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THE STRATEGIC SIGNIFICANCE OF NEGATIVE EXTERNALITIES

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Negative externalities have competitive relevance in a market when they have selective impacts – as, for example, when a product in use imposes greater costs on consumers of rival products than on other people. Because managers have discretion over aspects of product design that affect external costs, the externality in such cases may be viewed as a strategic variable. This paper presents evidence of the existence of competitively-relevant negative externalities. I introduce a metric for the externality's competitive effect, the external cost elasticity of demand, which I estimate econometrically using data from the motor vehicle industry. Managerial implications are considered.

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1. INTRODUCTION

There are many situations in which the transaction or use of goods and services imposes negative externalities – costs borne by parties other than the seller or buyer. While the managerial literature has recognized the presence of negative consumption externalities in various situations (e.g., Haviv and Ritov, 1998; Grinols and Mustard, 2001; Luxmore and Hull, 2010), for the most part they have been viewed as nuisances that, while interfering with economic efficiency, have little strategic significance.

However, in a subset of situations, externalities created through product consumption affect to a greater extent non-users of the products or the users of competing products. Consider, for example, "combatant goods," which bundle greater imposition of external costs with greater protection against the same costs, relative to alternatives. Light trucks, such as sport utility vehicles (SUVs) and pickups, impose greater risks of injury and death on other motorists than do cars, while at the same time providing their occupants with increased protection against these risks relative to cars. Visible car-theft deterrent devices (such as the Club) tend to push thieves to other cars, including those protected by invisible deterrent devices (such as Lojack); thus they redistribute crime rather than reducing it, while inoculating their owners against others who pursue the same strategy (see Ayres and Levitt, 1998). Other examples include noisome products, ranging from cigarettes to noisy leaf blowers, for which adoption reduces the displeasure from others' use; and situations in which non-adopters of a product or platform, such as ISO certification or expensive interview suits, incur a stigma that increases with the number of adopters.[1] In all these examples, incremental adopters of the product increase other consumers' preferences for adopting the product or platform relative to its alternatives because they impose external costs *selectively* (i.e., exclusively or to a greater extent) on non-adopters.

In these cases, the negative externalities have competitive relevance. For example, the fact that light trucks impose costs most heavily on the owners of vehicles other than light trucks has implications for consumers' vehicle choices in equilibrium. Setting price effects aside, one would expect an increase in the size of the selective externality to increase sales for light trucks. Because managers may have discretion over aspects of product design that affect external costs, the negative externality in such cases may be viewed as a strategic variable. To the extent that the externality increases sales, managers may an incentive to enlarge it.

This paper presents evidence of the existence of strategically relevant negative externalities and demonstrates a general method for their measurement. It uses econometric analysis to measure the effect of a selective negative externality on consumer choice in a particular context, the market for motor vehicles. In doing so, the paper proposes a tool for managers to approach the externalities imposed by their products as a strategic variable. Specifically, the results of the empirical analysis are used to calculate an *external cost elasticity of demand*, that is, the effect of a one-percent increase in the magnitude of the externality on the propensity of consumers to choose the imposing product over its rival. This measure is designed to serve as a generally-applicable metric of the intensity of the externality's competitive effect.

[1] For a more extensive list of examples and discussion, see Nagler (2011).

An important consideration in the analysis is that selective negative externalities, in influencing consumers' relative preferences for the imposing product and its competitors, affect relative prices. In a two-firm context, Nagler (2011) showed that an increase in the size of a selective externality might increase or decrease sales for the imposing product, depending upon the level of exogenous demand for an externality-imposing product relative to its rival. This is because a selective negative externality induces the imposing product's rival to cut price, such that the relative price differential between the imposer and the rival always increases with the size of the externality. When demand for the imposing product is high relative to its rival, the preference effect dominates the price effect and sales rise with the externality, but the opposite occurs when demand for the imposing product is relatively low.

To account for the role of demand in conditioning the sales effect of the externality, I estimate the external cost elasticities as demand-mediated. That is, I interact the influence of the externality on product choice with a measure of relative consumer preference for light trucks based on aggregate factors. Thus I am able to consider how the competitive effect of the externality varies across geographies and over time and, in so doing, demonstrate how its strategic value changes with the relevant market context.

