# Measuring the Effects of Advertising on Green Industry Sales: A Generalized Propensity Score Approach


## Abstract

The purpose of this article is to estimate the effects of advertising expenditures on annual gross sales of green industry firms using a quasi-experimental framework. In order to account for potential selection bias, a *generalized propensity score* and a *dose-response function* are used to estimate advertising treatment effects. The method used allows us to investigate the relationship between *the dose* (advertising expenditures) and *the response* (firm sales). We use data from the National Green Industry Surveys of 2009 and 2014 to conduct the analysis. To further investigate potential heterogeneous advertising effects of the size of the firms, we separate the sample into small firms and large firms, according to their annual gross sales. The results suggest an overall positive relationship between advertising expenditures and sales. However, the magnitude of the response and the shape of the response function depend on the size of the firm. Small firms have a wide range of advertising expenditures and hence their returns need to be carefully monitored. Large firms on the other hand tend to significantly underspend in advertising and larger returns can be attained with higher levels of advertising expenditures.



**Keywords:** causal inference, dose-response function, green industry, ornamental plants

**JEL Codes: Q13**

## 1. Introduction

Propensity score matching (PSM) is a causal inference analysis tool that has been widely applied in economics for policy and program evaluation. The method was introduced by Rosenbaum and Rubin (1983). Its popularity exploded in the economics literature in the early 2000s as a way to reduce causal effect bias from confounding variables in observational data (Austin 2011, Peikes, Moreno, and Orzol 2008, Caliendo and Kopeinig 2008). PSM approximates a randomized experiment by matching and comparing *treated* observations and *untreated* observations based on a propensity score. The propensity score represents the similitude of observations according to pretreatment covariates. The general approach is to find observations similar in every aspect except for the treatment outcome of interest. For example, green industry firms can be matched to be similar in every aspect except for advertising expenditure allocations.

One of the limitations of PSM is that it can only be applied to a binary treatment. However, in many cases, the treatment takes on a continuous form such as advertising expenditures. PSM can be used to evaluate the effects of the decision to advertise for green industry firms, but conditional on having positive advertising expenditures, nothing can be said about the magnitude of advertising effects on green industry sales (Flores et al. 2012, Kluve et al. 2012). Several studies of program and policy evaluation with a continuous treatment have been recently conducted in health economics (Kreif et al. 2015, Jiang and Foster 2013), production economics (Bia and Mattei 2012, Adorno, Bernini, and Pellegrini 2007, Fryges and Wagner 2008), international trade (Wagner 2012, Serrano-Domingo and Requena-Silvente 2013), and education economics (Doyle 2011, McCormick et al. 2013), etc.

Imbens (2000) and Lechner, Miquel, and Wunsch (2011) extend the analysis of PSM to continuous variables by estimating average effects of multi-level treatment categories. Hirano and Imbens (2004) developed a framework for the causal effect analysis of a continuous treatment, which includes the estimation of a generalized propensity score (GPS) and a *dose-response* function. GPS provides an alternative way, compared to conventional PSM, to assign an observation to the treatment (or control) group conditional on the observed pre-treatment covariates. Literally, the *dose* in the dose-response function means the treatment, and the *response* means the outcome. In our application the treatment is advertising expenditures and the outcome is green industry sales. As such, the dose-response function essentially establishes the relationship between advertising and sales. The dose-response function is modeled as a joint function of the estimated GPS and advertising expenditures. The GPS approach needs to consider two issues. First, the distributional assumptions of the treatment variable (i.e. usually assumed to be normally or lognormally distributed); and second, the model specification of the dose-response function (i.e. linear or higher-order polynomials). The validity of the GPS can be evaluated through a balancing property test (Bia, Flores, and Mattei 2012, Kreif et al. 2015). Recent work estimates the dose-response function using the generalized linear model (GLM) approach, and semi-parametric and nonparametric methods (Guardabascio and Ventura 2013, Bia et al. 2014, Flores et al. 2012, Bia, Flores, and Mattei 2012).

In order to obtain robust results, we incorporate the dose-response function estimated from the GLM approach and compare it to the results from the ordinary linear approach. The advantage of applying the GLM approach is that it allows for more flexible distributional assumptions of the advertising expenditure treatment variable (Guardabascio and Ventura 2013). Moreover, in order to capture potential heterogeneous effects of the size of the firms, we separate the sample into small firms and large firms, according to their annual gross sales. The results reveal heterogeneity in the magnitude and the shape of the dose-response functions for small firms and large firms. More specifically, the dose-response function for small firms takes an inverted U shape, while the dose-response function for large firms shows an increasing trend. The variations in the dose-response function provide evidence of differences in the marginal effects of advertising on green industry sales by firm size.

Dose-response functions have gained attention in applied economics research, but they have not been widely used in the field of agricultural economics. Our article is one of the first to apply this method to analyze treatment effects of business or marketing behavior of agricultural firms.[1] The objective of this article is to evaluate the relationship between advertising spending and annual sales of green industry firms. Advertising expenditure allocations are not exogenous. The decision of whether to advertise or not and how much to spend is endogenously determined by factors such as management style, scale of the operation, type of products and the general industry competitive environment. As such, any direct regression of sales on advertising is endogenous and might potentially lead to a biased estimate (Oustapassidis, Vlachvei, and Notta 2000). Previous studies examining the impact of advertising on sales try to isolate the effects of advertising by accounting for all the potential drivers of industry sales (Balagtas and Kim 2007, Adachi and Liu 2010, Baghestani 1991, Lewis and Reiley 2014, Yoo and Mandhachitara 2003, Leach and Duncan Reekie 1996). We contribute to the literature by providing a method to reduce causal effect bias by employing a quasi-random experimental approach.

The rest of the paper proceeds as follows. Section 2 provides a review of the relevant literature. Section 3 outlines the identification strategy. Section 3 describes the data. Section 4 presents the results and the balancing test. The last section concludes.

## 2. Review of the Literature

There is extensive literature evaluating the effectiveness of generic promotion programs on food and agricultural products (Brester and Schroeder 1995, Alston, Freebairn, and James 2001, Kinnucan and Myrland 2008, Adachi and Liu 2010, Kinnucan and Cai 2010, Richards, Van Ispelen, and Kagan 1997, Kinnucan et al. 1997). Generic promotion programs generally deal with highly homogeneous products. The empirical analysis of generic programs focus on elasticity; however, elasticity of demand may rise with advertising of product attributes, or it may decrease if it creates brand loyalty or other barriers to entry (Rickard et al. 2011). Firms that sell highly differentiated products or appeal to specialized niche markets use advertising to rotate the demand for their brand. The focus of this article is evaluating incremental advertising expenditures effects on firm level sales. The green industry has a small number of very large firms with large market shares and a large number of small firms with small market shares (Hodges, Hall, et al. 2015). As such, green industry products are highly heterogeneous and firms normally seek to advertise to differentiate their products.

