Senior Project

Department of Economics

Are Anti-Theft Signs Effective? Evidence from The University of Akron's Parking Lots.

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Abstract

The study conducted was on the implementation of anti-theft signs in the University of Akron parking lots. There were 12 out of 49 parking lots that received these signs that suggested people to lock their car doors and keep valuables out of sight. With data used from the campus police, a two-way fixed effect difference-in-difference model is produced to measure the causal effect of these signs. The sample size of data after the signs were placed is very small and the findings included no statistical impact. Multiple robustness checks were run to differentiate the model, and all showed the signs having no significance in the altering of crimes reported.

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1. Introduction

In this research paper, the effectiveness of anti-theft signs placed in University of Akron parking lots is being explored. Signs are an extremely prevalent tool used throughout society. The usefulness of these signs will be measured by comparing parking lots with this anti-theft method with those that have received no change. Here is a picture of one of the signs taken inside a parking lot. Each sign is the same and looks identical to the one pictured.

I have data from the University of Akron Police Department for all the crimes reported to them and separated this into only campus parking lot crimes. This study then uses a two-way fixed effects difference-in-difference model to compare this treatment group with signs to our control group. Analysis of the effects of signs has previously been done but not on signs that are there to protect your belongings. Many of the studies done on signs measure smaller, more inconsequential acts that also may not affect the audience of the sign directly like turning lights off or not littering. This study deals with people potentially losing property of theirs or becoming victims of other criminal activities as well. Property crime is an issue all over the world and the more research done on preventing it, only helps step closer to the most probable solutions in increasing overall benefit. The findings of this research may not be able to show the reasoning behind the sign's effectiveness, but it can provide empirical support to whether signs are effective in regard to preventing criminal activities. This paper will look to answer these questions through the Literature Review, Data, Theory, Methodology, Results and Conclusion.

2. Literature Review

Signs have an interesting dynamic in our society today. They give opportunity to display many kinds of insights and messages that can reach any person capable of seeing it. These signs also have a low upkeep for continuous use, to try and maintain that message (Meis and Kashima, 2017). There are a few aspects of signs that have previously been studied that pertain to this research paper such as the environment they are in, the effectiveness, and the use of them in crime prevention.

In a study done by Toet and Schaik (2012) on reality versus virtual simulations, researchers looked to find differences of perceived threat in a neighborhood. They find that "signs of disorder" such as litter, warnings signs, vandalism, etc. gave participants more suggestion of social disorder. This can be an important factor outside of the constraints of my research as a sign may have more or less impact depending on the environment it's confined in. In a similar study Schultz and Tabanico (2009) find that neighborhood watch signs placed visibly on a virtual community tour created an increase fear of crime and an anxiety of victimization. They conclude that there is an association to not only what was displayed on the signs but also the environmental context of where they were posted. Another aspect of the location of the sign involves streetlights. This study finds that improved street lighting greatly reduced crime in public areas (Farrington and Welsh, 2008). There was also found to be no difference in change between daytime and nighttime crimes lending a theory that unofficial social control may be a more probable solution rather than increasing direct surveillance or deterrents (Farrington and Welsh, 2008).

Conceptually a sign's value in its existence is based on its effectiveness. If there were no results to show for the message of the sign, then there would be no purpose for it. There are different ways a sign can convey its message. It can be direct, in which case would tell the exact message it wants to give or indirect, which may give contextual clues that then becomes up to the interpreter to figure out the message intended. This difference can be important in a sign's usefulness as someone may not comprehend the intended idea. Meis and Kashima (2017) separated signs that were familiar such as a recycling sign and unfamiliar signs. They find that for unfamiliar signs, the "clarity of purpose" is positively correlated with perceived effectiveness, but the familiar signs are not. This idea is similar to other findings that prior exposure is a determinant regarding the effectiveness of signs (Reiter and Samuel, 1980; Sussman and Gifford, 2012). These two findings pooled together show that after someone has read and interpreted a sign, it is more so likely to be up to the person to decide whether they want to respect the notion of the sign or not. The complementary viewpoint may be where a person just initially follows the sign's protocol without repute. The interpretability of the sign may be important, but the tonality of the message does not seem to be. Signs that are more threatening compared to a more inviting and supportive message do not have a different effect (Reiter and Samuel, 1980).

In the view of this study, the signs of disorder or other environmental impacts will be tough to capture as there are different parking lots such as parking garages or outdoor lots, in different locations. This would be hard to control for within the limits of this study. Another finding that may be hard to confirm or counter is the effectiveness over time the signs have. The data with the signs in use in very small but with that small portion, this study expects to capture the beginning portion where the signs are most effective. The signs are also very clear in their message so this should not be a problem in terms of their audience interpreting them.

3. Data

My data is obtained from the University of Akron Police Department (UAPD) and includes every campus offense from 2017 through 2022. The department switched databases in May 2021, so these two databases were slightly different and needed to be synced to provide a consistent panel of crimes-by-location over time. The two main cleaning steps included parsing through to only select crimes reported from a campus parking lot and matching the formats of addresses. The University of Akron Parking and Transportation Services provided information on all the campus parking lots, which was used to cross-reference with the databases to also make sure the addresses were displayed identically stipulating the same location. There is some ambiguity with the labeling of the crimes. The two databases have some different labels that might be for the same crime which is why the number of reported crimes is chosen instead. This way it is more consistent between the databases, but some reports may have more than one crime within them that cannot be tracked. Through all of this data cleaning, the three most important variables that come out include the number of crime reports at campus parking lots, the location of the parking lots, and the date of the crime report. These variables were used to measure the amount of crimes in each parking lot monthly over the course of my dataset range. This the variable that will be measured to see the effect. One downfall to my data is the sample size of crimes reported after the signs were implemented. The signs were placed before the fall semester in 2022 so in August. This leaves only about 5 months of data with the signs as I do not have any 2023 data. The signs' placement themselves sounded to be somewhat anecdotal but not any true method of placement. This may have caused a little bias in the methodology but also has some randomness as well. How the means differ between parking lots will be shown later in the methodology section where a balance of regressors test is ran.