An extensive literature on network effects already recognizes the relevance of *positive* consumption externalities to a number of strategic decisions of the firm. Katz and Shapiro (1985), for example, consider inter-brand compatibility and interoperability decisions. Farrell and Saloner (1986) and Katz and Shapiro (1992) examine the effect of positive consumption externalities on product introduction and pre-announcement decisions. Church and Gandal (1992) consider the decision of whether to provide software for competing hardware platforms. In an empirical analysis of ATM networks, Saloner and Shepard (1995) look at technology adoption decisions. With respect to the implications of negative consumption externalities, however, little work has been done previously. Nagler (2011) analyzes theoretically the competitive effects of these externalities and their implications for social welfare. The present paper complements this work by offering empirical estimates and an analysis focused on managerial strategy rather than social welfare.

The rest of the paper is structured as follows. Section 2 outlines the theoretical framework of the analysis and advances hypotheses. Section 3 sets forth my empirical approach. Section 4 lays out the application of the empirical approach to the market for motor vehicles and describes the data. Section 5 presents empirical results. Section 6 concludes.

2. THEORETICAL FRAMEWORK

The theoretical framework for the analysis is derived from a "Hotelling beach" duopoly model introduced by Nagler (2011). Two products, SUVs and cars, are sold by correspondingly named single-product firms, S and C, at prices p_S and p_C, respectively. Consumers are distributed uniformly on the interval (0,1) based on their preferences for SUVs versus cars, with the total number of consumers normalized to 1. Consumers choose whether to purchase an SUV or a car; each consumer will choose at most one unit of one of the two products (i.e., there is no outside good). It is assumed that each SUV in use imposes cost λ on other consumers. Meanwhile, purchasing an SUV shields the consumer against a fixed portion of the costs imposed by other SUVs in use.

A consumer located at a point j ($1 \geq j \geq 0$) who purchases an SUV receives utility

$$U_S(j) = v + \theta - t(1-j) - (1-\sigma)\lambda Q_S - p_S \tag{1}$$

and if she purchases a car she instead receives

$$U_C(j) = v - \theta - tj - \lambda Q_S - p_C \tag{2}$$

Here, the parameter v represents the exogenous value to the consumer of having a vehicle, common across all consumers and independent of vehicle type. The parameter θ, which may be positive or negative, represents the exogenous *relative* preference of the consumer for having an SUV as compared to a car, also common across all consumers; it may be thought of as measuring relative market demand for SUVs as compared to cars based on exogenous factors that consumers value similarly (e.g., common tastes, style trends, etc.). Q_S is the number of consumers who purchase an SUV, hence the number of SUVs in use; it is determined endogenously by the system in equilibrium. σ, known as the *selectivity* parameter, represents the degree of shielding that SUVs, but not cars, provide their owners against the risks posed by other SUVs in use ($1 \geq \sigma \geq 0$). The parameter t represents the intensity of individual consumers' relative preferences for SUVs and cars ($t > 0$). A consumer who chooses neither an SUV nor car receives utility of zero. Each consumer makes the choice that maximizes her utility.

Importantly, in addition to indicating the effects of exogenous valuation components, vehicle prices, and individual preferences for one vehicle type versus the other, Equations (1) and (2) specify how a consumer's utility from purchasing a vehicle of a given type depends on the SUV-imposed externality λ. Since each SUV in use imposes an external cost on other consumers, the cumulative negative impact on the consumer's utliity is the sum of external costs across the total installed base of SUVs, modified downward for owners of SUVs by the protection that their own SUVs provide (due to large size, greater weight, and so forth) against the costs imposed by other SUVs on the road.

Firm decision-making occurs in two stages. First, firm S sets the negative externality λ to maximize

$$\Pi_S = p_S Q_S - C(\lambda) \tag{3}$$

where $C(\lambda)$, representing S's cost of modifying its product design to alter the size of the externality (for example, by creating an SUV with a stiffer front end), is convex everywhere and increasing in λ's distance from a non-negative baseline value, $\underline{\lambda}$. Second, S sets p_S to maximize (3) and C simultaneously sets p_C to maximize

$$\Pi_C = p_C Q_C \tag{4}$$

with both firms taking λ (hence, firm S's product design decision) as fixed. Here, Q_C is the number of consumers who purchase a car; like Q_S, it is endogenously determined by the system in equilibrium.

Assume *v* is large enough that all consumers will choose to purchase an SUV or car at equilibrium prices, implying $Q_S + Q_C = 1$. Setting (1) equal to (2) and solving for p_S reveals

$$\Psi_j = 2\theta + \sigma\lambda Q_S - t(1-2j) + p_C \tag{5}$$

as the consumer's reservation price for an SUV relative to a car – that is, the level of p_S that makes the consumer indifferent between owning a car and owning an SUV. (5) seems to allow immediate conclusions to be drawn about the negative externality. First, it appears to show a network effect that increases in size with both the selectivity and size of the negative externality. Thus, it appears that sales of SUVs should increase with the externality when it selectively affects cars more than SUVs (i.e., $\sigma > 0$). Second, it appears that there is a complementary relationship between selectivity σ and the size of the externality, such that the profit-maximizing level of the externality increases with selectivity, taking into account that the externality is costly for S to increase from its baseline value. In summary, then, one is tempted to conclude that the greater the exogenous relative benefit of driving an SUV in terms of protection against other SUVs, the larger the negative externality chosen by firm S, the larger the sales of SUVs, and the smaller the corresponding sales of cars.

