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Impact of Varying Coronavirus Regulations on Green-industry Sales

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Abstract. **In 2020, the COVID-19 pandemic changed the way many businesses conducted business. Notably, regulations imposed by states impacted how green-industry firms sold their plants and landscape products. However, not all states implemented the same stringency of regulations. Using an online consumer survey implemented in Jan 2021, we examine the impact of varying regulation stringencies across five treatment groups (Michigan, and New York, and low, medium, and high stringency). We estimate the difference between 2020 and 2019 self-reported expenditures, in conjunction with propensity score matching to compare each treatment with the other treatments. Results indicate that, for the most part, states with greater stringency associated with their COVID regulations did not impact plant and landscape expenditures negatively between 2019 and 2020. However, Michigan consumers did spend significantly less than medium- and high-stringency states for landscape products. Michigan was one of only two states that put qualifications on green-industry firms, and it was the only state to list green-industry firms as nonessential. Also, New York consumers spent more than low-stringency states, and low-stringency states spent less than high-stringency states for plants. Furthermore, there were no differences in online expenditures between state treatment groups. From a policy perspective, regulation type (i.e., shutting down green-industry sectors as Michigan did) had varying impacts across product categories within the green industry.**

In early 2020, coronavirus disease 2019 (COVID-19) was identified in the United States. As COVID-19 spread throughout the United States, state and local governments made difficult decisions about shutting down businesses, imposing new operational regulations on businesses, and/or implementing quarantine measures for residents in their jurisdictions. In an attempt to help states make these decisions, the Center for Disease Control and Prevention offered guidance to help states categorize industries as "essential" or "nonessential." Workers were categorized as essential or nonessential based on their industry (according to the 2017 North American Industry Classification System), not their occupation within the industry (Center for Disease Control 2021; US Department of Homeland Security 2021).

With respect to businesses, states classified industries, and thereby businesses, as essential or nonessential, with specific classification made at the state level. State governments allowed essential industries to stay open and continue operating under the new public safety guidelines (e.g., limiting the number of customers in a building, allowing curbside service). Essential businesses experienced increased demand and a shortage of inputs as a result of the rising demand and global supply chain issues (US Bureau of Labor Statistics 2021). The federal government recommended that food and agriculture be categorized as essential industries, but state and local jurisdictions made the final decisions (US Department of Homeland Security 2021).

For the most part, state and local jurisdictions classified the green industry (nursery/greenhouse production/retailing) as essential, and the industry experienced a boom in demand as consumers followed stay-at-home orders. Green-industry firms' sales are often seasonal, with a large portion of their sales in the spring, a drop in sales in the summer, and then increased sales in the fall. The timing of the COVID-19 outbreak tended to increase sales during the spring window. Campbell et al. (2021) found an average 3.4% and 4.6% increase in plants and landscape items (e.g., pots, fertilizers, mulch) sales, respectively across the southeastern United States from Jan to Jul 2020. Independent garden centers (IGCs) also started stocking and selling 13% more houseplants than they did in 2019 (Spirgen 2020). Ultimately, 48 states classified green-industry firms as essential. However, Michigan and New York were the lone exceptions by placing restrictions on the green industry. Michigan did not give nurseries, greenhouses, and IGCs an essential designation for the first month and a half of their lockdown (15 Mar–29 Apr). During April 2020, Michigan mandated full closings, which corresponded to the state's strictest lockdown period (Ford 2020). After 29 Apr, IGCs were named essential businesses and were allowed to open under statewide regulations (Hicks 2020). New York granted nurseries, greenhouses, and IGCs essential status under the caveat that they sold or produced food-producing crops.

Outside of business mandates (essential vs. nonessential), states enacted different policies that varied in strictness-associated stay-at-home mandates and other regulations. For instance, some states had extended quarantine periods, travel restrictions, and so on. Hallas et al. (2021) found that regional and political variation in stringency was a factor in the strictness of COVID-19 policies. Northeastern and Democrat-led states had the most stringent policy responses; Midwest and Republican-led states had the least restrictions (Hallas et al. 2021).