4. Theory

Three possible conclusions can be expected based on economic theory. After the implementation of the signs, crime could stay consistently lower than beforehand. If crimes lowered after putting signs in the parking lots, this could be because people saw these signs and took initiative to lock their cars and be more preventative in potential thefts. This would cause criminals to have a harder time to break into potential victim's cars or they may not see any valuables worth their risk of attempting a theft. Another possibility is that these signs might've implied a new push from police to crack down on thefts in the parking lots. This might cause potential offenders to rethink the idea of breaking into the car and that the police have a more watchful eye in the given conditions. Either of these would reinforce crimes being lowered and staying that way over time. This based on the theory of the rational criminal and their cost-benefit comparison. If these ideas mentioned before were the case, then the cost of committing crimes would outweigh the benefit and thus decrease crimes.

The crimes could also decrease initially but then slowly begin to return to their previous levels over time. If crimes were to increase back over time, this could be from involving parties losing interest in the sign. If people began to stop following the signs message or the sign itself begins to become just another part of the environment overlooked and forgotten about, people may begin to leave doors unlocked or valuables left to be seen out of sheer obliviousness. On the other hand, potential criminals may lose their fear or hesitation of committing these crimes after time has passed and begin again. This can be connected to the literature before that the signs' effectiveness deteriorates over time. This can attributed to the criminal's perspective or the targeted crowd.

Finally, the signs may have no impact in the number of crimes reported at all. This could be from the signs potentially not being the most optically efficient. The signs could be overlooked without people noticing them at all and therefore not changing their behavior. Criminals also may not be intimated by the presence of these signs and continue the same trend of crimes. This means that the rational criminal would not have their costs outweigh their benefits and proceed as before with no change in attitude, thus detecting no change in the number of crimes.

The variable that measures the number of crimes will answer whether the crimes decreased significantly or not. If after the signs were implemented and crimes reported decreased in their respective parking lot and there were no changes to the other parking lots, then the causal analysis will indicate that the signs were the source of the change.

5. Methodology

This research paper will be using three different model equations but will primarily focus on a two-way fixed effects difference-in-difference model. There is a select number of parking lots that received parking lot signs that will be a part of my treatment group while the rest of the lots will be in my control group. This method will use two fixed effects in order to control for the different parking lot locations as well as when these crimes occurred. The parking lot fixed effect will control for the differences between the parking lots themselves because they do not change in location or size throughout my observed data and the time fixed effect measured in months and years, controls for the changes throughout the year that all the parking lots would experience. This isolates the causal effect to find if the parking lot signs had a significant impact on the number of crimes reported from university parking lots.

Equation 1 refers to a simple DID model

$$NumberOfCrimes = B_0 + B_1 DID + Treatment + After + \varepsilon \quad (1)$$

The *NumberofCrimes* variable represents the number of crimes reported to the UAPD located at each university parking in each month. *Treatment* is an indicator variable that is equal to 1 if there was ever sign a placed in it and 0 otherwise. *After* is an indicator variable that is equal to 1 if the date is after the signs were implemented and 0 otherwise. *DID* is the interaction of *Treatment* and *After* so will equal 1 if it is a parking lot with a sign after they were placed and 0 otherwise. Finally, ε represents the random error or white noise of the model.

Equation 2 refers to a simple DID model with controls

$$NumberOfCrimes = B_0 + B_1 DID + Treatment + After + Controls + \varepsilon \quad (2)$$

The *Controls* variable represents the total number of parking spaces for each lot and the type of parking lot it is (Resident, Commuter, etc.). The rest of the variables are the same.

Equation 3 refers to a two-way fixed effect DID model

$$NumberOfCrimes_{\mathrm{pt}} = B_0 + B_1 DID_{\mathrm{pt}} + Parking_{\mathrm{p}} + MonthYear_{\mathrm{t}} + \varepsilon_{\mathrm{pt}} \quad (1)$$

The *NumberofCrimes* variable represents the number of crimes reported to the UAPD located in a university parking lot, p, and the month and year, t. The variable, *DID*, is an indicator variable that is equal to 1 if there is an anti-theft sign placed in a parking lot, p, in a given month and year, t, and 0 otherwise. *Parking* and *MonthYear* are parking lot and the month and year fixed effects, respectively. Finally, ε represents the random error or white noise of the model.

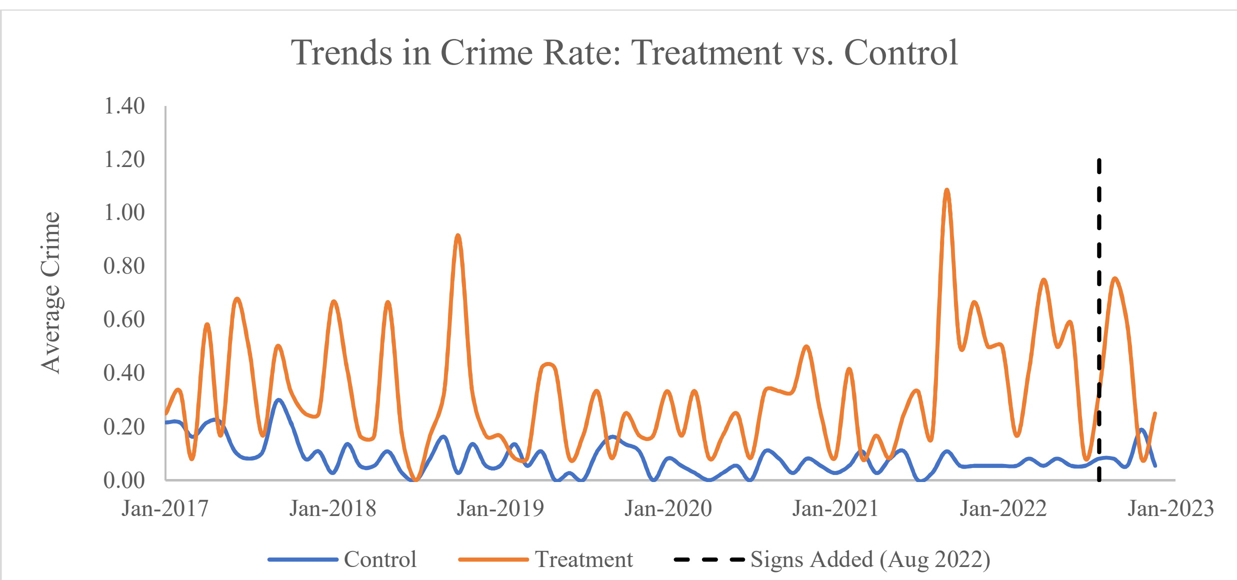
In order to make sure that the causal effect is being measured rather than a correlational effect, a parallel trends test and balance of regressors test are run to strengthen the analysis. The parallel trends test is used to compare the means of the control and treatment group before the treatment has started.