However, (5) is not a reduced form. In particular, the reservation price and the competitor's price *both* may be affected by the negative externality. It is essential to solve for the equilibrium and examine comparative statics to understand the effects of the negative externality and its strategic implications (see Nagler, 2011, for a full derivation).

The equilibrium solution reveals that the price differential between SUVs and cars increases with λ. Related to this, the sign of the effect of the externality on the sales of SUVs is ambiguous and actually depends upon the relative demand parameter, θ. When demand for SUVs is relatively high, S's sales increase with the externality. However, when demand for SUVs is low, the negative effect of the externality on SUV sales through the price differential dominates the externality's positive bandwagon effect on sales, such that sales decrease with λ. It can be seen from the analysis, moreover, that the selectivity parameter and the externality do not have an unambiguous complementary relationship: when demand for SUVs is low enough, an increase in selectivity may imply a *lower* profit-maximizing level of the externality. Intuitively, the size of the installed base of SUV customers matters when considering the effect of the externality, imposed by each of those customers, on car drivers. This is analogous to how installed base matters when considering the effects of conventional network externalities.

These results have two testable implications for managerial strategy, which I state as the following general hypotheses:

Hypothesis 1: When negative externalities are selective – that is, when they affect users of the rival product more than users of the imposing product – they generally have a significant effect on the consumer's choice between the imposing product and its rival.

Hypothesis 2 (Installed Base Effect): The marginal effect of the selective negative externality on the consumer's propensity to choose the imposing product grows more positive (less negative) with greater relative exogenous demand for the imposing product.

Phrased in terms of SUVs and cars, Hypothesis 1 states that when the SUV-imposed externality affects car owners more than it affects SUV owners, it is relevant to the consumer's choice of vehicle and, so, influences the demand for SUVs relative to cars in equilibrium. Put simply, Hypothesis 1 is a general statement that selective negative externalities are competitively relevant. Hypothesis 2 states that whether the externality's effect on the propensity to choose an SUV is positive or negative depends on the relative size the installed base of SUVs of as compared to cars; specifically, the larger the underlying demand for SUVs, the more positive the effect of the externality on SUV demand.[2]

3. EMPIRICAL STRATEGY

To demonstrate the strategic implications of selective negative externalities, I use binomial probit to estimate the following equation based on the duopoly framework described in the previous section:

$$y_{it} = \alpha + \beta_1 EXT_{jt} + \beta_2 EXT_{jt} D_{jt} + \sum_{k=1}^{K} \gamma_k X_{ki} + \sum_{l=1}^{L} \gamma_k Z_{ljt} + \varepsilon_{it} \qquad (6)$$

Here, i indexes individual households, j indexes geographies (e.g., states), and t time periods (e.g., years). Each observation represents a product choice by an individual household at a given point in time. y_{it} is a binary variable that takes a value of 1 if the household in question chooses the imposing product, and 0 if it chooses the alternative non-imposing rival product. EXT_{jt} is a measure of the negative externality, observed at the level of the state and year; it is assumed to be impossible to observe the externality imposition at

[2] These hypotheses and the other theoretical results of Nagler (2011) were developed in the context of the duopoly model and may be, to some degree, specific to that model. However, selective negative externalities likely occur under a variety of other market structures as well. (The U.S. motor vehicle industry, for example, is best characterized as a multi-product oligopoly rather than a duopoly; see further discussion of this in the concluding section.) Investigating the extension of the theoretical results to other market structures represents a useful area for potential future research.

the individual household level. D_{jt} measures aggregate demand for the imposing product in geography *j* and year *t*. The X_{ki} are a vector of household characteristics, and the Z_{ljt} a vector consisting of state-level, year-level, or state-by-year characteristics.