Although the majority of states allowed nurseries, greenhouses, and IGCs to remain open, they still had to adhere to state guidelines on the amount of people allowed on the premises and on social distancing. Many plant retailers switched to offering curbside and/or online purchasing options alongside or in replacement of in-store purchases (Oakes 2020). These alternative purchasing options allowed these businesses to remain open while following state mandates. As people spent more time at home, many started gardening. Approximately one in every three households started gardening in 2020 because they were home more (San Fratello et al. 2021). Hentshcel (2020) pointed out that throughout the entire growing season of 2020, veteran gardeners reported they spent about 42% more time gardening than they had in 2019.

Homeowners also showed an increased interest in landscaping. Data from 2020 and early 2021 reveal that the lawn care and landscaping sectors were not as impacted by the COVID-19 pandemic as other home services. The sector saw greater growth in the second half of the year, which continued into 2021. The end of 2020 saw an increase of 30% new work scheduled, and median revenue was also up 28% (Schwartz et al. 2021). Many homeowners put in new grass lawns and did outdoor renovations as well. IGCs reported that growing operations, landscape design, and patio furniture sales all grew by 5% during 2020 (Spirgen 2020).

There were many factors that led to increased spending in the green industry. At the beginning of the pandemic, the government gave out roughly US$850 billion in three

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different installments of direct cash payments. The three payments—US$1200, US$600, and US$1400—boosted personal income by more than 21% during those months. When the country received the first round of payments, Lisa (2021) reported that just 14% of recipients saved the money and only 11% used it to pay down debt, which leaves about 75% of recipients who put that money directly into the economy. The Personal Consumption Expenditures Price Index, which measures consumer spending, showed a year-over-year gain of 1.8%. After falling by 1% in Feb 2020, it shot up by 4.2% in March, starting the foundation for economic recovery (Lisa 2021).

Although overall sales in the green industry trended higher, the impact of different COVID-19 policies on green-industry firms is not understood. Given the size of the green industry and its importance to the economies of many states, understanding how state regulations impact the industry is essential. For instance, in 2018, the direct industry output for all sectors of the green industry was about $159.57 billion, and total output contributions, including indirect and induced regional economic multiplier effects of export sales, were $348.08 billion. Total added value to the gross domestic product was $190.98 billion, including total employment contributions of 2,315,357 jobs (Hall et al. 2020).

This study assesses whether there was a connection between state COVID-19 policies and the level of green-industry spending within a state for both plants and landscape materials. Our hypothesis is that as policies became more stringent, spending on green-industry products increased as homeowners found themselves with more time at home. Notably, we expect the difference in expenditures in 2020 compared with 2019 to be greater in states with increased COVID-19 stringencies. Furthermore, we hypothesize that firms declared as nonessential (Michigan) or as partially nonessential (New York) would have reductions in spending in 2020 compared with 2019 on green-industry products, as firms in these states would have been shut down or had limited sales opportunities during a key purchasing time frame (i.e., the spring).

Materials and Methods

An online survey of US consumers during Jan 2021 collected data on purchasing habits to assess plant and plant-related purchasing during 2020. The University of Georgia Institutional Review Board (no. 00002558) approved the survey as exempt. Respondents came from the database of Toluna, Inc. (Dallas, TX, USA). Toluna, Inc. contacted potential respondents and directed them to the survey. A total of 4242 consumers completed the survey from all 50 states plus Washington, DC. Respondents answered questions about their purchasing of plant and plant-related products, including how much their household spent in 2019 and 2020. Respondents self-reported expenditures, which implies the data could be biased as a result of respondents either under- or overestimating how much they spent in 2019 and 2020. However, given this bias should be random across states, under- and overestimations would cancel out, leaving the results as unbiased.