Table 1: Parallel Trends Test

Regressors	Estimate
TM	0.0001
	(-0.0013)
TM2	0.0000
	(0.0000)
TM3	0.0000
	(0.0000)

Note: standard errors are in parentheses. *, **, and ***indicate 10%, 5%, and 1% significance levels respectively and values in parentheses represent the standard errors.

Here Table 1 shows that these three interaction terms between the treatment variable and the time variable, MonYear show no statistical significance to the third polynomial.



This graph looks to show a little bit of a different story in regard to the parallel trends. The treatment group looks to be much more inflated than the control but there was still no significance shown in the test ran. Either way, this potential problem should be avoided from my fixed effect variables because they account for each parking lot over each month. The balance of regressors test is used to compare the means of the control variables across the treatment and control groups. This is used to show that again these two groups are comparable with each other.

Table 2: Balance of Regressors Test

Regressors	Treatment	Control	Difference
Total Spaces	670	96.19	-573.8***
All Permit	0.5	0.14	-0.36**
Commuter	0.58	0.59	0.01
Resident	0.17	0	-0.17
Special	0	0.16	0.16**
Disability	0	0.03	0.03
Visitor	0	0.11	0.11**

Table 2 shows the results of the test. Four out of the seven control variables do show statistical difference between the two groups which is not good and the Total Spaces variable showing the strongest significance. This again should be accounted for within my fixed effects as we control for each parking lot individually.

6. Results

The results found, seem to show that the anti-theft signs have no significant effect on the reported number of crimes.

Table 3: Effect of Anti-Theft Signs

Regressors	Simple DID	DID With Controls	Two-Way Fixed Effects
DID	0.07	0.07	0.07
	(0.13)	(0.12)	(0.10)
Treatment	0.23***	0.10***	
	(0.03)	(0.03)	
after	0.01	0.01	
	(0.03)	(0.03)	
Intercept	0.08***	-0.26***	-0.01
	(0.01)	(0.06)	(0.06)
Control Variables	No	Yes	No
Parking/Time Fixed Effects	No	No	Yes
Number of Observations	3,528	3,528	3,528
Adjusted R-Square	0.03935	0.1070	0.2788
Overall Significance	24.73***	20.27***	3.60***

Note: standard errors are in parentheses. *, **, and ***indicate 10%, 5%, and 1% significance levels respectively and values in parentheses represent the standard errors.

As you can see in Table 1, the DID coefficient did not change among the different models and each is statistically insignificant. The adjusted R-squared did improve the most in our two-way fixed effect model but unfortunately cannot tell us much with the main variable being insignificant. After finding these initial results, some robustness checks were run as well.

Table 4: Effect of Anti-Theft Signs Robustness Checks

Regressors	Log of Crimes	Separated Size Parking Lots
DID	0.03	
	(0.05)	
DID1 (Spaces < 1000)		-0.02
		(0.07)
DID2 (Spaces > 1000)		0.20
		(0.21)
Intercept	0.01	0.00
	(0.03)	(0.06)
Parking/Time Fixed Effects	Yes	Yes
Number of Observations	3,528	3,528
Adjusted R-Square	0.2858	0.2792
Overall Significance	4.41***	3.58***

Note: standard errors are in parentheses. *, **, and ***indicate 10%, 5%, and 1% significance levels respectively and values in parentheses represent the standard errors.

The first check ran was using the log of the outcome variable, NumberOfCrimes in the two-way fixed effect model. Again, our DID variable was insignificant. Another different robust model ran was splitting the parking lots by the size of them. One group included parking lots with less than 1000 spaces and another with more than 100 spaces. The coefficient for the smaller lots is negative thus indicating a decrease in crime and the bigger lot was positive and much more significant but again both of these were insignificant so we cannot draw any concrete conclusions from the results of the data.

7. Conclusion

In conclusion the signs did not have any statistical impact found through the various models run. This may be due to the short amount of time it has been implemented and the smaller sample size. With more time it could show significant impacts, or the signs could just be inconsequential. The signs may need to be moved to a more ideal position that people may notice more or enhance the signs themselves to become more attention-grabbing. This study could be continued further on in the future when more data is readily available. There could also be more research on changing the rest of the parking lots with a different tactic and see which one becomes more impactful. Another step that could be taken would be to send surveys to the students of the university in order to gain more insight into how the signs make them feel. If they make them feel safer or in greater danger, this could tip whether the signs are overall beneficial or costly. With no evidence of physically changing the crime rate, if students felt safer, then this benefit could outweigh the physical costs of the signs and be overall useful. If the signs made students feel a greater sense of distress, then with no physical benefit as well, the UAPD should consider taking them down and investing in a new tactic going forward.

References

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Welsh, B. C., & Farrington, D. P. (2008). Effects of improved street lighting on crime. *Campbell Systematic Reviews*, *4*(1), 1–51. https://doi.org/10.4073/csr.2008.13

Wener, R. E., & Kaminoff, R. D. (1983). Improving environmental information. *Environment and Behavior*, *15*(1), 3–20. https://doi.org/10.1177/0013916583151001