Equation (6) incorporates two salient aspects of the equilibrium results from the theoretical framework discussed in section 2. First, it explicitly accounts for the effect of the externality on the consumer's choice between the imposing product (SUVs in our simple theory model) and its rival (cars). Based on Hypothesis 1, one would expect a selective negative externality to have some significant effect on the propensity to choose the imposing product over its rival; thus either β_1, β_2, or both, should be significantly different from zero. Second, specifically through the interactive demand term, (6) accounts for the possibility that the externality's effect might vary with aggregate demand for the imposing product relative to its rival. Based on Hypothesis 2, one would expect β_2 to be positive, indicating that the effect of the externality on imposing product (SUV) sales grows, or becomes more positive, with aggregate demand. Estimated marginal effects from the probit regression may be interpreted as indicating variations in the household's propensity to choose the imposing product versus its rival. In the aggregate they represent variations in sales or market share.

Because the negative externality is observed at the state-year level rather than the individual household level, there is a risk that observed effects on consumer choices will reflect selection based on other state-by-year variables that affect both the consumer's choice and the size of the externality. The state-level and state-by-year level control variables Z_{ljt} are included to account for these other potential sources of variation, thereby minimizing the potential for selection bias.

4. AN APPLICATION TO THE MARKET FOR MOTOR VEHICLES

I apply the empirical methodology described in the last section to examine the effect on the consumer's choice between purchasing a light truck and purchasing a car of the road risks that light trucks impose on car occupants. SUVs and pickup trucks are typically longer, wider, taller, and heavier than cars. Their size makes them desirable to consumers, in part because consumers equate size with occupant protection in the event of a crash (Gladwell, 2004; White, 2004). Another feature of light trucks is that they impose increased risks to car occupants relative to other cars. Gayer (2004), for example, finds that a car driver is 1.50 to 1.88 times as likely to die given a crash with a light truck than if the crash were with another car. Such outcomes may be attributable not just to the sheer size of SUVs, but to a number of aspects of SUV design (Latin and Kasolas, 2002; Bradsher, 2002; Gladwell, 2004; White, 2004).[3] If consumers draw a connection between light-truck protections and light-truck-imposed risks, as some recent studies have suggested, then the propensity to purchase a light truck may respond positively to the size of the risks (Brozovic and Ando,

[3] For example, SUVs have been designed with high front-ends that override safety designs implemented in cars, such as crumple zones, and cause collision forces instead to be directed into the relatively unprotected passenger compartment (Latin and Kasolas, 2002, p. 1170).

2009; Li 2011). Light-truck makers may therefore have incentives to manipulate the risky features of the design of their vehicles to increase their marketability.[4]

Data for the dependent variable, consisting of a household's binary choice between a light truck ("1") and a car ("0"), were drawn from the Consumer Expenditure Survey ("CEX") of the U.S. Bureau of Labor Statistics.[5] The sample for estimation was composed of the household-level data on new car and new light-truck purchase decisions reported during the period 1997-2003 for those households for which it was possible to determine the state of residence. This resulted in approximately 4,500 purchase decision observations.[6]

To model the externality, ideally one would want to observe the size of the light-truck-induced risk imposed on each individual consumer or household for whom the choice of vehicle is observed. However, individual-level risk data of this sort were not available. Because it was possible to identify households with their state of residence, but at no finer level of locality, the analysis associates light-truck-induced risk with households at the state-by-year level.

Specifically, the negative externality, *EXT* in (6), is represented in the estimated model by the effect of the state-level light-truck share in the vehicle mix on the state-level probability of involvement in a fatal accident. To create this measure, fitted values were

[4] The external effects created by product design and other marketing decisions are not as dire in the case of many products as they are for SUVs and pickup trucks. Ethical considerations for the manager in the strategic use of negative externalities are discussed in the concluding section.

[5] For purposes of the analysis, "light trucks" are defined to include SUVs, vans, minivans, and pickup trucks. This definition is consistent with the approach of White's (2004) analysis of the risks associated with light trucks, and with the classification system of the U.S. Government, which was the source of most of the data for the present study.

[6] The household's state of residence was suppressed by the CEX for about 15% of observations to meet the Census Disclosure Review Board's criterion that the smallest geographically identifiable area have a population of at least 100,000.

obtained from regressing the probability over the course of a year that a given car or light truck in the household's state of residence will be involved in a crash in which at least one occupant is killed, on the share of registered vehicles that are light trucks. The main intention of the approach is to capture how incremental increases in variable characteristics of light trucks related to external risk imposition are reflected in the increased external cost imposed on other motorists. On a number of such characteristics – for example, weight, front-end height, and front-end stiffness – light trucks typically differ from cars to a greater or lesser extent (Latin and Kasolas, 2002; Bradsher, 2002; Gladwell, 2004; White, 2004). These characteristics might be manipulated and may therefore be thought of as strategic variables: a manufacturer can make an SUV lighter, lower, and more car-like; or heavier, higher, and less car-like. The light-truck share is viewed here, then, not just as a measure of the number of light trucks in use, but as reflecting a continuum of variations in the relevant strategic variables across light trucks in use that make them more or less like cars in terms of their tendency to impose external cost.[7]