Advertising and promotion practices can be beneficial for green industry firms who are facing increasingly competitive business landscapes. Advertising helps to expand the consumer base and attract those who lack information about their own preferred characteristics or plant benefits. Although most brand advertising research efforts report positive own-advertising and negative cross-advertising elasticity estimates (Capps, Seo, and Nichols 1997), the green industry is one of the least pro-active agricultural sectors to sufficiently engage in advertising and promotions. There are many reasons that can explain such conduct. First, as with other food and agricultural products there is uncertainty of green industry stakeholders about the effectiveness of advertising expenditures (Zheng, Bar, and Kaiser 2010, Piggott, Piggott, and Wright 1995). The skepticism of firms may be rooted in the industry lacking a generic promotion program with previous efforts being strictly voluntary raising questions about effectiveness and equity (Messer, Kaiser, and Schulze 2008). Second, in order to maintain (and extend) contractual relationships, most wholesale suppliers in the industry are primarily concerned with satisfying the requirements and needs of the “big box” retailer clients and not necessarily the end-consumers. Finally, large retailers control advertising and promotional programs at the retail level, somewhat limiting supplier access, engagement, and product differentiation.

In turn, minimal product differentiation within the industry can be associated with consumers’ low awareness of ornamental plant benefits. Given the relatively low brand recognition and loyalty in the ornamental plant market, growers could successfully use push strategies to encourage marketing intermediaries to promote green industry products and ensure availability to customers (Yang et al. 2009). For example, a study by Collart, Palma, and Hall (2010) investigated consumers’ brand awareness and willingness to pay premiums for plant brands. The authors report that frequent shoppers (i.e., weekly/monthly) were more likely to be aware of brands. Overall, the study found that branding programs helped to differentiating products and generate price premiums of approximately 10 percent higher than unbranded plants. A follow-up study by Collart, Palma, and Carpio (2013) reported that brand-aware consumers were willing to pay 5.5 percent more, predicting similar direction into the effectiveness of brand advertising programs. Consistent with these studies, Behe, Huddleston, and Sage (2016) reported that branded plants generated price premiums over non-branded alternatives, and that younger consumers were more likely to choose branded plants.

Compared to brand advertising, the literature of generic promotion of food and agricultural products is much more extensive. Several commodities have been analyzed, including flowers (Rimal and Ward 1998), citrus (Williams, Capps, and Palma 2008), apples (Richards, Van Ispelen, and Kagan 1997), orange juice (Capps Jr, Bessler, and Williams 2004), milk (Ward and Dixon 1989, Thompson and Eiler 1977), pecan (Moore et al. 2009), and meat (Brester and Schroeder 1995) to mention a few. The literature of advertising in the green industry is very limited. Rimal and Ward (1998) investigated the distributional impact of both generic and brand advertising of plants by three major retail outlet types. By using households' cut flower expenditures as a determinant of relative market shares among florists, supermarkets and other retail outlets, the authors report that generic promotion effects of fresh-cut flower sales were positive and outlet neutral. In contrast with generic promotional effects, the distributional effects from brand advertising showed increased market share for florists.

## 3. Identification Strategy

In this article, the treatment is the allocation of advertising expenditures. Therefore, firms with positive advertising expenditures are assigned into the treatment group, and firms with no-advertising expenditures are assigned into the control group. We assume that advertising allocations depend on several observed and unobserved factors such as financial investments in research and development, managerial decisions and experience, structure of the industry and the size of the firm. The size of the firm tends to be highly correlated with advertising expenditures (i.e. larger firms spend more in advertising). As such, any direct regression of sales on advertising is endogenous and might potentially lead to bias estimates (Oustapassidis, Vlachvei, and Notta 2000).

We estimate the effects of advertising expenditures by estimating the GPS and the dose-response function following Hirano and Imbens (2004). The estimated GPS is essential to identify treated observations (positive advertising) with untreated observations (no-advertising) based on pre-treatment covariates. As for the dose-response function, the continuous dose is defined as specific levels of advertising expenditures, and the response is defined as the corresponding annual gross sales. By design, firms in the control and treatment groups are identical according to predefined factors in the GPS, and they only differ in their advertising expenditure allocations.

### 3.1 Basic Setup

Suppose there are $i$=1…N firms in the green industry survey sample. For simplicity, the observation index $i$ is omitted. Let $t$ represent different levels of the advertising treatment, and $T$ is the continuous treatment space with range $[t_0, t_1]$. Let $X$ be a vector of pretreatment covariates that are used to estimate the GPS.[2] $Y(t)$ represents the outcome corresponding to a specific level of the advertising treatment. The GPS is computed as the conditional density of the advertising treatment on pretreatment covariates. The GPS is denoted as $R = r(T, X)$, where $r(t, x) = f_{T|X}(t|x)$.

### 3.2 Assumptions

#### *3.2.1 Unconfoundedness*

To implement GPS, we assume unconfoundedness following Rosenbaum and Rubin (1983). The unconfoundedness assumption ensures the random assignment of the treatment group, conditional on the pretreatment covariates (Hirano and Imbens 2004). Given the definition of the GPS $\boldsymbol{r}(\boldsymbol{t}, \boldsymbol{X})$ and unconfoundedness, the advertising treatment assignment is independent of the estimated GPS: $\boldsymbol{Y}(\boldsymbol{t}) \perp \boldsymbol{T}|\boldsymbol{r}(\boldsymbol{t},\boldsymbol{X})$ and $f_{T|X}(t|r(t,X),Y(t)) = f_{T|X}(t|r(t,X))$. That is to say, firms with the same GPS have the same density function of firm characteristics and hence the advertising treatment assignment is *random* conditional on having the same GPS. Hirano and Imbens (2004) prove that GPS could remove the bias resulting from differences in the pretreatment covariates. Therefore, the dose-response function is $\boldsymbol{\beta}(\boldsymbol{t},\boldsymbol{r}) = \boldsymbol{E}[Y(t)|r(t,X) = r] = \boldsymbol{E}[Y|T = t, R = r]$ and $\boldsymbol{\mu}(\boldsymbol{t}) = \boldsymbol{E}[\beta(t, r(t,X))]$, where $\boldsymbol{\beta}(\boldsymbol{t},\boldsymbol{r})$ and $\boldsymbol{\mu}(\boldsymbol{t})$ stand for the conditional expectation of the outcome, and the dose–response function respectively.

### *3.2.2 Balancing Property*

The balancing assumption ensures balanced means of the advertising *treatment group* at each advertising treatment interval and the (no-advertising) *control group*. The control group has zero advertising expenditures. For the treatment group, we divide the range of advertising expenditures into three treatment intervals with each interval accounting for approximately 33% of the entire range. More specifically, we define the treatment interval as (0, 450], (450, 2,000], (2,000, 40,000] for *small firms* and (0, 13,000], (13,000, 45,000], (45,000, 800,000] for *large firms*. The pretreatment covariates are usually very different between observations in the control group and the treatment group. Conditional on the estimated GPS, the adjusted means of covariates between observations in the control group and treatment group should not be statistically different.