Demographic statistics of the sample are found in Table 1. The age of respondents in the sample has a similar breakdown to the US Census. The median age of the sample is 45 years, which is slightly greater than the estimated US median age of 39 years (US Census Bureau 2019). The greater median age for the sample is a result of the US Census Bureau estimates containing persons younger than the age of 18 years, whereas respondents to the survey are all 18 years or older. Women are oversampled in the survey (62.84%) because they are often the primary shoppers in a household (Flagg et al. 2013; Wolfe 2013; Zepeda 2009). The median household income for the participants is $74,755, which is greater than the census estimates for the US general population ($64,994) (US Census Bureau 2021). Higher income earners tend to be more active in lawn and garden activities than households with lower incomes (Cohen and Baldwin 2018).

To understand how COVID-19 regulatory stringency impacted green-industry sales, we used the University of Oxford COVID-19 Government Response Tracker (Response Tracker) (OxCGRT 2022). The Response Tracker is useful in understanding public and private responses (Gupta et al. 2021) and government effectiveness during the COVID-19 pandemic (Chisadza and Gupta 2021), as well as tracking COVID-19 incidence over time (Ma et al. 2021). The Response Tracker contains 21 indicators and a miscellaneous notes field organized into five groups. These groups include containment and closure policies, economic policies, health system policies, vaccination policies, and miscellaneous policies. The Response Tracker then calculates an overall stringency index by day for each state. Given this, a state's stringency score changes as it changes its COVID-19 regulations.

For this study, we calculated a yearly average stringency index for each state in 2020. After calculating the stringency index, we divided states into five different treatment groups (Table 2). We assign Michigan and New York to treatment 1 (T1) and treatment 2 (T2) because these states deemed nurseries and greenhouses as nonessential or added constraints on these firms to be considered essential, respectively. T1 and T2 have 137 and 373 observations, respectively. Treatment 3 (T3) is composed of the states with the lowest stringency indices. These states had indices <45.5969, or 1 standard deviation away

Table 1. Demographics associated with the online sample of 4242 US respondents conducted in Jan 2021.

Variable	Value
Age, years (median)	45
Generation (%)	
Baby boomer or Older	31.13
Gen-X	27.95
Millennial or younger	40.92
Caucasian (%)	80.23
Male (%)	37.16
Political affiliation (%)	
Democrat	42.69
Republican	28.58
Independent	23.06
Other	5.67
Education (%)	
High school or less	14.83
Some college	31.70
Bachelor's degree	30.90
Higher than bachelor's degree	22.57
No. of kids in household	0.77
No. of adults in household	2.18
Household median income (US$)	74,755
Urbanicity (%)	
Metro	25.01
Suburban	53.27
Rural	21.73

Table 2. Average 2020 state stringency scores from the University of Oxford Coronavirus Disease 2019 Government Response Tracker.

State	Stringency index	Treatment
South Dakota	39.29	3
North Dakota	39.56	3
Oklahoma	39.90	3
Alabama	42.51	3
Iowa	43.31	3
Missouri	44.06	3
Utah	44.95	3
Arkansas	46.23	4
Indiana	46.66	4
New Hampshire	46.86	4
Arizona	47.59	4
South Carolina	48.17	4
Wisconsin	48.23	4
Mississippi	48.43	4
Nebraska	48.44	4
Texas	48.52	4
Idaho	48.69	4
Nevada	48.80	4
Montana	48.82	4
Virginia	49.36	4
West Virginia	49.42	4
Tennessee	49.43	4
Kansas	49.58	4
Florida	49.87	4
Georgia	51.67	4
Wyoming	51.68	4
Louisiana	51.80	4
Colorado	51.87	4
Alaska	52.02	4
Oregon	52.06	4
Pennsylvania	52.32	4
New Jersey	52.37	4
Minnesota	52.40	4
Massachusetts	53.07	4
Illinois	53.16	4
North Carolina	53.42	4
Ohio	53.67	4
Maryland	54.59	4
Michigan	55.02	1
Washington	55.08	4
Delaware	55.25	4
California	55.69	4
Vermont	56.39	4
Connecticut	57.27	5
Kentucky	57.39	5
Rhode Island	57.98	5
Washington, DC	59.22	5
Hawaii	61.27	5
New York	61.77	2
Maine	62.30	5
New Mexico	64.40	5

(*SD*) from the mean stringency level. Treatment 4 (T4) contains states that were within 1 *SD* from the mean—between 45.5969 and 56.8272. Treatment 5 (T5) is made up of all the states that were more than 1 *SD* above our overall mean of 56.8272. T3, T4, and T5 have 540, 2422, and 770 observations, respectively. As a robustness check, we used the average stringency from March to May, as well as a stringency measure from January to July to examine the robustness of results across the major spring and summer purchasing seasons for plants. Results are robust in that there was little change in categorization of states into different stringency categories.

