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Measuring the effects of advertising on green industry sales: a generalized propensity score approach

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ABSTRACT
This article estimates 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 indicate that the magnitude and shape of the response function depend on the size of the firm. For small firms, increasing advertising spending yields to higher sales within a range of advertising spending. Beyond this range, advertising spending increases do not impact sales any more. Thus, small firms’ management should carefully monitor advertising input. For large firms, on the other hand, the current evidence does not support a positive relationship between advertising spending and sales since the marginal treatment effect is insignificant almost over the entire range of advertising spending.

I. Introduction
The environmental horticultural industry, also known as the ‘green industry’, includes production and wholesale nursery, retail garden centres, marketing intermediaries, landscape designers, architects, and maintenance (Hall, Hodges, and Haydu 2005). The green industry has been one of the fastest developing sectors in the US agricultural economy over the past several decades, even during economic recession periods (Hodges, Hall, and Palma 2011; Hall, Hodges, and Haydu 2006). The economic impacts of the green industry were estimated at $196.1 billion in 2013 (Hodges et al. 2015).

Measuring advertisement effectiveness can influence management related decisions for resource allocation in green industry firms. To answer whether and how much a firm should invest in advertisement, the management team should understand how much sales are impacted by the amount of money invested in advertising.

Early efforts to measure advertisement effectiveness can be traced back to the 1960s (Lavidge and Steiner 1961). The authors mention potential effects of advertising in terms of: the stages customers go through for purchasing products (for example: knowledge, preference and purchase), behaviour changes in each stage (for example: attitudes and feeling changes, and purchase desire stimulation), and provide examples of advertising at each stage (for example: competitive advertisement and point-of-purchase retail store advertisement). Following this line of research, scholars have examined how customers’ attitudes, emotions, behavioural intention and cognitive response affect advertising effectiveness (Mehta 2000; María and Andrea 2018; Ha, Park, and Lee 2014; Huang and Hutchinson 2008; Hamelin, Moujahid, and ThaiChon 2017).

Some researchers have directly investigated the effects of advertising on sales. Assmus, Farley, and Lehmann (1984) point out several issues related to estimation techniques by examining the
relationship between advertising and sales, which include model specification, variable definition, and estimation methods. Demirdjian (1983) studies the effect of comparative advertising and non-comparative advertising on sales through a classroom field experiment. A similar study investigates the relationship between online advertising and offline sales via a controlled field experiment (Lewis and Reiley 2014). Peter J. Danaher, André Bonfrer, and Dhar (2008) aggregate scanner data and model sales using average price and market level advertising. Recently, new econometric methods have been applied to examine the advertising-sales relationship, such as cointegration analysis (Esteve and Requena 2006; Mahendru and De 2013; Darrat et al. 2016).

Although traditional econometric analysis shows significant positive effects of advertising on sales, the main contribution of this study is to provide a general understanding of sales increases responding to each level of investment increases in advertising (Conchar, Crask, and Zinkhan 2005; Tellis and Weiss 1995). Given the magnitude and importance of the green industry, we focus directly on this sector. Our study differs from previous work in the following aspects: first, we apply program evaluation analysis to investigate the relationship of sales increases to each level of advertising spending increase without specifying any demand-supply functions; second, this study uses the generalized propensity score method and dose-response function for estimation. By using this method, biases (such as aggregation bias, misspecification bias, and simultaneity bias) are assumed to be addressed via the research design and the unconfoundedness assumption.

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 studies (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 the case of binary treatments. However, in many cases, the treatment takes on a continuous form such as expenditures and duration of the training program. 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).

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) develop 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 the conventional PSM, to assign an observation to the treatment (or control) group conditional on observed pre-treatment covariates. Literally, the dose in the dose-response function means the treatment, and the response means the outcome.

In our application, we examine the effects of advertising spending (dose) on sales (response) in the green industry. Traditional PSM can also be used to evaluate the effects of the decision to advertise on sales 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; Kluev et al. 2012). The empirical strategy of this study involves estimating GPS and modelling the dose-response function as a joint function of estimated GPS and advertising expenditures. During the estimation process, it is worth noting the following issues related to the GPS estimation: first, the distributional assumptions of the treatment variable (i.e. usually assumed to be normally or log-normally 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 the balancing property test (Bia, Flores, and Mattei 2011; 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 2011).