Appendix 1 (SAS CODES)

```
/* Sam Smith */

/* Final Project */

/* Data Importation */

proc import datafile="/home/u60669666/FinalSeniorProject/2017-May 2021 Campus
        Offenses.xlsx"

            dbms=xlsx

            out=work.Crime1

            replace;

            sheet= "Sheet1 (2)";

                        getnames=yes;

run;


proc import datafile="/home/u60669666/FinalSeniorProject/May - Dec. 2021 Campus
        Offenses.xlsx"

            dbms=xlsx

            out=work.Crime2

            replace;

            sheet= "May - Dec. 2021 (2)";

                        getnames=yes;

run;


proc import datafile="/home/u60669666/FinalSeniorProject/2022 Campus Offenses.xlsx"

            dbms=xlsx
```

```
        out=work.Crime3
            replace;
        sheet= "Case Results (2)";
                  getnames=yes;
run;

proc import datafile="/home/u60669666/FinalSeniorProject/Parking Lot Data.xlsx"
        dbms=xlsx
        out=work.Parking
        replace;
        sheet= "Sheet1 (2)";
                  getnames=yes;
run;

proc import datafile="/home/u60669666/FinalSeniorProject/CrimeParkZeros.xlsx"
        dbms=xlsx
        out=work.ZeroCrime
            replace;
        sheet= "Sheet1";
                  getnames=yes;
run;

/* Clean dataset with zero crimes */
```

```
proc sort data=ZeroCrime;
by lot;
run;

data ZeroCrime;
set ZeroCrime;
where lot is not missing;
run;

proc transpose data=ZeroCrime out=ZeroCrime2;
var '201701'n - '201712'n
'201801'n - '201812'n
'201901'n - '201912'n
'202001'n - '202012'n
'202101'n - '202112'n
'202201'n - '202212'n;
by lot;
run;

data ZeroCrime3;
set ZeroCrime2;
MonYear = input(_NAME_, 10.);
rename Col1= Frequency;
```

```
drop _NAME_ _LABEL_;
run;


/* Clean Crime datasets */
data Crime1New;
set Crime1;
      month = MONTH(Date);
   year = YEAR(Date);
   MonYear = Year*100 + Month;
   if month >= 1 and month <= 3 then QuartYear = Year*100 + 1;
   else if month >= 4 and month <= 6 then QuartYear = Year*100 + 2;
   else if month >= 7 and month <= 9 then QuartYear = Year*100 + 3;
   else if month >= 10 and month <= 12 then QuartYear = Year*100 + 4;
   where "Report #"n is not missing;
run;


data Crime2New;
set Crime2;
      month = MONTH(Date);
   year = YEAR(Date);
   MonYear = Year*100 + Month;
   if month >= 1 and month <= 3 then QuartYear = Year*100 + 1;
   else if month >= 4 and month <= 6 then QuartYear = Year*100 + 2;
```

```
   else if month >= 7 and month <= 9 then QuartYear = Year*100 + 3;

   else if month >= 10 and month <= 12 then QuartYear = Year*100 + 4;

run;


data Crime3New;

set Crime3;

        month = MONTH(Date);

   year = YEAR(Date);

   MonYear = Year*100 + Month;

   if month >= 1 and month <= 3 then QuartYear = Year*100 + 1;

   else if month >= 4 and month <= 6 then QuartYear = Year*100 + 2;

   else if month >= 7 and month <= 9 then QuartYear = Year*100 + 3;

   else if month >= 10 and month <= 12 then QuartYear = Year*100 + 4;

run;


data MergeCrime(keep= "Incident Address"n MonYear rename=("Incident Address"n =
        Address));

set  Crime1New Crime2New Crime3New;

run;


/* Merge and clean Crime and Parking datasets */

proc sort data= MergeCrime;

by Address;

run;
```

```
proc sort data= Parking(keep= Lot Address "TOTAL SPACES"n "All Permit"n Commuter
        Resident Special Disability Visitor Treatment);

by Address;

run;


data ParkCrime;

merge Parking MergeCrime;

by Address;

run;



data ParkCrime2;

set ParkCrime;

where lot is not missing;

run;


Proc Sort Data=ParkCrime2;

        by MonYear ;

Run;


/* Create frequency table to count crimes */

ods output OneWayFreqs=AggregatedCrime;

Proc Freq Data=ParkCrime2;
```

```
        Table lot;
        by MonYear;
Run;

proc sort data=AggregatedCrime;
by lot MonYear;
run;

proc sort data=ZeroCrime3;
by lot MonYear;
run;

/* Combine zeros and frequency tables */
data FinalSet;
merge ZeroCrime3 AggregatedCrime;
by lot MonYear;
keep lot frequency MonYear;
where MonYear is not missing;
run;

/* Create Final dataset that is used */
proc sort data=Parking;
by lot;
```

```
run;

proc sort data=FinalSet;
by lot;
run;

/* Creates variables in statement*/
data FinalSet2;
merge FinalSet Parking;
by lot;
where lot is not missing;
if MonYear > 202207 then after = 1;
else after = 0;
DID = treatment * after;
rename frequency = NumOfCrimes;
CrimePerSpace = frequency / "TOTAL SPACES"n;
LogCrime = log(frequency + 1);
if treatment = 1 and "TOTAL SPACES"n < 1000 then treatment1 = 1;
else treatment1 = 0;
DID1 = Treatment1 * after;
if treatment = 1 and "TOTAL SPACES"n > 1000 then treatment2 = 1;
else treatment2 = 0;
DID2 = Treatment2 * after;
```

```
Year = int(Monyear / 100);
month = MonYear - Year * 100;
if month >= 1 and month <= 3 then QuartYear = Year*100 + 1;
   else if month >= 4 and month <= 6 then QuartYear = Year*100 + 2;
   else if month >= 7 and month <= 9 then QuartYear = Year*100 + 3;
   else if month >= 10 and month <= 12 then QuartYear = Year*100 + 4;
run;

proc sort data=FinalSet2;
by MonYear;
run;

/* Create frequency table to count crimes */
ods output OneWayFreqs=AggregatedCrime;
Proc Freq Data=FinalSet2;
		Table lot;
		by MonYear;
Run;

/***********/
/* Model Equations */
/***********/
```

```
/* Simple DID only Treat After DID */

ods output ParameterEstimates=PEforModel1 DataSummary=ObsModel1
        FitStatistics=AdjRsqModel1 Effects=OverallSigModel1;

Proc SurveyReg data=FinalSet2 plots=none;



        Model1: Model NumOfCrimes = Treatment after DID  /Solution Adjrsq;

run;



/* Simple DID with controls */

ods output ParameterEstimates=PEforModel2 DataSummary=ObsModel2
        FitStatistics=AdjRsqModel2 Effects=OverallSigModel2;

Proc SurveyReg data=FinalSet2 plots=none;



        Model2: Model NumOfCrimes = Treatment after DID "TOTAL SPACES"n "All Permit"n
        Commuter Resident Special Disability Visitor  /Solution Adjrsq;

run;



/* Two-WAY fixed effects DID, DID lot MonYear */

ods output ParameterEstimates=PEforModel3 DataSummary=ObsModel3
        FitStatistics=AdjRsqModel3 Effects=OverallSigModel3;

Proc SurveyReg data=FinalSet2 plots=none;

        class lot MonYear;

        Model3: Model NumOfCrimes = DID lot MonYear /Solution Adjrsq;

run;
```

```
/* Testing log of crimes */

ods output ParameterEstimates=PEforModel4 DataSummary=ObsModel4
        FitStatistics=AdjRsqModel4 Effects=OverallSigModel4;

Proc SurveyReg data=FinalSet2 plots=none;

        class lot MonYear;

        Model4: Model LogCrime = DID lot MonYear /Solution Adjrsq;

run;



/* Testing difference of big and small parking lots in treatment */

ods output ParameterEstimates=PEforModel5 DataSummary=ObsModel5
        FitStatistics=AdjRsqModel5 Effects=OverallSigModel5;

Proc SurveyReg data=FinalSet2 plots=none;

        class lot MonYear;

        Model5: Model NumOfCrimes = DID1 DID2 lot MonYear /Solution Adjrsq;

run;



/***********/

/* Table Creation and Editing

/***********/

Data Table_Long;

        length Model $10; /* Makes sure the variable Model has the right length and its values are
        not truncated */

        length Parameter $30; /* Makes sure the variable Parameter has the right length and its
        values are not truncated */
```

```
        set  PEforModel1 PEforModel2 PEforModel3 PEforModel4 PEforModel5 indsname=M;
        /*"indsname" creates an indicator variable (here I call it "M") that tracks the name of
        databases use in the "set" statement */