To assess the impact of COVID-19 restrictions on sales, we compared the difference in 2020 expenditures to 2019 expenditures for both plants and landscape materials. We used propensity score matching (PSM) to help reduce confounding biases. According to Wang (2020), researchers have widely used PSM to reduce confounding biases in observational studies. PSM allows for the comparison of treatment groups by creating a counterfactual, such that groups are identical across all factors except the treatment group. In our study, treatment groups were assigned based on the similarities of their stringency index, and we compared each treatment to the other treatments (i.e., T1/T2, T1/T3, T1/T4, T1/T5, T2/T3, T2/T4, T2/T5, T3/T4, T3/T5, T4/T5). Because survey respondents are from a wide range of demographics, the failure to account for these differences across treatment groups could bias results stemming from other variables outside of the state's COVID-19 regulation stringency. Some variables that may likely impact consumer spending include household income level and how populated the area is where a respondent lives (i.e., urban vs. rural). For example, not accounting for differences in household income could then lead to comparing someone with a household income of $100,000 to someone with a household income $50,000.

The first step in PSM is to estimate a logit model, which calculates the probability that each observation will be assigned into the treatment group based on the independent variables associated with that observation. The equation

$$P(x) = \text{prob}(D = 1|x) = E(D|x) \qquad [1]$$

shows this mathematically, where $P(x)$ is the conditional probability that one given observation will be assigned to the treatment group based on x, a vector of independent variables. The dependent variable, D, equals one if an observation is in the treatment group (Katchova 2010). In selecting the set of variables included in the logit models, researchers must take care to satisfy the balancing criteria. We follow the recommendation of Becker and Inchino (2002), whereby we split the sample into intervals before matching, then use the average propensity scores for the within-interval treated and control groups for comparison of significant differences across covariates. For the logit models, some models have more or less variables depending on which set of variables satisfied the balancing criteria while also maximizing the hit-or-miss and pseudo-R^2 guidelines that help assess the reliability of the propensity scores (Heckman et al. 1997). After we calculated each respondent's propensity score, we matched observations across treatments being compared using varying matching algorithms. Table 1 shows the variables used for matching.

When the logit modeling satisfied the balancing property and calculated the propensity scores, we used several matching algorithms to assess differences between the treatments. We used several algorithms to test robustness of the results and identify the "best" algorithm using common criteria such as bias and pseudo-R^2 reduction. For this study, we used local linear regression; kernel gaussian; kernel Epanechnikov; radius matching at radii 0.01, 0.05, and 0.1; K-nearest neighbor matching, no caliper, with replacement; and K-nearest neighbor matching, no caliper, without replacement. We use STATA (version 17.0; StataCorp, College Station, TX, USA) to test alternative matching algorithms for each treatment.

PSM matches an observation within a treatment group with one or more similar observations that is not in the same treatment group to estimate the impact of the treatment on the dependent variable. This difference is referred to the average treatment effect on the treated (ATT) and is represented as