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, we separate the overall sample into small and large firms according to their annual gross sales to capture potential heterogeneous effects by firm size. The results reveal heterogeneity in the magnitude and the shape of the dose-response functions by firm size. 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.

Dose-response functions have gained attention in applied economics research, but they have not been widely used for business and marketing decisions yet. This study is one of the first to apply this method to analyse treatment effects of business or marketing behaviour of agricultural 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 spending is endogenous and might potentially lead to biased estimates (Oustapasidis, Vlachvei, and Notta 2000). Previous studies examining the impact of advertising on sales attempt 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). The validation of the dose-response function method is built on the assumptions related to the independence of the outcome and the levels of treatment, and the balancing distribution of the firm characteristics. The method itself does not eliminate the endogeneity problem. We contribute to the literature by providing a different method to ameliorate causal effect bias, which conditions on the weak unconfoundedness assumption and controls for a rich set of confounding factors. More details are discussed in Section 3.

The rest of the paper proceeds as follows. Section 2 provides a review of the relevant literature. Section 3 outlines the identification strategy. Section 4 describes the data. Section 5 presents the balancing test and the results. The last section concludes.

II. Literature review

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 focuses on elasticity; however, the 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 curve of their brand. The focus of this article is to evaluate incremental advertising expenditure 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 et al. 2015). As such, green industry products, which include a variety of ornamental and landscape plants, are highly heterogeneous and firms normally seek to advertise to differentiate their products.

Advertising and promotion practices can be beneficial for green industry firms that are facing increasingly competitive business environments. 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, the green industry is
one of the least pro-active agricultural sectors to sufficiently engage in advertising and promotions (Capps, Seo, and Nichols 1997). There are many reasons that can explain such conduct. First, as with other food and agricultural products, there is uncertainty among green industry stakeholders about the effectiveness of advertising expenditures (Zheng, Bar, and Kaiser 2010; Piggott, Piggott, and Wright 1995). The scepticism 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) investigates 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 finds that branding programs helped to differentiate products and generate price premiums approximately 10 per cent higher than unbranded plants. A follow-up study by Collart, Palma, and Carpio (2013) reports that brand-aware consumers were willing to pay 5.5 per cent more, predicting similar direction into the effectiveness of brand advertising programs. Consistent with these studies, Behe, Huddleston, and Sage (2016) report 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 on generic promotion of food and agricultural products is much more extensive. Several commodities have been analysed, including flowers, citrus, apples, orange juice, milk, pecan, and meat, to mention a few (Rimal and Ward 1998; Williams, Capps, and Palma 2008; Richards, Van Ispelen, and Kagan 1997; Capps Jr, Bessler, and Williams 2004; Ward and Dixon 1989; Thompson and Eiler 1977; Moore et al. 2009; Brester and Schroeder 1995). The literature of advertising in the green industry is very limited. Rimal and Ward (1998) investigate 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.

III. Identification strategy

In this article, the treatment is the allocation of advertising expenditures. Therefore, firms with positive advertising expenditures are assigned to treatment groups with different levels of expenditure. We assume that advertising expenditures depend on observed factors such as financial investments in research and development, managerial decisions and experience, the structure of the industry and the size of the firm. For example, the size of the firm tends to be highly correlated with advertising expenditures (i.e. larger firms spend more in advertising). By controlling these observed confounding factors, it is normally assumed that sales are independent of the level of advertising expenditures.

We estimate the effects of advertising expenditures on sales by estimating the GPS and the dose-response function following Hirano and Imbens (2004) and Bia and Mattei (2008). The correctly estimated GPS is essential to assure insignificant differences among pre-treatment covariates at each level of advertising expenditures. That is to say, the treatment firms at each level of expenditures should not be significantly different from each other if the GPS is estimated correctly. 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 at the different treatment levels are identical according to predefined factors used for estimating the GPS, and they only differ in their advertising expenditure allocations.

**Basic setup**
Suppose there are \( i = 1 \ldots N \) 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. \( Y(t) \) 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 \( r(t, x) = f_{T|X}(t|x) \), following Hirano and Imbens (2004).