        keep Model Parameter EditedResults;

        if        M="WORK.PEFORMODEL1" then Model="Model1";

          else if M="WORK.PEFORMODEL2" then Model="Model2";

          else if M="WORK.PEFORMODEL3" then Model="Model3";

          else if M="WORK.PEFORMODEL4" then Model="Model4";

          else if M="WORK.PEFORMODEL5" then Model="Model5";

        where Estimate ne 0;    /* Drops all the 0's from the reference variables */



        if Probt le 0.01 then Star="***";

          else if Probt le 0.05 then Star="**";

          else if Probt le 0.1 then Star="*";



        Results=Estimate;

        EditedResults=Cats(put(Results,comma16.2),Star);

        output;



        Results=stderr;

        EditedResults=Cats("(",put(Results,comma16.2),")");

        output;

run;
```

```
proc sort data=Table_Long out=Table_Long_Sorted;
    by Model Parameter;
run;

data Model1Results(rename=(EditedREsults=Model1))
     Model2Results(rename=(EditedREsults=Model2))
     Model3Results(rename=(EditedREsults=Model3))
     Model4Results(rename=(EditedREsults=Model4))
     Model5Results(rename=(EditedREsults=Model5));
    set Table_Long_Sorted;
    if Model="Model1" then output Model1Results;
     else if Model="Model2" then output Model2Results;
     else if Model="Model3" then output Model3Results;
     else if Model="Model4" then output Model4Results;
     else if Model="Model5" then output Model5Results;
    drop Model;
run;

data Table_Wide;
    merge Model1Results Model2Results Model3Results Model4Results Model5Results;
    by Parameter;
    if mod(_n_,2)=1 then Regressors=Parameter;
```

```
        length Order 3;

        if Parameter="Intercept" then Order=1;

          else if Parameter="DID" then Order=2;

          else Order=100;

run;


proc sort data=Table_Wide out=Table_Wide_Sorted (drop=Order Parameter);

        by Order;

run;


data NumOfObs(keep=Label1 Model1 Model2 Model3 Model4 Model5);

        merge obsModel1(rename=(nvalue1=nvModel1))
        obsModel2(rename=(nvalue1=nvModel2))

                obsModel3(rename=(nvalue1=nvModel3))
        obsModel4(rename=(nvalue1=nvModel4))

                obsModel5(rename=(nvalue1=nvModel5));

        by Label1;

        where Label1="Number of Observations";

        Model1=put(nvModel2,comma16.0);

        Model2=put(nvModel2,comma16.0);

        Model3=put(nvModel2,comma16.0);

        Model4=put(nvModel2,comma16.0);

        Model5=put(nvModel2,comma16.0);

run;
```

```
data AdjRsq;

         merge AdjRsqModel1(rename=(cvalue1=Model1))
         AdjRsqModel2(rename=(cvalue1=Model2))

                      AdjRsqModel3(rename=(cvalue1=Model3))
         AdjRsqModel4(rename=(cvalue1=Model4))

                      AdjRsqModel5(rename=(cvalue1=Model5));

         where Label1="Adjusted R-Square";

         drop nvalue1;

run;



/* The row for Overall Significance */

data OSM1(rename=(EditedValue=Model1)) OSM2(rename=(EditedValue=Model2))

           OSM3(rename=(EditedValue=Model3)) OSM4(rename=(EditedValue=Model4))

           OSM5(rename=(EditedValue=Model5));

         set OverallSigModel1 OverallSigModel2 OverallSigModel3 OverallSigModel4
         OverallSigModel5 indsname=M;

         where Effect="Model";

         Label1="Overall Significance";



         if ProbF le 0.01 then Star="***";

           else if ProbF le 0.05 then Star="**";

           else if ProbF le 0.1 then Star="*";



         EditedValue=Cats(put(FValue,comma16.2),Star);
```

```
        if M="WORK.OVERALLSIGMODEL1" then output OSM1;
          else if M="WORK.OVERALLSIGMODEL2" then output OSM2;
          else if M="WORK.OVERALLSIGMODEL3" then output OSM3;
          else if M="WORK.OVERALLSIGMODEL4" then output OSM4;
          else if M="WORK.OVERALLSIGMODEL5" then output OSM5;
        keep Label1 EditedValue;
run;



data OverallSig;
        merge OSM1 OSM2 OSM3 OSM4 OSM5;
        by Label1;
run;

/* Combine all rows for other statistics */
data OtherStats;
        set NumOfObs AdjRsq OverallSig;
        rename Label1=Regressors;
run;

data Table_Wide_Sorted_WithStats;
        set Table_Wide_Sorted OtherStats;
```

```
run;

proc format;

        value $VariableName(default=50)

;

run;


/* Print the clean results table */

ods excel file="/home/u60669666/FinalSeniorProject/FinalSeniorProject.xlsx"
        options(Embedded_Titles="ON" Embedded_Footnotes="ON"); /*Use the path to your
        MySAS folder */

Title "Table 1: Effect of Anti-Theft Signs";

footnote justify=left "Note: standard errors are in parentheses. *, **, and ***

indicate 10%, 5%, and 1% significance levels respectively

and values in parantheses represent the standard errors.";

proc print data=Table_Wide_Sorted_withstats noobs label;

        var regressors;

        var model1 model2 model3 /style(header)={just=center} style(data)={just=center
        tagattr="type:String"}; /* the - will add all of the variables ex. model1-model10*/

        label Model1='Simple DID'

                model2='DID With Controls'

                model3='Two-Way Fixed Effects';

        format Regressors $VariableName.; /*need to include . with the format*/

run;

ods excel close;
```

```
/* Print the clean robustness checks table */

ods excel file="/home/u60669666/FinalSeniorProject/FinalSeniorProject2.xlsx"
        options(Embedded_Titles="ON" Embedded_Footnotes="ON"); /*Use the path to your
        MySAS folder */

Title "Table 2: Effect of Anti-Theft Signs Robustness Checks";

footnote justify=left "Note: standard errors are in parentheses. *, **, and ***

indicate 10%, 5%, and 1% significance levels respectively

and values in parantheses represent the standard errors.";

proc print data=Table_Wide_Sorted_withstats noobs label;

        var regressors;

        var model4 model5 /style(header)={just=center} style(data)={just=center
        tagattr="type:String"}; /* the - will add all of the variables ex. model1-model10*/

        label model4='Log of Crimes'

                model5='Seperated Size Parking Lots';

        format Regressors $VariableName.; /*need to include . with the format*/

run;

ods excel close;


/* Parallel Trend */

data PTTest;

set finalset2;

MonYear = MonYear - 201700;

MonYear2 = MonYear*MonYear;

Monyear3 = Monyear2*Monyear;
```

```
TM = Treatment*MonYear;

TM2 = Treatment*MonYear2;

TM3 = Treatment*MonYear3;

run;


ods excel file="/home/u60669666/FinalSeniorProject/ParallelTest.xlsx"
        options(Embedded_Titles="ON" Embedded_Footnotes="ON"); /*Use the path to your
        MySAS folder */

Title "Table 1: Parallel Trends Test";

proc surveyreg data = PTTest;

WHERE MonYear < 202208;

Model4: Model NumOfCrimes = Treatment MonYear MonYear2 MonYear3 TM TM2 TM3
        /Solution Adjrsq;

run;

ods excel close;


proc sort data=finalset2 out = ptGraph;

by treatment monyear;

run;


ods output Summary = ptGraph2;

proc means data=ptGraph;

var numofcrimes;

by Treatment monyear;

run;
```

```
ods excel file="/home/u60669666/FinalSeniorProject/ptGraph2.xlsx"
        options(Embedded_Titles="ON" Embedded_Footnotes="ON"); /*Use the path to your
        MySAS folder */

proc print data=ptGraph2;

var treatment monyear numofcrimes_mean;

run;

ods excel close;


/*  Balance of Regressors */

proc ttest data=finalset2 plots=none;

where monyear = 202208;

class treatment;

var "TOTAL SPACES"n "All Permit"n Commuter Resident Special Disability Visitor;

run;
```