## 3.3 Implementation

The main goal of the empirical strategy is to estimate the dose-response function and examine the effects of different levels of advertising expenditures on green industry firm sales. To obtain the dose response function, it is necessary to estimate the GPS and the green industry sales outcome $Y(t)$ based on the advertising treatment variable and the estimated GPS in sequence. The last step is to estimate the dose-response function over the entire range of advertising levels. The following sections show the technical details of estimating the GPS and dose-response functions using the ordinary linear and GLM approach respectively.

### *3.3.1 Ordinary Linear Approach*

The ordinary linear approach assumes that the conditional level of advertising expenditures follows a normal distribution: $T|\mathrm{X} \sim N\{\beta_0 + \beta_1 X, \sigma^2\}$. The parameters $\beta_0$, $\beta_1$, and $\sigma^2$ are estimated using maximum likelihood (Doyle 2011).

Following Hirano and Imbens (2004) and Bia and Mattei (2008), the GPS is modeled as:

$$GPS = \frac{1}{\sqrt{2\pi\hat{\sigma}^2}} \exp[\frac{1}{2\hat{\sigma}^2}(T - \hat{\beta}_0 - \hat{\beta}_1 X)^2] \tag{1}$$

After obtaining the GPS, we estimate the expectation of the sales outcome variable $E(Y|T,R)$, conditional on the advertising expenditure treatment levels and the estimated GPS. Second order polynomials of the treatment variable and the GPS are included in the model to allow for a nonlinear specification as follows:

$$\varphi\{E(Y|T,GPS)\} = a_0 + a_1 T + a_2 T^2 + a_3 GPS + a_4 GPS^2 + a_5 T * GPS \tag{2}$$

$\varphi\{\cdot\}$ is a link function chosen by the continuous nature of the outcome variable (green industry sales). The quadratic form is applied to account for a potential non-linear relationship between advertising expenditures and annual gross sales.

The dose-response function is obtained by estimating the average potential outcome at different levels of advertising expenditures:

$$E\{\widehat{Y(t)}\} = \frac{1}{N}\sum_{i=1}^{N} \hat{\beta}\,\{t, \hat{r}(t,X)\} \tag{3}$$

By combining equations (2) and (3), we obtain:

$$E\{\widehat{Y(t)}\} = \frac{1}{N}\sum_{i=1}^{N} \hat{a}_0 + \hat{a}_1 T + \hat{a}_2 T^2 + \hat{a}_3 \widehat{GPS} + \hat{a}_4 \widehat{GPS}^2 + \hat{a}_5 T * \widehat{GPS} \tag{4}$$

### *3.3.2 Generalized Linear Model (GLM)*

As a robustness measure, the GPS was also estimated using the GLM approach to obtain the dose-response function. The purpose of estimating the GLM approach is to test the sensitivity of the results to different distributional specifications of advertising expenditures. The general estimation process follows the same sequential steps as the ordinary linear approach. In essence, the main difference between the ordinary linear and the GLM approach is the flexibility of the distributional assumptions of the treatment variable (i.e. advertising expenditures may not necessarily follow a normal distribution) and the linear relationship of covariates and (any) transformation of the mean of the advertising expenditure treatment variables (Guardabascio and Ventura 2013). More precisely, the GLM approach allows for *flexible distribution* assumptions of advertising expenditures, which also account for a potential wide range of non-normal distributions of advertising expenditures. These two properties are formalized as: $f(T) = c(T, \emptyset)\exp\{\frac{T\theta - a(\theta)}{\emptyset}\}$ and $g\{E(T)\} = \beta X$ , where $a(\theta)$ denotes the distribution function in the exponential family and $g\{.\}$ denotes the link function. The parameters $(\emptyset, \theta)$ are associated with certain exponential family distributions. In order to test the robustness of the results, we specifically incorporate: (1) a negative binomial distribution with a natural log link function, (2) a gamma distribution with a log link function, and (3) fractional logit distributions with a logit link function.[3] The GPS is estimated as:

$$\hat{R} = r(t, X) = c(T, \hat{\emptyset})\exp\{\frac{T\hat{\theta} - a(\hat{\theta})}{\hat{\emptyset}}\} \quad (5)$$

The dose-response function follows the same model as in equation (4).

### 3.4 Control Variables

The selection of matching variables is built on a literature review of advertising effects on agricultural products (Brooker et al. 2005, Palma et al. 2012, Hodges et al. 2008, Hall, Hodges, and Palma 2011, Andrade and Hinson 2009). Some of the factors that influence green industry sales include the number of years the firm has been in operation, the use of computerized processes in the operation (to signal technology adoption), number of trade shows attended per year (professional networking), published price discounts, advertising media types (internet promotion, printed materials, mass media), and geographical location (Pacific, Midwest, Appalachian, Northeast, Southcentral, Mountain, Great Plains). We believe that these variables not only affect nursery sales but also decisions related to advertising expenditures due to unobserved common variables such as management styles and competitive environments. Therefore, the GPS matching variables are organized using four types of variables: *(1) characteristics of the firms* (i.e. years of operation, size of the firm, geographical location, and number of employees), *(2) business practices* (nursery product types, nursery production forms, and integrated pest management adoption), *(3) sales channels* (retail, wholesale), and *(4) professional development activities* (trade show participation). Table 1 presents the summary statistics of the matching variables.

**4. Data**

We use data from the National Green Industry Surveys (NGIS) of 2009 and 2014. The NGIS is conducted by the *Green Industry Research Consortium* of land grant universities in the United States (Hodges, Khachatryan, et al. 2015). The NGIS collects production, marketing business and operation practices of green industry firms in all 50 states in the United States using internet and mail surveys. Information collected in the survey are classified into four business aspects, including characteristics of the firms, management and production information, distribution methods and sales, and advertising expenditures.

There are a total of 5,701 firms in the dataset, 3,044 observations from 2009 and 2,657 observations from 2014. Survey respondents are geographically located in all fifty states of the United States. The highest number of respondents is from Florida (17.48%), while the second and third highest are from Pennsylvania (8.88%) and California (7.32%). New Hampshire accounts for the lowest percentage of respondents (0.07%). Approximately 22.06% of the sample responded to the surveys via the internet and 77.94% of respondents using traditional mail questionnaires. See Table 2 for detailed information about the survey implementation.

In terms of the general business practices, most firms operate their business within their home state boundaries (97.40%), and a little more than half employ two permanent employees or less (52.24%). About 46.72% of firms have three or more different product types (for reference the total number of product types on the survey was 18); nearly a third (32.26%) of the firms have two or more different product forms (the total number of product forms was seven); almost half (47.98%) of the firms apply seven or more different integrated pest management practices (the total number of different IPM was 22).