**Assumptions**

*Weak unconfoundedness*
To implement GPS, we assume weak unconfoundedness (also known as selection on observables) following Rosenbaum and Rubin (1983). The weak unconfoundedness assumption ensures the random adoption of different levels of advertising expenditures, conditional on observed pretreatment covariates (Hirano and Imbens 2004). Given the definition of the GPS \( r(t, X) \) and weak unconfoundedness, the advertising treatment assignment is independent of the estimated GPS: \( Y(t) \perp T \mid X \) (Hirano and Imbens 2004). That is to say, firms with the same GPS have the same density function of firm characteristics and hence the selection of advertising spending level is random conditional on having the same GPS. Hirano and Imbens (2004) prove that the GPS could remove the bias resulting from differences in the pretreatment covariates. Therefore, the dose-response function is \( \beta(t, r) = E[Y(t)|r(t, X) = r] = E[Y|T = t, R = r] \) and \( \mu(t) = E[\beta(t, r(t, X))] \), where \( \beta(t, r) \) and \( \mu(t) \) stand for the conditional expectation of the outcome, and the dose-response function, respectively (Hirano and Imbens 2004). Although the weak unconfoundedness assumption cannot be tested directly, we believe the rich set of pre-treatment covariates renders the plausibility of the method. It is worth noting that we cannot rule out the possibilities of other unobserved factors influencing both advertising spending and sales. The GPS cannot account for the unobserved factors. Therefore, there still might exist a certain level of selection bias in the estimators, although it is much smaller than any direct regression on sales.

*Balancing property*
The balancing assumption ensures balanced means of pre-existing characteristics of advertising firms at each expenditures interval. Among those firms that spend on advertising, 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 at different advertising levels. Conditional on the estimated GPS, the adjusted means of pretreatment covariates between observations at each treatment level should not be statistically different.

*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 (Bia and Mattei 2008). The last step is to estimate the dose-response function over the entire range of advertising levels (Bia and Mattei 2008). The following sections show the technical details of estimating the GPS and dose-response functions.

\(^1\)The pretreatment covariates are specifically discussed in section 3.
using the ordinary linear and GLM approach, respectively.

**Ordinary linear approach**

The ordinary linear approach assumes that the conditional level of advertising expenditures follows a normal distribution: $T|X \sim N\{\beta_0 + \beta_1 X, \sigma^2\}$. 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 modelled as:

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

After obtaining the GPS, we estimate the expectation of the 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 non-linear specification as follows (Hirano and Imbens 2004):

$$\varphi\{E(Y|T, GPS)\} = a_0 + a_1 T + a_2 T^2 + a_3 GPS + a_4 GPS^2 + a_5 T \times GPS$$ \hspace{1cm} (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:

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

By combining equations (2) and (3), we obtain (Hirano and Imbens 2004):

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

**Generalized linear model (GLM)**

As a robustness measure, the GPS is 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 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 accounts for a potential wide range of non-normal distributions of advertising expenditures (Guardabascio and Ventura 2013 and Guardabascio and Ventura 2014). These two properties are formalized as: $f(T) = c(T, \theta) \exp\{\frac{T \theta - a(\theta)}{\theta}\}$ and $g\{E(T)\} = \beta X$, where $a(\theta)$ denotes the distribution function in the exponential family and $g\{\cdot\}$ denotes the link function (Guardabascio and Ventura 2014). The parameters $(\theta, \theta)$ 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. Following Guardabascio and Ventura (2014), the GPS is estimated as:

$$\hat{R} = r(t, X) = c(T, \theta) \exp\{\frac{T \theta - a(\theta)}{\theta}\}$$ \hspace{1cm} (5)

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

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2Please refer to Guardabascio and Ventura (2013) for a detailed discussion of the distribution function and the link function.
2012; Hodges et al. 2008; Hall, Hodges, and Palma 2011; Andrade and Hinson 2009). Some 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. Additionally, we set survey years as a dummy variable to account for different macroeconomic conditions firms were confronted given the dataset we use includes 2009 and 2014 surveys and the Recession was around 2009.

IV. 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 US (Hodges, Khachatryan, et al. 2015). The NGIS collects production, marketing business and operation practices of randomly picked growers and plant dealer firms in all 50 states using internet and mail surveys (Hodges, Hayk Khachatryan, and Hall 2015). 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. This survey has been used to analyse the national green industry by scholars and practitioners and characterized by its representation of the industry.

Grouping variables

Advertising expenditures are correlated with 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 clas-
sified 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. The cut-off values for firm sizes are from one published work, see Palma et al. (2012). 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’).

There is 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 50 states of the US. The highest number of respondents come 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 firms employ two permanent employees or less (52.24%). About 46.72% of the 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). We also report the firm statistics based on firm size. Generally, the firm statistics are consistent across small and large firms.