Appendix 2 (Tables)

Table 1: Parallel Trends Test

The SURVEYREG Procedure

Regression Analysis for Dependent Variable NumOfCrimes

Estimated Regression Coefficients				
Parameter	**Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	0.1718	0.0291	5.90	<.0001
Treatment	0.1938	0.0722	2.69	0.0073
MonYear	-0.0011	0.0004	-2.54	0.0112
MonYear2	0.0000	0.0000	1.75	0.0798

Monyear3	0.0000	0.0000	-1.26	0.2083
TM	0.0001	0.0013	0.09	0.9309
TM2	0.0000	0.0000	-0.15	0.8818
TM3	0.0000	0.0000	0.32	0.7502

Note: The degrees of freedom for the t tests is 3527.

Table 3: Effect of Anti-Theft Signs

Regressors	**Simple DID**	**DID With Controls**	**Two-Way Fixed Effects**
Intercept	0.08***	-0.26***	-0.01
	(0.01)	(0.06)	(0.06)
DID	0.07	0.07	0.07
	(0.13)	(0.12)	(0.10)
All Permit		0.25***	
		(0.06)	
Commuter		0.32***	
		(0.06)	
DID1			
DID2			
Disability		0.27***	
		(0.06)	
LOT 1			0.19**
			(0.09)
LOT 10			0.14**
			(0.06)
LOT 11			-0.01
			(0.04)
LOT 13			-0.04
			(0.03)
LOT 14			-0.01
			(0.04)
LOT 15			-0.01
			(0.04)
LOT 18			0.81***
			(0.12)
LOT 19			-0.02
			(0.03)

LOT 2			-0.05*
			(0.03)
LOT 21			-0.05*
			(0.03)
LOT 22			-0.04
			(0.03)
LOT 24			-0.02
			(0.04)
LOT 25			-0.04
			(0.03)
LOT 26			0.40***
			(0.11)
LOT 27			-0.01
			(0.04)
LOT 28			0.36***
			(0.09)
LOT 29			-0.03
			(0.03)
LOT 30			-0.05*
			(0.03)
LOT 32			-0.05*
			(0.03)
LOT 34			0.08
			(0.05)
LOT 36			1.51***
			(0.18)
LOT 37			0.31***
			(0.08)
LOT 39			0.07
			(0.06)
LOT 4			-0.04
			(0.03)
LOT 40			-0.05*
			(0.03)
LOT 43			0.06
			(0.05)
LOT 44			0.15***
			(0.06)
LOT 45			-0.02
			(0.03)
LOT 46			0.06
			(0.06)
LOT 47			0.22***
			(0.07)

LOT 49			0.17***
			(0.06)
LOT 5			-0.02
			(0.03)
LOT 50			-0.02
			(0.03)
LOT 52			-0.02
			(0.04)
LOT 56			-0.05*
			(0.03)
LOT 57			0.19**
			(0.08)
LOT 6			-0.05*
			(0.03)
LOT 61			-0.05*
			(0.03)
LOT 62			0.01
			(0.04)
LOT 66			-0.02
			(0.04)
LOT 69			-0.05*
			(0.03)
LOT 6B			-0.04
			(0.03)
LOT 7			0.03
			(0.05)
LOT 70 North			-0.05*
			(0.03)
LOT 70 South			0.67***
			(0.12)
LOT 71			-0.05*
			(0.03)
LOT 72			-0.05*
			(0.03)
LOT 8			-0.04
			(0.03)
MonYear 201701			0.14*
			(0.08)
MonYear 201702			0.16
			(0.10)
MonYear 201703			0.06
			(0.08)
MonYear 201704			0.22**
			(0.09)