$$\text{ATT} = E[Y_{i1} - Y_{i0}|D = 1], \qquad [2]$$

where Y_{i1} is the value of the dependent variable for the treatment group, Y_{i0} is the value of the dependent variable for the control group, and D is a binary variable equal to one if an observation receives the treatment (Katchova 2010). For our model, the ATT represents the impact of regulations on expenditure differences between 2020 and 2019 for plant and landscape products. The ATT does not show directly whether expenditures increased or decreased before and during the COVID-19 pandemic. For instance, expenditures across treatments may have increased (decreased) during the pandemic across all treatments, but the ATT compares the amount of change in expenditures (i.e., difference in 2020 and 2019) across treatments being compared. To this end, we cannot say that varying regulation stringency lowered/increased expenditures compared with 2019, but we can say whether the amount of growth/decline from 2019 to 2020 was different statistically between treatments. In addition to the ATT, we also obtained the Rosenbaum bound (r-bound) for each value. We present results from the radius matching at radius of 0.01, because this matching algorithm consistently had the greatest bias and pseudo-R^2 reduction as well as the greatest hit percentage (correctly predicting treatment membership within the logit model). We calculated bootstrapped standard errors for the ATT estimates with 500 replications. The r-bound is a measurement of robustness in which the r-bound approach allows the analyst to determine how strong an unmeasured confounding variable must affect selection into treatment to undermine the conclusions about causal effects from a matching analysis (DiPrete and Gangl 2004). r-Bounds are calculated from the K-nearest neighbor matching, no caliper, without replacement algorithm.

Results and Discussion

In the following, we examine each treatment individually, then discuss the impact of the results on the green industry as a whole, and finish with a discussion of both plant and landscape PSM results and implications.

Treatment 1 (Michigan). Michigan is placed in its own treatment group (T1) because of the unique way it handled the pandemic shutdown. Michigan forced all nurseries and greenhouses to close from 15 Mar to 29 Apr. After this period, they were able to reopen following local and state mandates. With regard to Michigan results, there are no statistically significant results for the plant expenditure treatment comparisons. This implies that although Michigan declared green-industry firms as nonessential during Spring 2020, Michigan consumers still experienced the same expenditure effect (i.e., the difference in 2020 and 2019 plant expenditures) for plants as the other treatments

Table 3. Propensity score–matching results (difference between 2020 and 2019 expenditures) for plant expenditures comparing treatment groups of varying state governmental coronavirus disease 2019 restrictions.

			95% Confidence interval			
Treatment comparison[i]	ATT	*SE*[ii]	Lower	Upper	*P* value	Rosenbaum bounds
T1 (MI) vs. T2 (NY)	–10.14	41.74	–111.60	60.83	0.808	—
T1 (MI) vs. T3 (low)	6.83	18.55	–31.06	42.53	0.713	—
T1 (MI) vs. T4 (medium)	28.20	26.61	–33.89	74.04	0.290	—
T1 (MI) vs. T5 (high)	23.13	39.18	–66.31	78.09	0.555	—
T2 (NY) vs. T3 (low)	–30.65	14.41	–61.21	–4.90	0.034	1.80
T2 (NY) vs. T4 (medium)	–9.03	14.31	–39.23	17.34	0.528	—
T2 (NY) vs. T5 (high)	–15.80	16.17	–50.66	14.84	0.329	—
T3 (low) vs. T4 (medium)	21.26	11.15	2.67	43.71	0.057	1.42
T3 (low) vs. T5 (high)	20.53	13.76	–4.75	49.78	0.136	—
T4 (medium) vs. T5 (high)	–0.69	12.64	–24.82	24.84	0.957	—

[i] The average treatment effect on the treated (ATT) is based on the first treatment listed being the control and the second treatment listed as the comparison. So in this case, treatment 2 (T2) [New York (NY)] is –10,14 less than treatment 1 (T1) [Michigan (MI)]. T3 = treatment 3; T4 = treatment 4; T5 = treatment 5.
[ii] *SE* = standard error.

Table 4. Propensity score–matching results (difference between 2020 and 2019 expenditures) for landscape expenditures comparing treatment groups of varying state governmental coronavirus disease 2019 restrictions.