### 4.2 Grouping Variables

Advertising expenditures are correlated to the size of the firm (Chauvin and Hirschey 1993, Chan and Garg 1995). Conducting the analysis for different firm sizes provides more meaningful implications for researchers and business managers. The observations were originally categorized into three firm sizes based on annual gross sales: small, medium and large. Firms with annual gross sales of $250,000 or less were classified as small; those with annual gross sales between $250,000 and $1,000,000 were classified as medium; and those selling over $1 million were classified as large. Based on this categorization, small, medium and large firms accounted for 71.33% (n=1,587), 16.45% (n=366) and 12.22% (n=272) respectively. Due to the small portion of medium and large firms in the sample, we combine these two groups into one group (hereinafter referred to as “large”).

## 5. Results

Before we present the results of the treatment effects, the balancing test results are presented in order to validate the use of the GPS and the dose-response function. All the results below are reported for small firms and large firms respectively.

### 5.1 Balancing Property Tests

In order to implement the balancing property test, we first compare the means of the pretreatment covariates at three different advertising expenditure levels. Based on the distribution of advertising spending, the treatment interval is defined as ($0, $450], ($450, $2,000] and ($2,000, $40,000] for *small* firms and ($0, $13,000], ($13,000, $45,000] and ($45,000, $800,000] for *large* firms. The difference of each covariate is obtained by comparing the observations at one advertising interval versus the other observations in the other two intervals. We report the *t*-test for the equality of means in the left part of Table 3 (small firms) and Table 4 (large firms). For example, the first row of Table 3 compares the average number of years in operation of small firms with less than $450 advertising expenditures to other small firms with more than $450 in advertising expenditures. The table indicates that firms with less than $450 advertising expenditures have on average 3.9 more years in operation.

The *t*-tests of equality of the means after the GPS adjustment are reported in Table 3 and Table 4. The numbers in both tables are p-values of the *t*-test and bold numbers indicate statistical significance below the 10% level. In order to obtain the statistics, the GPS is estimated at the median level of advertising expenditures and then separated into five quantiles. Within each quantile, differences are calculated by comparing the means of the pretreatment covariates in that quantile with those not in the quantile. Generally, the results in Table 3 and Table 4 reveal that after the GPS adjustment, the differences in the pretreatment covariates between the advertising treatment group and the no-advertising control group are mitigated. According to a standard two-sided *t*-test, the balancing property is satisfied at the 1% significance level.

### 5.2 Estimated Effects

The parameter estimates from equation (2) are shown in Table 5 using the ordinary linear approach and Table 6 with the GLM approach. The left part of Table 5 (Panel A) shows the results for small firms and the right part (Panel B) the results for large firms. From left to right, Table 6 shows the parameter estimates assuming gamma, negative binomial and binomial distributions. The coefficients estimated from equation (5) do not provide any direct causal interpretation; however, they are utilized in estimating the dose-response function (Hirano and Imbens 2004).

A more important interpretation of the results is represented in the dose-response function estimated according to equations (3) and (4). The dose-response function is averaged at each level of advertising expenditures and it offers a direct interpretation of the causal effect of advertising expenditures and annual gross sales. The dose-response function and the marginal treatment function are shown in Figure 1 for small (panel A) and large firms (panel B) respectively. The solid line is the predicted annual gross sales by advertising expenditures, and the dotted lines indicate the 95% confidence interval with 200 bootstrap replications. The dose-response function shows the predicted annual gross sales, conditional on the pretreatment covariates, at each level of advertising expenditures. The marginal treatment effect function presents the marginal effect on annual gross sales at each level of advertising expenditures. Similarly, the dotted lines in the graph show the confidence bounds at the 95% level with 200 bootstrap iterations.

The dose response functions for small and large firms are quite different in terms of monotonicity, magnitude, and shape. Monotonicity implies that given the range of advertising expenditures, when advertising increases, i.e. $x_2 \geq x_1$, then sales also increase, i.e. $\mathrm{f}(x_2) \geq \mathrm{f}(x_1)$, which implies monotonic increases. For small firms, there is no effect of advertising on green industry sales when advertising expenditures are below $2,000. This result is in line with Adachi and Liu (2010) and Norman, Pepall, and Richards (2008) who find a minimum threshold below which advertising has no effect on sales. When advertising spending is higher than $2,000, the dose-response function takes on an inverted U shape. Before advertising spending reaches $20,000, the average gross annual sales increase from approximately $93,879 to $178,542. When advertising spending doubles from $20,000 to $40,000, the average annual gross sales decrease from approximately $178,542 to $79,823. The marginal treatment effect function shows the rate of change at every level of advertising expenditures. The solid blue line shows that marginal annual gross sales are monotonically decreasing.

For large firms, there is a positive relationship between annual gross sales and advertising in the entire advertising expenditures treatment range. The shape of the dose-response function increases monotonically. Combining the dose-response function results and the marginal treatment function indicates three intervals of advertising spending with different rates of change in annual gross sales. A visual inspection of Figure 1 provides evidence that when large firms spend less than \$170,000 on advertising, green industry sales increase at a decreasing rate. If advertising expenditures more than double from \$170,000 to \$350,000, the rate of increase in sales remains constant. If firms spend more than \$350,000 on advertising, annual green industry sales increase at an increasing rate. For example, annual gross sales increase from \$4,759,117 to \$7,573,138 when advertising spending increases from \$240,000 to \$480,000, and when advertising spending increases from \$640,000 to \$800,000, the sales increase from \$11,000,000 to \$15,700,000.

As a robustness test, the dose-response functions estimated using the GLM approach for small firms and large firms are presented in Figure 2 and Figure 3 respectively. Each figure shows the dose-response function assuming a negative binomial distribution (panel A), gamma distribution (panel B) and fractional logit (panel C). The results are similar to those in Figure 1 for small and large firms, except for the gamma distribution results in panel B. In comparison, the dose-response functions estimated using the GLM have relatively smaller variances and smaller treatment effects.

### 5.3 Comparison with the Conventional OLS Analysis

Back to the selection bias problem mentioned in the introduction and literature review sections, we investigate the magnitude of the bias between the OLS and dose-response function analysis. An OLS regression of the log form of sales on the log form of advertising spending together along with other pretreatment variables that affect green industry sales was used as it is commonly implemented in the literature. Unsurprisingly, both coefficients of the log of advertising spending for small firms and large firms using OLS regression are significant at the 0.01 level. Figure 4 graphically shows the estimated sales and advertising expenditures for small firms (Panel A) and large firms (Panel B) respectively. Visually, the OLS estimation did not capture any shape or trend patterns comparable to those shown in Figure 1. We further compare several point estimations between OLS and the dose-response function analysis.