V. Results

Before we present the results, the balancing test results will be 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.

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 at 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

Table 2. Survey Implementation Summary.

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Small Firms</th>
<th>Large Firms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observations</td>
<td>5,701</td>
<td>1,600</td>
<td>4,101</td>
</tr>
<tr>
<td>2009</td>
<td>53.39%</td>
<td>58.88%</td>
<td>51.26%</td>
</tr>
<tr>
<td>2014</td>
<td>46.61%</td>
<td>41.13%</td>
<td>48.74%</td>
</tr>
<tr>
<td>Source of Response (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Internet</td>
<td>22.06%</td>
<td>15.25%</td>
<td>24.70%</td>
</tr>
<tr>
<td>Survey</td>
<td>77.94%</td>
<td>84.75%</td>
<td>75.30%</td>
</tr>
<tr>
<td>State Highest and Lowest Response Rate</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Highest</td>
<td>Florida (17.48%)</td>
<td>Florida (15.07%)</td>
<td>Florida (18.42%)</td>
</tr>
<tr>
<td></td>
<td>New Hampshire (0.07%)</td>
<td>New Hampshire (0.06%)</td>
<td>New Hampshire (0.07%)</td>
</tr>
<tr>
<td>Lowest</td>
<td>Florida (17.48%)</td>
<td>Florida (15.07%)</td>
<td>Florida (18.42%)</td>
</tr>
<tr>
<td></td>
<td>New Hampshire (0.07%)</td>
<td>New Hampshire (0.06%)</td>
<td>New Hampshire (0.07%)</td>
</tr>
<tr>
<td>Business Practices</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Operate Business within their Own State</td>
<td>97.40%</td>
<td>99.36%</td>
<td>96.58%</td>
</tr>
<tr>
<td>Average Years of Operation</td>
<td>31</td>
<td>25</td>
<td>33</td>
</tr>
<tr>
<td>Permanent Employer of Two People or Fewer</td>
<td>52.24%</td>
<td>79.82%</td>
<td>42.95%</td>
</tr>
<tr>
<td>Management &amp; Production</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Three or More (≤ 18) Different Product Types</td>
<td>46.72%</td>
<td>45.15%</td>
<td>47.33%</td>
</tr>
<tr>
<td>Two or More (≤ 7) Different Product Forms</td>
<td>32.26%</td>
<td>31.02%</td>
<td>32.74%</td>
</tr>
<tr>
<td>Seven or More (≤ 22) Different IPM</td>
<td>47.98%</td>
<td>44.34%</td>
<td>49.40%</td>
</tr>
</tbody>
</table>
number of years in the operation of small firms with less than $450 advertising expenditures to other small firms with more than $450 in advertising expenditures. The result 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 Tables 3 and 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, the differences are calculated by comparing the means of the pretreatment covariates in that quantile with those not in the quantile. Generally, the results in Tables 3 and 4 reveal that after the GPS adjustment, the differences in the pretreatment covariates are mitigated. According to a standard two-sided $t$-test, the balancing property is satisfied at the 1% significance level.

**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) shows the results for large firms. From left to right, Table 6 shows the parameter estimates assuming gamma, negative binomial and binomial distributions, respectively. 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 treatment 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 (CI) 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. \( f(x_2) \geq f(x_1) \), 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 (2010).

Table 5. Parameter Estimates of Dose-Response Function from Ordinary Linear Approach.

<table>
<thead>
<tr>
<th>GLM</th>
<th>Panel A: Small Firms</th>
<th>Panel B: Large Firms</th>
</tr>
</thead>
<tbody>
<tr>
<td>GPS</td>
<td>−2311.129 (246,727.400)</td>
<td>−842,354.700 (7,778,163.000)</td>
</tr>
<tr>
<td>( GPS^2 )</td>
<td>481,032.700 (709,841.200)</td>
<td>−7,070,221.000 (18,300,000.000)</td>
</tr>
<tr>
<td>Advertising Expenditures</td>
<td>12.329*** (2.804)</td>
<td>−1.272 (6.452)</td>
</tr>
<tr>
<td>Advertising Expenditures(^2)</td>
<td>−0.000*** (0.000)</td>
<td>0.000** (0.000)</td>
</tr>
<tr>
<td>GPS* Advertising Expenditures</td>
<td>36.171*** (13.907)</td>
<td>145.735*** (31.890)</td>
</tr>
<tr>
<td>Intercept</td>
<td>−969.704 (18,807.390)</td>
<td>1,178,591.000 (762,339.800)</td>
</tr>
<tr>
<td>Adjusted ( R^2 )</td>
<td>0.550</td>
<td>0.344</td>
</tr>
<tr>
<td>Observations</td>
<td>269</td>
<td>362</td>
</tr>
</tbody>
</table>

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.