Treatment comparison[i]	ATT	*SE*[ii]	95% Confidence interval Lower	Upper	*P* value	Rosenbaum bounds
T1 (MI) vs. T2 (NY)	–42.53	55.83	–132.87	65.88	0.447	—
T1 (MI) vs. T3 (low)	17.86	22.82	–24.50	58.99	0.434	—
T1 (MI) vs. T4 (medium)	41.63	23.36	–14.03	78.34	0.075	1.10
T1 (MI) vs. T5 (high)	45.14	23.61	–0.36	86.25	0.056	1.10
T2 (NY) vs. T3 (low)	–6.07	13.73	–34.73	18.75	0.658	—
T2 (NY) vs. T4 (medium)	4.63	14.02	–27.17	29.86	0.741	—
T2 (NY) vs. T5 (high)	–7.60	16.25	–45.67	20.04	0.640	—
T3 (low) vs. T4 (medium)	12.01	12.11	–11.99	33.80	0.322	—
T3 (low) vs. T5 (high)	9.77	14.76	–21.19	37.02	0.509	—
T4 (medium) vs. T5 (high)	–5.30	13.07	–29.84	23.08	0.685	—

[i] The average treatment effect on the treated (ATT) is based on the first treatment listed being the control and the second treatment listed as the comparison. So in this case, treatment 2 (T2) [New York (NY)] is –42.53 less than treatment 1 (T1) [Michigan (MI)]. T3 = treatment 3; T4 = treatment 4; T5 = treatment 5.

[ii] *SE* = standard error.

(Table 3). The only treatment group that had a decreased household ATT compared with Michigan was T2 (New York), but the ATT difference was not significant.

In examining the impact of Michigan's (T1) COVID-19 regulations on landscape expenditures, Michigan households spent $41.63 and $45.14 less on landscape expenditures compared with medium- and high-stringency states, respectively (Table 4). This is most likely a result of Michigan households not having access to landscape products during the lockdown. This does not mean that Michigan consumers spent less on landscape products during the COVID-19 pandemic compared with prepandemic; it only indicates that medium- and high-stringency states had a larger increase in spending compared with Michigan consumers. As such, it points to Michigan COVID-19 protocols having a detrimental effect as spending did not increase at the rate of medium- and high-stringency states.

A hypothesis for the significant difference associated with medium- and high stringency and Michigan could be movement toward online shopping. With respect to online shopping, Michigan consumers reported an increase in online purchasing from before to during the COVID-19 pandemic. However, the 1.73% increase is not significantly different (Table 5). However, for the medium- and high-stringency states, the online purchasing increase is statistically greater at 3.90% and 4.55%, respectively. Looking more in depth at online shopping (Table 6), although online shopping increased at a greater rate in medium- and high-stringency states, the difference is not statistically significant. Based on this finding, online shopping does not appear to be the reason for increased landscape expenditures for medium- and high-stringency states. Based on this finding, it seems that by classifying the green industry as nonessential during peak sales season, the Michigan regulations limited the amount of sales that could have been achieved for landscape products.

Treatment 2 (New York). New York is also in a separate treatment group because of its caveat that nurseries, greenhouses, and IGCs were mandated to sell food-producing plants to remain an essential business. The state also had the third-highest stringency index of 61.77 (Hallas et al. 2021). We found that New York's level of shutdown affected positively household consumer spending by $30.65 on plants over states that had a low level of stringency (Table 3). In other words, New York's strategy resulted in almost a $31 increase in plant expenditures per household compared with low-stringency states. Given the r-bounds, the comparison of New York and low-stringency states is fairly robust to an unobserved covariate given the greater r-bound value (1.8). Furthermore, there are no significant differences between New York and medium- and high-stringency states. With respect to landscape expenditures, there is no significant difference in expenditures for New York vs. low-, medium-, or high-stringency states (Table 5). New York consumers increased shopping online by an estimated 2% (Table 5). However, there are no statistical differences between before and during the COVID-19 pandemic across treatment groups (Table 6).

Treatment 3 (low-stringency states). There was an increase of $21.26 in consumer household spending on plants in states with medium stringency compared with low stringency levels. The r-bounds indicate confidence that the ATT is robust to unobserved covariates. For instance, an unobserved covariate would need to impact the odds ratio of treatment assignment by a factor of 1.42 to change a statistically significant result to a statistically insignificant result. In contrast, there is not a significant difference between low- and high-stringency treatments. There are no significant differences between low-stringency states vs. medium- or high-stringency states.