For small firms, when advertising expenditures reach $20,000, the estimated sales are $178,541 based on the dose-response function but sales are substantially higher at around $500,000 using OLS regression. It is noteworthy that the OLS results provide a sales estimate that is well above the sales boundary of $250,000 for small firms. This result suggests an overestimation of the advertising effects on green industry sales for small firms if a traditional OLS approach is used. For large firms, when advertising expenditures reach $400,000, the estimated sales are much closer for the two methods. Sales are estimated to be $6,337,726 with the dose-response function and around $6,000,000 using the OLS regression. Therefore, in general there is no clear evidence that the OLS results bias the estimates in the same direction. It is important to emphasize that in our application, advertising expenditures are modeled in a quasi-experimental approach and considered as the "treatment" in a treatment-effect analysis framework. The estimate of the annual gross sales in the dose-response function is an estimate of the sales volume firms would have achieved at each actual advertising expenditure level. Firms were matched to be similar in all pretreatment covariates, and they only differed in advertising expenditure allocations.

## 6. Conclusions

The estimated dose-response function explains the relationship between advertising expenditures and annual gross sales of green industry firms in a quasi-experimental framework. Overall, there is a positive relationship between advertising and sales; however, the effects are heterogeneous by firm size. Since the data used in this study were collected from a U.S. nationwide representative sample, the results are useful to green industry managers and owners for business decisions and advertising allocation decisions. While this study did not concentrate on optimal advertising allocation, the results provide useful information on the incremental effects of advertising expenditures on green industry sales.

Due to the sample size, we could not further evaluate the impact of advertising effects by media types. GPS has the potential for future research to other industries or in other business decision contexts. The implications for decision makers in the green industry are quite clear. Small firms have a wide range of advertising expenditures and hence their returns need to be carefully monitored. Large firms on the other hand tend to significantly underspend in advertising and larger returns can be attained with higher levels of advertising expenditures.

**Footnotes**

1 Previous studies in agricultural economics applied does-response functions (rates) in estimating the levels (or dosage) for fertilizer, toxin, pollutants, etc, to which humans (such as farmers) can be safely exposed to (Arndt, Pauw, and Thurlow 2016, Sunding and Zivin 2000, Eskeland 1997, Roe 2004, Kan et al. 2013).

2 The pretreatment covariates are specifically discussed in section 3.4.

3 Please refer to Guardabascio and Ventura (2013) for a detailed discussion of the distribution function and link function.

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**Table 1. Summary of matching variables**

| Variables | Obs | Mean | Std. Dev. | Description |
|---|---|---|---|---|
| **Characteristics of the Companies** | | | | |
| Survey Year (=1) | 2220 | 0.389 | 0.488 | whether the survey was conducted in 2014 |
| Years of Operation (=1) | 2146 | 0.522 | 0.500 | whether the firm is operated over 25 years |
| Size: Small (=1) | 2220 | 0.715 | 0.452 | whether the gross value of product sales is smaller or equal to $250,000 |
| Size: Medium (=1) | 2220 | 0.165 | 0.371 | whether the gross value of product sales is in between of $250,000 and $1,000,000 |
| Size: Large (=1) | 2220 | 0.120 | 0.325 | whether the gross value of product sales is larger or equal to $1,000,000 |
| Region: Mid-west (=1) | 2220 | 0.178 | 0.383 | whether the firm is located in the mid-west part of the US |
| Region: South (=1) | 2220 | 0.443 | 0.497 | whether the firm is located in the south part of the US |
| Region: Northeast (=1) | 2220 | 0.214 | 0.411 | whether the firm is located in the north east part of the US |
| Region: West (=1) | 2220 | 0.145 | 0.353 | whether the firm is located in the west part of the US |
| Employment (=1) | 1480 | 0.520 | 0.500 | whether the firm has more than two employers |
| **Business practice** | | | | |
| Product Type (=1) | 2220 | 3.770 | 3.393 | whether the firm has more than two nursery product types |
| Product Form (=1) | 2220 | 1.408 | 0.799 | whether the firm has more than one product form |
| IPM (=1) | 2220 | 0.515 | 0.500 | whether the firm has more than six IPM practices |
| **Sales Channel** | | | | |
| Retail (=1) | 2119 | 0.714 | 0.452 | whether the firm has retail distribution |
| Wholesale (=1) | 2095 | 0.713 | 0.452 | whether the firm has wholesale channel |
| **Profession Show** | | | | |
| Tradeshow (=1) | 1214 | 0.647 | 0.478 | whether the firm has attended the trade show |

**Table 2. Survey Implementation Summary**

| | | NGIS |
|---|---|---|
| Observations | | 5,701 |
| | 2009 | 3,044 |
| | 2014 | 2,657 |
| Source of Response (%) | | |
| | Internet | 22.06% |
| | Survey | 77.94% |
| State Highest and Lowest Response Rate | | |
| | Highest | Florida (17.48%) |
| | Lowest | New Hampshire (0.07%) |
| Business Practices | | |
| | Operate Business within their Own State | 97.40% |
| | Average Years of Operation | 30 |
| | Permanent Employer of Two People or Fewer | 52.24% |
| Management & Production | | |
| | Three or More (<=18) Different Product Types | 46.72% |
| | Two or More (<=7) Different Product Forms | 32.26% |
| | Seven or More (<=22) Different IPM | 47.98% |

**Table 3. Covariates balancing test before and after adjustment: *t*-statistics for the equality of means (small firms).**

| | **Prior to Balancing** | | | **After Balancing** | | |
|---|---|---|---|---|---|---|
| | Treatment Category [0,450] | Treatment Category [450,2000] | Treatment Category [2000,40000] | Treatment Category [0,450] | Treatment Category [450,2000] | Treatment Category [2000,40000] |
| Years of Operation | **3.867** | 0.659 | **-3.833** | 0.409 | 0.580 | -0.811 |
| Region: Mid-west | -0.175 | **-2.330** | **2.094** | 0.911 | **-1.687** | 0.658 |
| Region: South | 1.041 | **1.912** | **-2.477** | -1.154 | **1.721** | -0.506 |
| Region: Northeast | -1.550 | 0.779 | 0.652 | -0.138 | 0.009 | -0.182 |
| Region: West | 0.348 | -1.440 | 0.910 | 0.596 | -0.531 | 0.359 |
| Employment | 0.348 | 0.563 | -0.386 | **-1.693** | **2.188** | -0.674 |
| Product Type | 0.500 | -1.227 | 0.604 | 0.542 | 1.109 | -0.946 |
| Product Form | **-1.727** | -1.413 | **2.639** | 0.398 | 0.244 | -0.057 |
| Survey Year | -1.548 | **-1.975** | **2.960** | -0.513 | -0.151 | -0.282 |
| IPM | 0.080 | **-2.114** | **1.698** | -0.374 | 1.438 | -0.438 |
| Retail | **-3.422** | **-1.843** | **4.452** | 0.246 | -0.952 | 1.473 |
| Wholesale | **5.543** | -1.465 | **-3.396** | 0.824 | 0.567 | -0.949 |
| Tradeshow | **3.818** | -0.191 | **-3.128** | 0.430 | 0.836 | 0.143 |

Notes: The numbers shown here are p-values of t-stat*istic*s. All the p-values significant at or below 0.1 level are indicated in bold.