The probability of fatal accident involvement was calculated for each state for each year in the sample by dividing the number of cars and light trucks involved fatal crashes by the number of registered cars and light trucks.[8] The data on fatal accidents are from the National Highway Traffic Safety Administration, while the data on vehicle registrations are

[7] Note that large trucks and buses are not included in this calculation. Though these larger vehicles also impose negative externalities on smaller vehicles due to their relative size, they are not relevant to measuring light-truck manufacturers' use of strategic increases in externalities to affect sales of light trucks, which is the main focus of the analysis.

[8] The number of cars and light trucks involved in fatal crashes is calculated by multiplying the number of vehicles involved in fatal crashes by the percent that were cars or light trucks. The result is divided by the total number of car and light truck registrations by state to obtain a probability estimate. The approach is preferable to dividing by total vehicle miles traveled, as one would expect an increase in road risks due to an exogenous increase in vehicle miles traveled to affect vehicle choice, though fatal crashes per mile traveled might remain unchanged.

from the Federal Highway Administration ("FHWA"). The light-truck share of vehicles was based on vehicle registrations of minivans, pickup trucks, SUVs, and other light trucks as a share of all light truck and car registrations. These data came from the FHWA. Table 1 presents summary statistics for vehicle choice, the probability of fatal accident involvement, light-truck share of vehicles, and the light-truck-share-fitted probability of fatal accident involvement.

< PLACE TABLE 1 APPROXIMATELY HERE >

The demand variable, *D* in (6), is represented in the estimated model by the fitted values from a separate probit regression of the choice of vehicle on geography-by-year indicators, standardized to mean zero and standard deviation of one. Thus my demand variable represents the (standardized) aggregation of all factors affecting demand for the imposing product that vary by geography and over time. Standardization allows for easy interpretation of the externality's marginal effects. The marginal effect associated with coefficient β_1 represents the effect of the negative externality on sales of the imposing product when aggregate relative demand for the imposing product is at its mean value. The sum (difference) of marginal effects corresponding to $\beta_1 + \beta_2$ ($\beta_1 - \beta_2$) yields the influence of the negative externality on sales when aggregate relative demand is one standard deviation above (below) the mean level.

Consistent with the strategy discussed in the previous section, and in order to reduce selection bias, a number of control variables are included in the model estimation as well. These include economic-cultural characteristics of the household's state in the year of the observed choice (farm acreage per capita; head of cattle per capita, level and squared; and real growth rate in gross state product per capita, level and squared), corresponding topology and road condition variables by state or state-year (percentage of land in the state designated as wilderness area; average snow depth, October to March; and the percentages of local and total public road mileage indicated as unpaved), relevant characteristics of the household (dummy variables for whether the household resides in a metropolitan area with a population less than 330,000 or earns more than US$75,000 per year; and standard-valued variables for the number of cars and light trucks owned by the household, the number of people under the age of 18 living in the household, and the inflation-adjusted amount of money spent on tobacco products by the household in the current quarter), and relevant characteristics of the CEX survey respondent in particular (age; and dummy variables for whether the respondent is black, is male, is single, or works in a blue collar profession).[9] Household-level weights based on sampling in the CEX were used in all regressions to make the samples representative of all households.

5. RESULTS

Let us begin with the results of the first-stage regression to fit the externality variable. The coefficient estimate of the effect of light-truck share in the vehicle mix on fatal accident risk is 0.0004108, with a standard error of 0.0000136. This estimate is significant at the 1% critical level.[10] R-squared for the regression is 0.166, quite large for a simple univariate

[9] A list of data sources for the control variables is available from the author upon request.
[10] The small size of the coefficient is attributable to the base probability of being involved in a fatal crash in a given year being very small (as shown in Table 1), whence factors such as light-truck share of vehicles that affect this probability generally do not cause it to become much larger.

model. These results confirm that the share of vehicles that are light trucks has a significant positive effect on the state-year level risk of a fatal accident.

Turning to the main regression, I estimate nine versions of (6) in all, alternating the use of a region-year-based demand interaction term D_{jt},[11] a state-year-based term, or no demand interaction term; and also the incorporation of a linear time trend, year indicators, and a region-specific linear time trend. The inclusion of the time trends and year indicators should help reduce selection bias, as these will pick up the effects of mean shifts in unobservable determinants across years, as well as variations in unobservables that occur linearly over time and over time within geographic regions.