Treatment 4 (medium-stringency states). The results of the PSM show no significant difference in consumer spending for plants or landscape expenditures between treatment 4 (medium-stringency states) and treatment 5 (high-stringency states) (Tables 4 and 5). This implies that states with medium stringency did not spend less/more on plants or landscape products than states with greater stringency levels.

Impact of results. The results of the study indicate mixed results on the impact of COVID-19 regulations. Michigan (T1), which enforced a month-long industry shutdown, did not see any impact on plants expenditures, but their regulatory strategy had a big impact compared with medium- and high-stringency states on landscape expenditures. In terms of dollar value, this would have resulted in $165.6 and $179.5 million [assuming 3,976,729 households in Michigan (US Census Bureau 2023)] in decreased spending on landscape products compared with medium- and high-stringency states, respectively. Furthermore, in several cases, states that imposed stricter mandates and guidelines (i.e., medium, high vs. Michigan) saw positive impacts on consumer spending at nurseries, greenhouses, and IGCs.

Conclusion

Newer technologies and an increasingly connected world will continue to leave the world (including consumers and businesses) susceptible to widespread viruses and possible pandemics. Research on COVID-19 is plentiful, but little is known about how state regulations impact agricultural firms, especially nurseries, greenhouses, and IGCs.

Using respondents from a sample from Toluna, Inc. from Jan 2021, we examined the effect that state COVID-19 regulations had on consumer expenditure changes in the green industry. Understanding the relationship between consumer habits and consumer spending is essential for businesses, industries, and policymakers throughout the United States. Our results indicate that the regulatory path chosen by states had an impact on green-industry expenditures during 2020. Although consumers adapted to the regulations with which they were presented, regulations did

Table 5. Comparison of before and during coronavirus disease 2019 online purchasing by treatment groups of varying state governmental coronavirus disease 2019 restrictions.

Treatment	Pre-COVID-19[i] Mean %	*SE*[ii]	2020 Mean %	*SE*[ii]	Difference	*t* value	*P* value
1 (Michigan)	28.77	3.16	30.50	3.22	1.73	–0.92	0.359
2 (New York)	42.92	1.96	46.96	1.99	4.04	–3.35	0.001
3 (low)	23.60	1.42	26.94	1.50	3.34	–4.03	0.000
4 (medium)	29.34	0.74	33.24	0.78	3.90	–8.43	0.000
5 (high)	28.75	1.26	33.30	1.34	4.55	–5.99	0.000

[i] COVID-19 = coronavirus disease 2019.

[ii] *SE* = standard error.

Table 6. Comparison of the difference (2020 – Before coronavirus disease 2019) in online purchasing across treatments groups of varying state governmental coronavirus disease 2019 restrictions.

Treatment comparison	Mean	*SE*[i]	*t* value	*P* value
1 vs. 2 (Michigan vs. New York)	2.30	2.32	–0.99	0.321
1 vs. 3 (Michigan vs. low)	1.60	1.89	–0.85	0.396
1 vs. 4 (Michigan vs. medium)	2.17	1.98	–1.09	0.275
1 vs. 5 (Michigan vs. high)	2.82	1.98	–1.42	0.155
2 vs. 3 (New York vs. low)	−0.70	1.41	0.49	0.621
2 vs. 4 (New York vs. medium)	−0.13	1.25	0.11	0.915
2 vs. 5 (New York vs. high)	0.52	1.37	–0.38	0.706
3 vs. 4 (low vs. medium)	0.57	1.06	–0.53	0.593
3 vs. 5 (low vs. medium)	1.22	1.15	–1.06	0.289
4 vs. 5 (medium vs. high)	0.65	0.92	–0.71	0.478

[i] *SE* = standard error.

have an impact, especially regulations that labeled green-industry firms as nonessential.

This work provides results that can be used by businesses, industries, and national-, state-, or local-level policymakers that are attentive not only to the well-being of individual firms, but also to the economy as a whole. Policies that work to increase consumer spending at nurseries, greenhouses, and IGCs should focus on how homeowners value their property—more specifically, their time spent on it—to take advantage of the results found in our study.

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