**Table 4. Covariates balancing test before and after adjustment: *t*-statistics for the equality of means (large firms).**

| | Prior to Balancing | | | After Balancing | | |
|---|---|---|---|---|---|---|
| | Treatment Category [0,13000] | Treatment Category [13000,45000] | Treatment Category [45000,800000] | Treatment Category [0,13000] | Treatment Category [13000,45000] | Treatment Category [45000,800000] |
| Years of Operation | 1.022 | 0.282 | -1.182 | -0.727 | 1.414 | -1.089 |
| Region: Mid-west | -0.180 | -1.436 | 1.444 | 0.933 | -0.832 | 0.099 |
| Region: South | -1.621 | 1.513 | 0.128 | -1.245 | 0.727 | -0.194 |
| Region: Northeast | -0.425 | -0.376 | 0.722 | -0.105 | -0.145 | 0.470 |
| Region: West | **2.622** | -0.391 | **-2.034** | 1.025 | -0.064 | -0.483 |
| Employment | **3.026** | 0.239 | **-2.960** | 0.787 | 1.217 | **-1.911** |
| Product Type | 0.975 | 0.449 | -1.290 | -0.206 | 2.045 | -1.357 |
| Product Form | 1.402 | -0.956 | -0.425 | 0.488 | 0.793 | 0.402 |
| Survey Year | **1.903** | 0.598 | **-2.271** | 0.702 | 0.165 | 0.302 |
| IPM | 0.578 | 0.493 | -0.967 | 0.051 | 0.917 | -1.166 |
| Retail | 0.655 | -0.925 | 0.231 | 0.499 | -0.135 | 0.655 |
| Wholesale | -0.354 | -1.345 | 1.530 | 0.024 | -0.742 | 1.348 |
| Tradeshow | 0.059 | 0.625 | -0.617 | 0.133 | 0.616 | -1.008 |

Notes: The numbers shown here are p-values of t-stat*istic*s. All the p-values significant at or below 0.1 level are indicated in bold.

**Table 5. Parameter estimates of dose-response function from ordinary linear approach.**

| **Ordinary Linear** | | |
|---|---|---|
| | Panel A: Small Firms | Panel B: Large Firms |
| GPS | -2311.129 | -842354.700 |
| | (246727.400) | (7778163.000) |
| $GPS^2$ | 481032.700 | -7070221.000 |
| | (709841.200) | (18300000.000) |
| Advertising Expenditures | 12.329*** | -1.272 |
| | (2.804) | (6.452) |
| Advertising $Expenditures^2$ | -0.000*** | 0.000** |
| | (0.000) | (0.000) |
| GPS* Advertising Expenditures | 36.171*** | 145.735*** |
| | (13.907) | (31.890) |
| Intercept | -969.704 | 1178591.000 |
| | (18807.390) | (762339.800) |
| Adjusted $R^2$ | 0.550 | 0.344 |
| Observations | 269 | 362 |

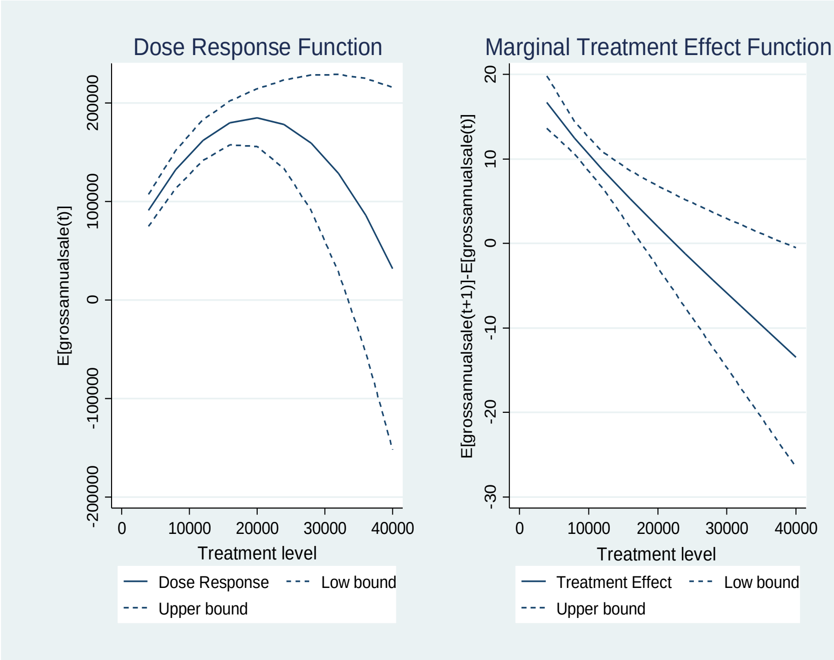
Notes: Standard errors are reported in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

**Table 6. Parameter estimates of the dose-response function from GLM.**

| **GLM** | Family: Gamma; Link: log | | Family: Nb; Link: log | | Family: Binomial; Link: logit | |
|---|---|---|---|---|---|---|
| | Panel A | Panel B | Panel A | Panel B | Panel A | Panel B |
| | Small Firms | Large Firms | Small Firms | Large Firms | Small Firms | Large Firms |
| GPS | -2.33E+08*** | -2.46E+11*** | -24623.430 | 0 | 788911.400*** | -1.88E+06 |
| | (7.63E+07) | (8.03E+10) | (1509975.000) | (omitted) | (275765.600) | (1.93E+07) |
| $GPS^2$ | 1.86E+11** | 4.19E+15** | 3055.587 | 0 | -2.65E+06** | 1.2E+08 |
| | (8.18E+10) | (1.71E+15) | (1608092.000) | (omitted) | (1.16E+06) | (1.05E+08) |
| Advertising Expenditures | 6.339** | 3.488 | 17.968*** | 24.088*** | 554950.900*** | 1.46E+07*** |
| | (2.646) | (6.336) | (1.581) | (3.315) | (77267.380) | (3. 5E+06) |
| Advertising $\text{Expenditures}^2$ | 0.000 | 0.000 | -0.000*** | -0.000** | -662642.900*** | -6.02E+06* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (114881.500) | (3.20E+06) |
| GPS* Advertising Expenditures | 165637.900*** | 2.08E+06 | -330816.300 | 0 | 776385.200 | 2.65E+06 |
| | (28250.790) | (1292398.000) | (7163988.000) | (omitted) | (567759.700) | (2.8E+07) |
| Intercept | 51803.810*** | 3249039.000*** | 24644.080*** | 945520.100*** | -19333.460 | 216662.700 |
| | (15241.390) | (966154.600) | (4646.169) | (185631.000) | (14677.710) | (853165.800) |
| Adjusted $R^2$ | 0.5741 | 0.3374 | 0.4977 | 0.3064 | 0.5281 | 0.3429 |
| Observations | 269 | 362 | 269 | 362 | 269 | 362 |