MonYear 201705			0.12
			(0.10)
MonYear 201706			0.16*
			(0.09)
MonYear 201707			0.10
			(0.07)
MonYear 201708			0.04
			(0.07)
MonYear 201709			0.26**
			(0.12)
MonYear 201710			0.16*
			(0.10)
MonYear 201711			0.04
			(0.07)
MonYear 201712			0.06
			(0.07)
MonYear 201801			0.10
			(0.08)
MonYear 201802			0.12
			(0.09)
MonYear 201803			-0.00
			(0.06)
MonYear 201804			-0.00
			(0.06)
MonYear 201805			0.16*
			(0.09)
MonYear 201806			-0.02
			(0.06)
MonYear 201807			-0.08
			(0.07)
MonYear 201808			0.02
			(0.08)
MonYear 201809			0.12
			(0.08)
MonYear 201810			0.16
			(0.11)
MonYear 201811			0.10
			(0.07)
MonYear 201812			-0.00
			(0.06)
MonYear 201901			-0.00
			(0.07)
MonYear 201902			0.04
			(0.08)

MonYear 201903			-0.02
			(0.07)
MonYear 201904			0.10
			(0.09)
MonYear 201905			0.02
			(0.07)
MonYear 201906			-0.04
			(0.07)
MonYear 201907			-0.04
			(0.06)
MonYear 201908			0.08
			(0.10)
MonYear 201909			0.06
			(0.07)
MonYear 201910			0.08
			(0.09)
MonYear 201911			0.04
			(0.07)
MonYear 201912			-0.04
			(0.06)
MonYear 202001			0.06
			(0.09)
MonYear 202002			-0.00
			(0.07)
MonYear 202003			0.02
			(0.07)
MonYear 202004			-0.06
			(0.07)
MonYear 202005			-0.02
			(0.06)
MonYear 202006			0.02
			(0.07)
MonYear 202007			-0.06
			(0.07)
MonYear 202008			0.08
			(0.07)
MonYear 202009			0.06
			(0.08)
MonYear 202010			0.02
			(0.08)
MonYear 202011			0.10
			(0.08)
MonYear 202012			0.02
			(0.07)

MonYear 202101			-0.04
			(0.06)
MonYear 202102			0.06
			(0.08)
MonYear 202103			0.02
			(0.07)
MonYear 202104			-0.02
			(0.07)
MonYear 202105			-0.00
			(0.07)
MonYear 202106			0.06
			(0.08)
MonYear 202107			-0.00
			(0.07)
MonYear 202108			-0.02
			(0.07)
MonYear 202109			0.26*
			(0.15)
MonYear 202110			0.08
			(0.11)
MonYear 202111			0.12
			(0.09)
MonYear 202112			0.08
			(0.08)
MonYear 202201			0.08
			(0.09)
MonYear 202202			-0.00
			(0.06)
MonYear 202203			0.08
			(0.08)
MonYear 202204			0.14
			(0.13)
MonYear 202205			0.10
			(0.11)
MonYear 202206			0.10
			(0.08)
MonYear 202207			-0.02
			(0.07)
MonYear 202208			0.04
			(0.08)
MonYear 202209			0.14
			(0.11)
MonYear 202210			0.08
			(0.08)

MonYear 202211			0.06
			(0.09)
Resident		0.06	
		(0.07)	
Special		0.21***	
		(0.05)	
TOTAL SPACES		0.00***	
		(0.00)	
Treatment	0.23***	0.10***	
	(0.03)	(0.03)	
Visitor		0.53***	
		(0.07)	
after	0.01	0.01	
	(0.03)	(0.03)	
Number of Observations	3,528	3,528	3,528
Adjusted R-Square	0.03935	0.1070	0.2788
Overall Significance	24.73***	20.27***	3.60***

Note: standard errors are in parentheses. *, **, and ***indicate 10%, 5%, and 1% significance levels respectively and values in parantheses represent the standard errors.

Table 4: Effect of Anti-Theft Signs Robustness Checks

Regressors	**Log of Crimes**	**Separated Size Parking Lots**
Intercept	0.01	0.00
	(0.03)	(0.06)
DID	0.03	
	(0.05)	
All Permit		
Commuter		
DID1		-0.02
		(0.07)
DID2		0.20
		(0.21)

Disability		
LOT 1	0.10**	0.18*
	(0.05)	(0.09)
LOT 10	0.09**	0.14**
	(0.04)	(0.06)
LOT 11	-0.01	-0.01
	(0.03)	(0.04)
LOT 13	-0.03	-0.04
	(0.02)	(0.03)
LOT 14	-0.01	-0.01
	(0.03)	(0.04)
LOT 15	-0.01	-0.01
	(0.03)	(0.04)
LOT 18	0.45***	0.80***
	(0.06)	(0.12)
LOT 19	-0.02	-0.03
	(0.02)	(0.03)
LOT 2	-0.04*	-0.06*
	(0.02)	(0.03)
LOT 21	-0.04*	-0.06*
	(0.02)	(0.03)
LOT 22	-0.03	-0.04
	(0.02)	(0.03)
LOT 24	-0.02	-0.03
	(0.02)	(0.04)
LOT 25	-0.03	-0.04
	(0.02)	(0.03)
LOT 26	0.22***	0.39***
	(0.05)	(0.11)
LOT 27	-0.01	-0.01
	(0.03)	(0.04)
LOT 28	0.21***	0.36***
	(0.05)	(0.09)
LOT 29	-0.02	-0.03
	(0.02)	(0.03)
LOT 30	-0.04*	-0.06*
	(0.02)	(0.03)
LOT 32	-0.04*	-0.06*
	(0.02)	(0.03)
LOT 34	0.05	0.08
	(0.03)	(0.05)
LOT 36	0.74***	1.50***
	(0.07)	(0.18)

LOT 37	0.19***	0.30***
	(0.05)	(0.08)
LOT 39	0.04	0.05
	(0.03)	(0.06)
LOT 4	-0.03	-0.04
	(0.02)	(0.03)
LOT 40	-0.04*	-0.06*
	(0.02)	(0.03)
LOT 43	0.04	0.05
	(0.03)	(0.05)
LOT 44	0.10***	0.15***
	(0.04)	(0.06)
LOT 45	-0.02	-0.03
	(0.02)	(0.03)
LOT 46	0.02	0.06
	(0.03)	(0.06)
LOT 47	0.14***	0.22***
	(0.04)	(0.07)
LOT 49	0.11***	0.15**
	(0.04)	(0.06)
LOT 5	-0.02	-0.03
	(0.02)	(0.03)
LOT 50	-0.02	-0.03
	(0.02)	(0.03)
LOT 52	-0.02	-0.03
	(0.02)	(0.03)
LOT 56	-0.04*	-0.06*
	(0.02)	(0.03)
LOT 57	0.10**	0.18**
	(0.04)	(0.08)
LOT 6	-0.04*	-0.06*
	(0.02)	(0.03)
LOT 61	-0.04*	-0.06*
	(0.02)	(0.03)
LOT 62	0.00	-0.00
	(0.03)	(0.04)
LOT 66	-0.02	-0.03
	(0.02)	(0.03)
LOT 69	-0.04*	-0.06*
	(0.02)	(0.03)
LOT 6B	-0.03	-0.04
	(0.02)	(0.03)
LOT 7	0.02	0.03
	(0.03)	(0.05)