<table>
<thead>
<tr>
<th>GLM</th>
<th>Family: Gamma; Link: log</th>
<th>Family: Nb; Link: log</th>
<th>Family: Binomial; Link: logit</th>
</tr>
</thead>
<tbody>
<tr>
<td>GPS</td>
<td>−2.33E+ 08***</td>
<td>−2.46E+ 11***</td>
<td>−24,623.430 (omitted)</td>
</tr>
<tr>
<td>( GPS^2 )</td>
<td>(7.63E+ 07)</td>
<td>(8.03E+ 10)</td>
<td>(1,509,975.000)</td>
</tr>
<tr>
<td>Advertising Expenditures</td>
<td>3055.587 (1,608,092.000)</td>
<td>0</td>
<td>(275,765.600)</td>
</tr>
<tr>
<td>( GPS^2 )</td>
<td>−2.65E+ 06**</td>
<td>−2.65E+ 06*</td>
<td>(1.16E+ 06)</td>
</tr>
<tr>
<td>Intercept</td>
<td>6.339** (6.336)</td>
<td>17.968*** (3.315)</td>
<td>(1.14E+ 06)</td>
</tr>
<tr>
<td>Advertising Expenditures</td>
<td>1.86E+ 11**</td>
<td>4.19E+ 15**</td>
<td>554,950.900***</td>
</tr>
<tr>
<td>( GPS^2 )</td>
<td>(8.18E+ 10)</td>
<td>(1.71E+ 15)</td>
<td>(1.16E+ 06)</td>
</tr>
<tr>
<td>Intercept</td>
<td>3.488 (6.336)</td>
<td>24.088***</td>
<td>(1.14E+ 06)</td>
</tr>
<tr>
<td>Adjusted ( R^2 )</td>
<td>0.000 (0.000)</td>
<td>0.000**</td>
<td>0.306**</td>
</tr>
<tr>
<td>Observations</td>
<td>269</td>
<td>362</td>
<td>362</td>
</tr>
</tbody>
</table>

Notes: Standard errors are reported in parentheses. * \( p < 0.1 \), ** \( p < 0.05 \), *** \( p < 0.01 \).
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. It is worth noting that the CI for marginal treatment effect function cross zero, which means that the marginal treatment effect is insignificant beyond zero point. In turn, it implies that sales increases to the increasing advertising spending beyond this point are no longer significant. This result seems to indicate that going beyond the optimal advertising allocation level ceases to increase sales.

For large firms, the shape of the dose-response function increases monotonically over the entire range. Accordingly, we can see that 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. The marginal treatment effect graph shows the decreasing and increasing trend around the first and top percentile. However, the marginal treatment effect is insignificant since the CI includes zero almost over the entire range of advertising spending. Hence, the null hypothesis that increasing advertising spending does not have an effect on sales cannot be rejected at the 5% level of statistical significance.

As a robustness test, the dose-response functions estimated using the GLM approach for small firms and large firms are presented in Figures 2 and 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 of Figure 2.

**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 is 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 1% 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 does not capture any shape or trend patterns comparable to those shown in Figure 1. We further compare several point estimates 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 regression 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 estimates are biased in the same direction. It is important to emphasize that in our application, advertising expenditures are modelled in a quasi-experimental framework and considered as the ‘treatment’

![Figure 2. Dose-Response Function and Marginal Treatment Effect Function for Annual Gross Sales Using GLM for Small Firms.](image-url)
in a treatment-effect analysis. The estimates of the annual gross sales in the dose-response function are estimates 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.

VI. 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, for small firms, increasing advertising spending yields to higher sales within a range of advertising spending. Since the data used in this study were collected from a US nationwide representative survey, the results are useful to green industry managers and owners for business decisions and advertising allocation decisions. While this study does 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. The method has the potential for future research to other industries or in other business decision contexts.
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References


Figure 4. Estimated Sales versus Advertising Spending.