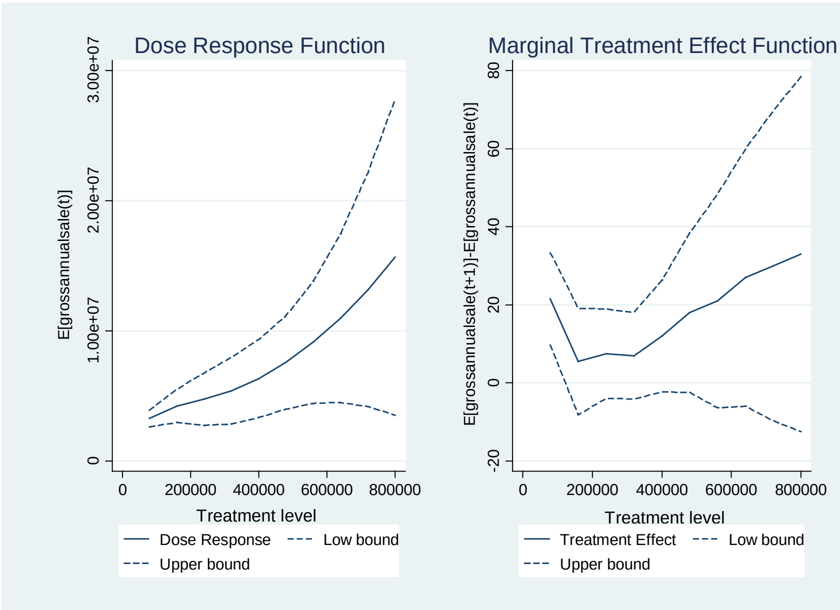
Notes: Standard errors are reported in parentheses.

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




Note: Confidence interval at 95 % level

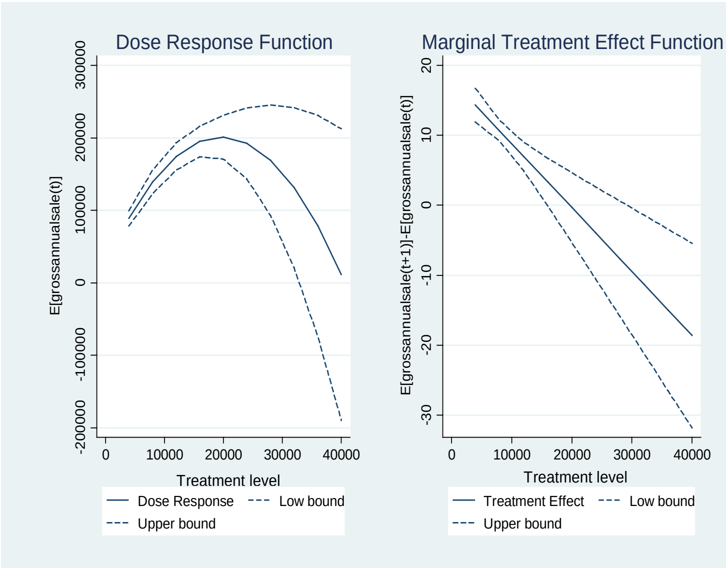
Panel A: Small firms



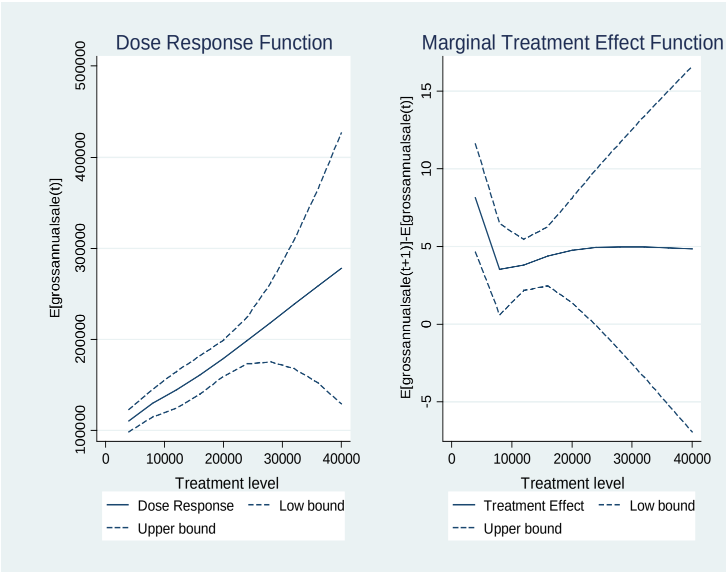

Note: Confidence interval at 95 % level

Panel B: Large firms

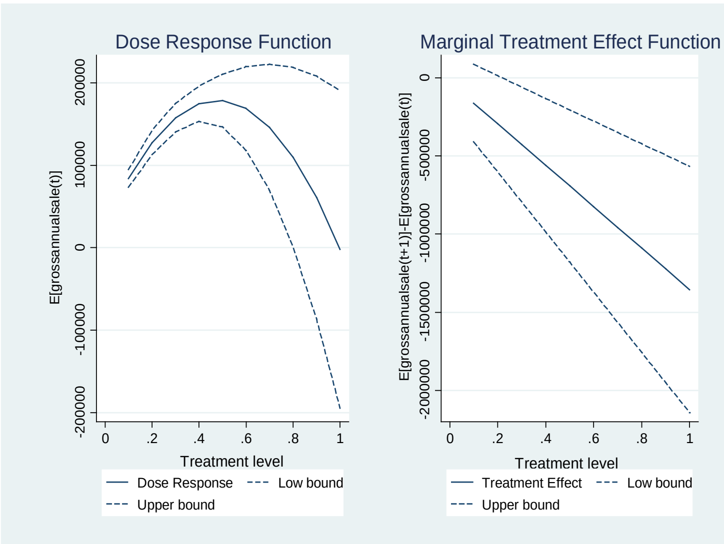
Figure 1. Dose-response function and marginal treatment effect function for annual gross sales.