The results are displayed in Table 2.[12] In all six runs that include a demand interaction term, an F-test finds joint significance of the coefficients on the externality term and the interactive term. Meanwhile, coefficient estimates from the three runs that do not include demand interaction show a statistically significant positive relationship between the externality and consumers' propensity to choose a light truck. Taken together, these findings indicate that the light-truck externality has a significant effect on the consumer's choice of vehicle, strongly supporting Hypothesis 1. Moreover, in the runs that include a demand interaction term, the interactive term coefficient is positive and significant. Thus,

[11] Assignment of U.S. states to nine regions is based on definitions from the *Statistical Abstract of the United States* (U.S. Census Bureau, 2008).

[12] All of the estimated models incorporate some explanatory variables aggregated to the state and state-by-year level, as well as other explanatory variables calculated at a disaggregate level. The use of variables at different levels of aggregation may cause conventionally calculated standard errors to be biased downward (Moulton, 1990). Rogers (1993, p. 23) notes that the resultant bias is negligible if no aggregation group exceeds 5% of sample size. While this is true of all state-by-year groupings in the dataset, it is not true of the state-level groupings. Accordingly, I have adjusted the standard errors in all regressions for clustering at the state level.

the results reveal that the relationship between the size of the externality and the propensity to choose an SUV varies positively with demand, supporting Hypothesis 2.

< PLACE TABLE 2 APPROXIMATELY HERE >

While it has been confirmed that the externality's effect on the decision to buy a light truck varies positively with light-truck demand, it is interesting to check specifically how the sign of the relationship changes as demand varies across the relevant range. Recall from section 4 that the marginal effect associated with coefficient β_1 represents the negative externality's effect on sales of the imposing product at mean demand. Meanwhile, the sum of marginal effects corresponding to $\beta_1 + \beta_2$ yields the negative externality's effect at one standard deviation above mean demand, while the difference corresponding to $\beta_1 - \beta_2$ yields the negative externality's sales effect at one standard deviation below mean demand. Using these calculations, one finds that the region-based demand estimates indicate a significant positive relationship between the externality and propensity to choose a light truck at mean demand; this relationship remains positive both one standard deviation above and below mean demand. Using state-based demand, one finds instead no significant relationship between the externality and light-truck-choice propensity at mean demand, a positive relationship at one standard deviation above the mean, and a negative relationship one standard deviation below. To summarize, in most demand conditions, the results show that increases in the size of the light-truck externality would be expected to increase the demand for light trucks. However, in low-demand conditions, it is possible that an increase in the size of the light-truck externality could *decrease* the demand for light trucks, consistent with Nagler's (2011) theoretical predictions.

External cost elasticities of demand are displayed in Table 3. These were calculated by adjusting the marginal effect estimates for the externality by the ratio of the mean of the externality to the mean of the vehicle choice variable. For the demand interaction equation estimates, this calculation provides the external cost elasticity at mean demand. External cost elasticities at one standard deviation above and below mean demand are calculated, respectively, by adding or subtracting the interaction term marginal effect before applying the adjustment. Consistent with the regression coefficients in Table 2, for most models and most exogenous demand levels, the elasticities indicate that light-truck demand is positively responsive to the externality. Moreover, demand responsiveness varies positively with exogenous demand – the expected installed base effect associated with the externality.

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These numbers provide information that is useful to the manager: variations in the externality of a certain percentage may be translated directly into an expected impact on market sales. Accounting for the costs associated with manipulating the externality (e.g., product or promotion strategies), a manager may make strategic decisions concerning how large to make the externality. Of course, to obtain a valid external cost elasticity of demand needed for effective strategy calibration, it is essential to identify the right model (i.e., no demand interaction, region-based demand interaction, or state-based demand interaction) and be able to figure the size of one's relative exogenous demand or installed base. Additional details on applying the empirical results to managerial strategy are discussed in the next section.

6. CONCLUSIONS

This paper has demonstrated that negative externalities can have strategic relevance in the competitive context. Just as it is responsive to changes in the product's price, demand for a product is similarly responsive to variations in the size of externalities that the product in use imposes on the consumers of rival products. And, similarly, this responsiveness is appropriately measured using an elasticity.

In developing estimates of external cost elasticities of demand for light trucks, the paper has demonstrated that the responsiveness of demand to externality size tends to vary positively with the baseline (or exogenous) demand for the product. It has shown, moreover, consistent with earlier theoretical work (Nagler, 2011), that it is possible for demand for the imposing product to vary negatively with the externality for low enough exogenous demand states. Thus, as a general principle, the paper has established the importance of taking account of conditions specific to the market – in particular, the imposing product's installed base – in predicting the competitive effect of varying the size of the externality imposed on rival product consumers.

