.

Our primary test, thus, involves not only the average impact over all air qualities but also the prediction of a non-monotonic relationship. Columns (2) and (4) present results from the third degree polynomials specifications under the two cases. In either case, the estimated coefficient on $A_2F(\beta_1)$ has a t-statistic of over 10, strongly suggesting that the level of air pollution affects consumers' preferences for fuel-inefficient cars in a way that, when faced with dirtier air, those in relatively cleaner cities shift toward greener cars but those in relatively dirtier cities shift toward less green cars. In other words, the relationship between air pollution and consumers' preference for fuel-inefficient cars is a U-shape. One possible interpretation of the finding is that, while consumers tend to choose more environmentally friendly vehicles when the environmental condition worsens, they will give up their pro-environmental behaviors if they feel the cause is hopeless (MacInnis and De Mello (2005)). As a result, consumers' responses to worse environmental condition are first positive and then negative after they despair.

Table 3 displays our results when we explicitly include city income in our various polynomials. We first examine the second degree polynomial results (columns (1) and (3)). To the extent that our income measure proxies for economic development, estimates' changes from the corresponding columns in Table 2 can reveal the robust-ness of our findings. While it is apparent that there is indeed some correlation between air quality and city income, this correlation was also working *against* our various conclusions. The estimate of α_1 indicates that the average negative impact of air pollution on the preference for fuel inefficiency is much larger with income included, more than doubling in both cases. In both simple logit and nested logit cases, the estimate of α_2 indicates consumers in higher-income cities prefer more fuel-inefficient (i.e., less fuel-efficient) cars. This preference presumably arises because fuel inefficiency is associated with many other favorable characteristics.

Table 3: Logit and nested-logit estimates, second and third degree, income included

	A: Simple logit		B: Nested logit	
	(1) w/ second degree polynomials	(2) w/ third degree polynomials	(3) w/ second degree polynomials	(4) w/ third degree polynomials
$Air_c \times fuel_k(\alpha_1)$	-5.00***	-39.14***	-1.56***	-12.07***
	(.78)	(7.94)	(.27)	(2.67)
$Fuel_k \times income_c(\alpha_2)$	3.53***	26.78***	.98***	8.03***
	(.16)	(1.51)	(.07)	(.59)
${Air_c}^2 \times fuel_k(\beta_1)$	-	46.28***	-	13.49***
		(3.07)		(1.16)
$Air_c \times {fuel_k}^2(\beta_2)$	-	-27.64	-	-1.49
		(34.10)		(11.54)
${Fuel_k}^2 \times income_c(\beta_3)$	-	-129.41***	-	-37.96***
		(6.73)		(2.68)
$Fuel_k \times {income_c}^2(\beta_4)$	-	.75***	-	.21***
		(.10)		(.04)
$Income_c \times air_c \times fuel_k(\beta_5)$	-	-8.17***	-	-2.57***
		(1.17)		(.39)
$ln(\tilde{s}_{j,c,m})(\sigma)$	-	-	.71***	.71***
			(.01)	(.01)

Our third degree polynomial estimates (columns (2) and (4)) likewise reinforce our previous conclusions regarding the non-monotonic relationship between air pollution and fuel inefficiency preference. The statistically negative coefficient on the triple interaction (β_5) reveals another interesting finding: the negative relationship between air pollution and fuel inefficiency is magnified in higher-income cities and manifests as the reversal threshold occurring at higher AQI levels. In other words, the reversal threshold in the U-shape relationship identified by β_1 increases with a city's income level. One possible interpretation is that people with greater disposable income tend to have a stronger desire for clean air and high-quality life. They may also be more aware of, and more highly value, the role of a better environmental condition on their health and longevity. Thus, consumers with higher incomes have more hope for environmentally friendly products, and consequently, the threshold for them to lose hope is higher than that of lower-income consumers.

The interpretation of such structural parameters is perhaps their greatest defect, and we turn to a counterfactual exercise to illustrate the real-world meaning of these estimates. Our estimates indicate that the average consumer's preferences regarding fuel inefficiency are affected systematically by the level of air pollution and that this impact varies by city income. In our counterfactual exercise, we consider three cities that correspond to the observed 10th/50th/90th income percentiles. Consumers in each city face the observed set of available transmissions of varying fuel inefficiencies. We then solve for each city's equilibrium market shares of each transmission at various hypothetical AQI levels. From these market shares, we construct each city's mean fuel inefficiency of cars purchased.

These counterfactual city-level mean fuel inefficiencies are plotted in Figure 2. The U-shape of the implied mean fuel inefficiencies is most obvious at the 10th percentile income city, but it is also apparent at the 50th percentile income city. At the 90th percentile income city, though, the relationship between air pollution and fuel inefficiency never reverses. These figures illustrate one of our key findings: the purchase of green products requires an income sufficient to permit consumers the luxury of hope.

5 Conclusion

Understanding what influences consumer choice is a crucial topic in marketing science. Marketing researchers and practitioners now have an extensive understanding of the effects of product features, display, and promotion, and they are focusing on new media such as social networks and online word of mouth. Macro factors such as natural environmental conditions, however, have not yet been addressed. In response to this lacuna, we examine the relationship between air quality and consumers' choices of passenger vehicles. Our estimation results suggest that air pollution is strongly associ-ated with consumers' decisions on which car to buy, in that consumers living in more heavily polluted cities tend to buy less fuel-inefficient cars.

There are actionable managerial implications of the result. Practitioners may capital-

Figure 2: Implied mean city-level fuel-inefficiencies by income (with +/- 2 S.E.s)

ize on this finding by adjusting the marketing strategy according to the environmental conditions. Just as popular items are heavily promoted during holiday seasons, promoting green products on dirty days may be especially impactful. As discussed, reports suggest that Chinese consumers are much greener than previously thought. Our research suggests that Chinese consumers' behaviors may be driven by dirty air rather than by underlying ethics.

This average trend, though, masks a considerably $non-monotonic$ relationship. Although relatively clean-air cities see consumers shift to greener cars when air quality worsens, this virtuous trend stops and reverses at some level of air pollution. Furthermore, this reversal threshold is pushed outward for richer cities, in which consumers are evidently more willing to make sacrifices for the common resource of less polluted air. This result suggests that different marketing schemes must be designed for and targeted at areas of different development stages. To the extent that environmental regulations require popular support, our results also suggest that policymakers might lean toward encouraging economic growth. Such growth, especially among the dirtiest cities, would then offer a complementary decentralized addition to centralized regulation, as fewer consumers despair and more consumers act on their hope for a cleaner future.

We conclude with some limitations and possibilities for future research. Foremost, although our results suggest strong relationships and interesting patterns between natural environmental condition and consumers' purchase behavior, absent a controlled experiment they cannot be definitively interpreted as a causal effect. Second, although we are able to speculate some possible interpretations of our empirical results, we cannot assert the mechanism through which our findings occur. Our results may also depend on our specific empirical setup. Validity research is thus warranted.

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