Panel A: Negative Binomial distribution Note: Confidence interval at 95 % level

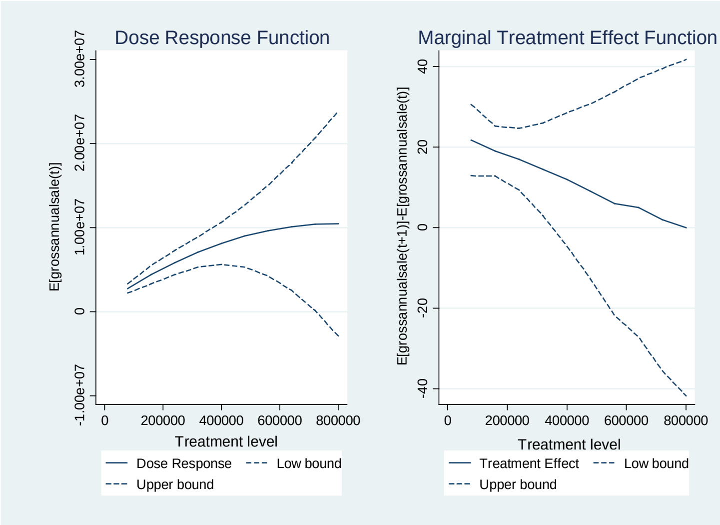



Panel B: Gamma distribution Note: Confidence interval at 95 % level

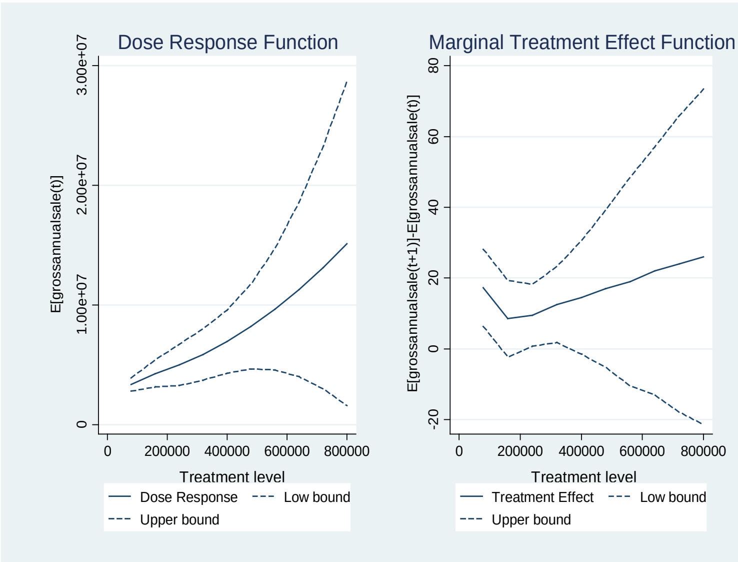



Panel C: Fractional logit Note: Confidence interval at 95 % level

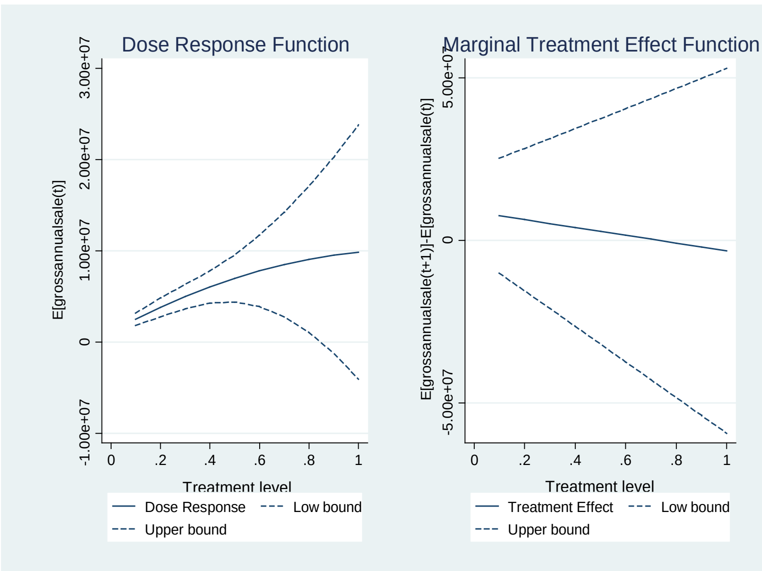
Figure 2. Dose-response function and marginal treatment effect function for annual gross sales using GLM for small firms.




Panel A: Negative Binomial distribution Note: Confidence interval at 95 % level



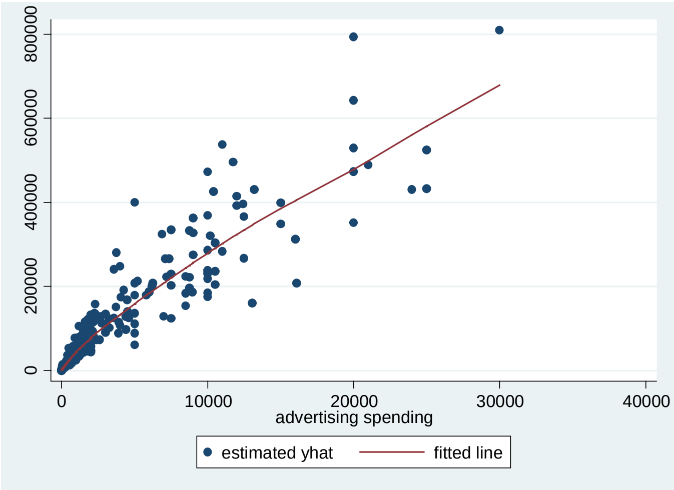

Panel B: Gamma Distribution Note: Confidence Bounds at 95 % level



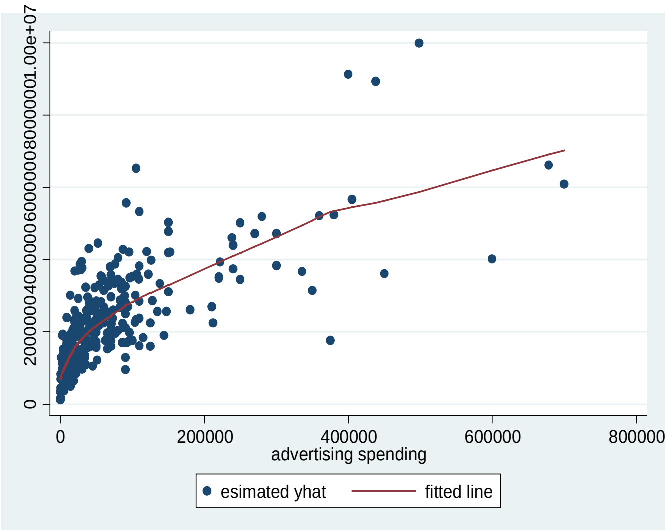

Panel C: Factional Logit Note: Confidence Bounds at 95 % level

Figure 3. Dose-response function and marginal treatment effect function for annual gross sales using GLM for large firms.

Appendix




Panel A Estimated sales versus advertising spending for small firms




Panel B Estimated sales versus advertising spending for large firms

Figure 4. Estimated sales versus advertising spending