In discussing managerial implications, it is essential that one immediately address an ethical question: is it right for a firm to strategically impose costs on its rivals' consumers? There can be little disagreement that it is unethical to *harm* a rival's consumer base. In the case of light trucks, for example, where imposing costs means imposing a greater risk of death and injury to people, the ethics of such strategic behavior may be rightly questioned. Setting aside outright harm, however, there remains ample scope for strategic uses of negative externalities that most people would agree are fair play. Few would argue that it is an inappropriate marketing tactic to make using a rival's product seem less desirable to consumers. Few would argue that it is wrong for a marketer to persuade consumers that they are missing out if they "sit on the sidelines" while their neighbors all try an exciting new product. Getting consumers to experience costs or to see costs where they previously had not seen them is part and parcel of standard marketing practice. This paper has simply provided a method to identify where such strategies might be most effective.

Still, even nuisance costs, when deliberately imposed, have an element of normative undesirability. Therefore, on a case-by-case basis, managers will need to consider the ethics of employing negative externalities as part of a marketing strategy. Ultimately the issue becomes one of weighing private goals, such as profits and market share, against the goal of being a responsible corporate citizen. This issue is one that managers must, of course, confront with respect to a variety of decisions.

One managerial implication of the analysis has to do with when marketers should pursue attack strategies. Conventional wisdom has it that a new entrant into a market can succeed by brashly attacking the leading brand. This paper suggests this may be unwise. A newcomer is likely to have a limited installed base relative to its leading rival. Where this is so, this paper has shown, attacks that specifically take the form of costs imposed by the product selectively on the rival's consumer base may well backfire. For example, advertising that warns "do not be the last in your neighborhood to get one" attempts to castigate those who sit on the sidelines and attempts to convince consumers that it is more costly to do so the more people join the promoted bandwagon. This will work well when a product has a large installed base, but may fail when it does not. The paper's analysis indicates that this is so quite apart from the issue of the message's *credibility* (i.e., that people might laugh at a mouse who claims to be an elephant).

Another implication has to do with the general perspective that managers should take with respect to the externalities their products impose. The standard textbook analysis of externalities emphasizes the firm's role as deciding how much abatement to engage in, based on a comparison of the private cost and private benefit of externality abatement. Where public policies adjust these to bring them more in line with social costs and benefits, the manager simply responds to her incentives as she finds them. The manager's attitude, in all events, is conceived as passive – except perhaps as regards lobbying against costly abatement mandates by the government. The recognition that negative externalities have a private strategic value recasts the analysis, the role of the externality, and the role of the manager. Competitively relevant externalities are tools, not nuisances. As such, it behooves marketers and corporate strategists to research their effects and use them optimally. Measuring an externality's effect on sales and relating to this to other strategic variables should be viewed as standard procedure for managers.

The empirical study, while offering an exploratory analysis of a newly identified phenomenon, exhibits some limitations that could be improved upon in future work. First of all, the state-year level of risk of death in an accident may be correlated with unobserved variables at the state-year level that determine the choice between a car and a light truck. If so, then my estimates of the effect of the externality on choice, and the related elasticities, may be biased. While the inclusion of time trends, year indicators, and a range of state-year level control variables likely reduce the selection bias, it remains a potential issue for my results. Future demonstrations of the effects of selective negative externalities should attempt to address the problem by including appropriate instrumental variables. Ideally, a "natural experiment" in which exogenously generated occurrences of an externality approximate the random assignment of an experimental process would provide a more econometrically sound demonstration.

Second, the results might have been improved by using as negative externality measures differences in fatality risk accruing to specific differences in light-truck design. One might reasonably wonder whether consumers will respond to increases in a given strategic variable, such as light-truck weight, the same as they would respond to an increase in light trucks as a percentage of all vehicles on the road. A good measure of the former, unfortunately, was not available, hence my use of the fatality risk accruing to the light-truck share of vehicles.

Finally, the focus of my empirical study, the U.S. motor vehicle industry, does not provide an exact match with the proposed conceptual framework. While the framework posits an imposing product and non-imposing product produced by two competing single-product firms, the motor vehicle industry actually exhibits several multi-product firms that compete with each other producing both light trucks *and* cars. The empirical finding that increases in the size of the externality generally affect sales of light trucks relative to cars is not invalidated. Nevertheless, one might reasonably expect firms' incentives for strategic behavior with respect to the light-truck externality to be reduced relative to the framework setup both because multi-product producers of light trucks would not wish to cannibalize their own car sales,[13] and due to incentives to free-ride on costly strategic manipulation of the externality by competitors. A follow-on study of another industry that more closely matches the framework would be useful both as a further demonstration of the effects of selective negative externalities and as an example of a context in which the strategic implications are clearer.