LOT 70 North	-0.04*	-0.06*
	(0.02)	(0.03)
LOT 70 South	0.37***	0.67***
	(0.06)	(0.12)
LOT 71	-0.04*	-0.06*
	(0.02)	(0.03)
LOT 72	-0.04*	-0.06*
	(0.02)	(0.03)
LOT 8	-0.03	-0.04
	(0.02)	(0.03)
MonYear 201701	0.07	0.14*
	(0.05)	(0.08)
MonYear 201702	0.07	0.16
	(0.05)	(0.10)
MonYear 201703	0.02	0.06
	(0.04)	(0.08)
MonYear 201704	0.13**	0.22**
	(0.05)	(0.09)
MonYear 201705	0.06	0.12
	(0.05)	(0.10)
MonYear 201706	0.09*	0.16*
	(0.05)	(0.09)
MonYear 201707	0.06	0.10
	(0.04)	(0.07)
MonYear 201708	0.01	0.04
	(0.04)	(0.08)
MonYear 201709	0.11*	0.26**
	(0.06)	(0.12)
MonYear 201710	0.08	0.16*
	(0.05)	(0.10)
MonYear 201711	0.03	0.04
	(0.04)	(0.08)
MonYear 201712	0.02	0.06
	(0.04)	(0.08)
MonYear 201801	0.05	0.10
	(0.04)	(0.08)
MonYear 201802	0.05	0.12
	(0.05)	(0.09)
MonYear 201803	-0.00	-0.00
	(0.04)	(0.07)
MonYear 201804	-0.01	-0.00
	(0.03)	(0.06)
MonYear 201805	0.09*	0.16*
	(0.05)	(0.09)

MonYear 201806	-0.02	-0.02
	(0.04)	(0.06)
MonYear 201807	-0.06	-0.08
	(0.04)	(0.07)
MonYear 201808	0.01	0.02
	(0.04)	(0.08)
MonYear 201809	0.06	0.12
	(0.04)	(0.08)
MonYear 201810	0.06	0.16
	(0.05)	(0.11)
MonYear 201811	0.05	0.10
	(0.04)	(0.08)
MonYear 201812	-0.00	-0.00
	(0.04)	(0.06)
MonYear 201901	-0.01	-0.00
	(0.04)	(0.07)
MonYear 201902	0.02	0.04
	(0.04)	(0.08)
MonYear 201903	-0.02	-0.02
	(0.04)	(0.07)
MonYear 201904	0.06	0.10
	(0.05)	(0.10)
MonYear 201905	0.01	0.02
	(0.04)	(0.07)
MonYear 201906	-0.03	-0.04
	(0.04)	(0.07)
MonYear 201907	-0.04	-0.04
	(0.03)	(0.06)
MonYear 201908	0.03	0.08
	(0.05)	(0.10)
MonYear 201909	0.03	0.06
	(0.04)	(0.07)
MonYear 201910	0.03	0.08
	(0.05)	(0.09)
MonYear 201911	0.02	0.04
	(0.04)	(0.07)
MonYear 201912	-0.03	-0.04
	(0.03)	(0.06)
MonYear 202001	0.01	0.06
	(0.05)	(0.09)
MonYear 202002	-0.01	-0.00
	(0.04)	(0.07)
MonYear 202003	0.01	0.02
	(0.04)	(0.07)

MonYear 202004	-0.04	-0.06
	(0.04)	(0.07)
MonYear 202005	-0.02	-0.02
	(0.04)	(0.06)
MonYear 202006	0.01	0.02
	(0.04)	(0.07)
MonYear 202007	-0.04	-0.06
	(0.04)	(0.07)
MonYear 202008	0.05	0.08
	(0.04)	(0.07)
MonYear 202009	0.04	0.06
	(0.04)	(0.08)
MonYear 202010	0.01	0.02
	(0.05)	(0.08)
MonYear 202011	0.06	0.10
	(0.05)	(0.08)
MonYear 202012	0.01	0.02
	(0.04)	(0.07)
MonYear 202101	-0.03	-0.04
	(0.03)	(0.06)
MonYear 202102	0.03	0.06
	(0.04)	(0.08)
MonYear 202103	0.01	0.02
	(0.04)	(0.08)
MonYear 202104	-0.02	-0.02
	(0.04)	(0.07)
MonYear 202105	-0.00	-0.00
	(0.04)	(0.08)
MonYear 202106	0.04	0.06
	(0.05)	(0.08)
MonYear 202107	-0.01	-0.00
	(0.04)	(0.07)
MonYear 202108	-0.02	-0.02
	(0.04)	(0.07)
MonYear 202109	0.11*	0.26*
	(0.06)	(0.15)
MonYear 202110	0.03	0.08
	(0.05)	(0.11)
MonYear 202111	0.06	0.12
	(0.05)	(0.09)
MonYear 202112	0.04	0.08
	(0.04)	(0.08)
MonYear 202201	0.04	0.08
	(0.05)	(0.09)

MonYear 202202	-0.00	-0.00
	(0.04)	(0.06)
MonYear 202203	0.04	0.08
	(0.04)	(0.08)
MonYear 202204	0.04	0.14
	(0.05)	(0.13)
MonYear 202205	0.02	0.10
	(0.04)	(0.11)
MonYear 202206	0.05	0.10
	(0.04)	(0.09)
MonYear 202207	-0.02	-0.02
	(0.04)	(0.07)
MonYear 202208	0.01	0.04
	(0.04)	(0.08)
MonYear 202209	0.06	0.14
	(0.05)	(0.11)
MonYear 202210	0.04	0.08
	(0.04)	(0.08)
MonYear 202211	0.04	0.06
	(0.05)	(0.09)
Resident		
Special		
TOTAL SPACES		
Treatment		
Visitor		
after		
Number of Observations	3,528	3,528
Adjusted R-Square	0.2858	0.2792
Overall Significance	4.41***	3.58***

Note: standard errors are in parentheses. *, **, and ***indicate 10%, 5%, and 1% significance levels respectively and values in parantheses represent the standard errors.