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[13] Actually it has been suggested that motor vehicle manufacturers earn greater margins on light trucks – particularly SUVs – than on cars, such that they actively attempt to shift demand, all else equal, toward light-truck purchases and away from other vehicles. See, e.g., Bradsher (2002).

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Table 1. Summary Statistics - Vehicle Choice and Light-Truck-Imposed Negative Externalities, Key Variables (N=4552)

Variable	Mean	St. Dev.	Min.	Max
Vehicle choice (1=light truck, 0=car)	0.409	0.492	0	1
Probability of fatal accident involvement†	0.000225	0.000030	0.000151	0.000322
Light-truck share of vehicles†	0.370	0.073	0.190	0.607
Light-truck-share-fitted probability of fatal accident involvement ("externality"	0.000225	0.000074	0.000090	0.000466

Notes: Observations consist of a vehicle purchase decision by a given consumer. † indicates state-by-year variables assigned to observations based on the consumer's state of residence and year of observed vehicle decision.

Table 2. Binomial Probit Regression - Effect of Light-Truck-Imposed Externality on Vehicle Choice

Region-year-based demand interaction term	(4)	(5)	(6)
Externality (EXT)			
Coefficient	2681.71**	2725.15**	4170.43***
Standard Error	(1077.28)	(1135.42)	(976.08)
Marginal Effect	*1032.59*	*1049.30*	*1605.44*
Interaction term (EXT × D)			
Coefficient	998.77***	1014.13***	1051.70***
Standard Error	(102.55)	(118.07)	(94.47)
Marginal Effect	*384.58*	*390.48*	*404.86*
F-test for joint significance of both coefficients	Signif: 1%	Signif: 1%	Signif: 1%
Pseudo R-squared	0.0620	0.0621	0.0638
State-year-based demand interaction term	(7)	(8)	(9)
Externality (EXT)			
Coefficient	1393.25	1431.75	1439.03
Standard Error	(1079.53)	(1128.85)	(1051.03)
Marginal Effect	*535.44*	*550.21*	*552.95*
Interaction term (EXT × D)			
Coefficient	1501.81***	1514.47***	1487.42***
Standard Error	(148.00)	(149.52)	(153.64)
Marginal Effect	*577.16*	*582.00*	*571.54*
F-test for joint significance of both coefficients	Signif: 1%	Signif: 1%	Signif: 1%
Pseudo R-squared	0.0831	0.0832	0.0837
No demand interaction term	(1)	(2)	(3)
Externality (EXT)			
Coefficient	4272.45***	4227.52***	4944.88***
Standard Error	(1408.10)	(1499.29)	(1150.25)
Marginal Effect	*1646.02*	*1628.66*	*1904.84*
Pseudo R-squared	0.0497	0.0504	0.0521
Time trend	Yes	No	No
Year indicators	No	Yes	No
Region-specific linear time trend	No	No	Yes

Notes: N=4552 for all models. The standard errors shown are robust and allow for clustering within states. The dependent variable is the household's choice between a light truck (1) and a car (0). All models also include the following control variables: farm acreage per capita (for household's state in year of choice); head of cattle per capita, level and squared; real growth rate in gross state product per capita, level and squared; percentage of land in the state designated as wilderness area; average snow depth, October to March; the percentages of local and total public road mileage indicated as unpaved; whether household is located in a metropolitan area with a population less than 330,000 (dummy variable); whether household earns more than US$75,000 per year (dummy variable); number of cars and light trucks owned by the household; the number of people under the age of 18 living in the household; the inflation-adjusted amount of money spent on tobacco products by the household in the current quarter; the survey respondent's age; and dummy variables for whether the respondent is black, is male, or works in a blue collar profession.

***Significant at 1% level **Significant at 5% level

Table 3. External Cost Elasticities of Demand

No demand interaction term	0.906	0.896	1.048
Region-year-based demand interaction term			
At mean	0.568	0.577	0.883
One standard deviation above mean	0.780	0.792	1.106
One standard deviation below mean	0.356	0.362	0.660
State-year-based demand interaction term			
At mean	0.295	0.303	0.304
One standard deviation above mean	0.612	0.623	0.619
One standard deviation below mean	-0.023	-0.017	-0.010
Time trend	Yes	No	No
Year indicators	No	Yes	No
Region-specific linear time trend	No	No	Yes

Notes: Estimates show the percent increase in sales of light trucks associated with a one-percent increase in the external cost imposed by light trucks on cars.