How art theft affects museum attendance, membership, and fundraising revenue.

1. Introduction

Art theft is the third largest source of criminal revenue, behind only drugs and arms[1]. While everyone can agree crime is bad and something we want to stop, in reviewing notable art thefts throughout history there are instances where the theft and the press surrounding it benefitted the artist, owner or the piece itself. For example, the Mona Lisa, one of the most well-theft. While one may think that the missing masterpieces would deter visitors, the media attention on thefts can actually entice visitors as well as create public sympathy and support, leading to an increase in attendance, membership, and contributions to a museum. This would challenge previous misconceptions that art theft leads to catastrophic losses for museums and would explain why museums invest little in security and insurance precautions.

I will test this idea by looking at a large art theft that makes international news and answering the question of whether museums who feature works by the same artists whose works were stolen see increases in attendance revenue, membership revenue, and fundraising revenue. Since all recent art thefts have taken place in Europe, where museums financials are private, I will be examining the effect of one of the largest art thefts in recent years from a museum in the Netherlands on a treatment group of American museums who feature artwork by artists whose work was stolen, compared to a control group of American museums who do not feature artwork by any of these artists.

2. Museum's Maximization of Attendance

Non-profit museums differ than perfectly competitive firms because they do not operate to maximize profits. Since they don't maximize profits we can assume they operate to maximize attendance and museum visitors. Some assumptions can be made about non-profit museums, that they have high fixed costs and small marginal costs since bringing one more person into the museum does not cost a lot, if anything. Non-profit museums set their ticket price equal to the average total cost so that their costs to operate are covered. Their attendance maximization is seen in Figure 1a.

After a theft, a museum will incur new costs. The museum may choose to purchase more insurance, increasing fixed costs and shifting the average total cost curve up. Museums may also choose to purchase more security, which is a variable cost, shifting the marginal cost / average variable cost curve up in Figure 1b. In this model, after the theft the ticket price is higher and the amount of attendance has fallen. While the microeconomic model may predict lower attendance, the model does not include factors such as an individual's tastes and preferences, which could include seeing or contributing to a museum that has been stolen from or features artwork by an artist who was stolen from. However, even if museums had a higher ticket price after a theft attendance may actually increase, which would be seen in my regression results through an increase in admission fees revenue.

After a theft a museum's contributions may increase due to public support and sympathy. When museums receive donations they are able to lower their ticket price and bring more people in the door. A museum that suffers a theft may have increased costs, however, if they receive more donations following the theft then their ticket price will not increase, and their attendance will not fall. In Figure 1c. a museum with increased costs, including a higher average total cost and a higher average variable cost is still able to lower their ticket price below their average total cost with the presence of donations.

3. Background and Related Literature

a. The problem of art theft

The art market is plagued with inefficiencies and various types of crime yet continues to operate in a state of market failure. As long as this market failure continues, art theft will continue as well, which Day (2014) notes in his study on the inefficiency of the art market. Despite these problems, buyers and sellers, including museums, seem hesitant to fix any of them. This shows a puzzling phenomenon that suggests there are some benefits to be gained from the inefficiencies, including theft. Sellers benefit from the lack of disclosure surrounding the provenance and history of the piece when it is sold. The don't ask don't tell nature of the art market creates both opportunity and rewards for theft.

A definite drive for art theft exists, and the most vulnerable to art crime are museums. Their public nature allows thieves to walk through the front door, observe the security precautions put in place or lack thereof, and plan out the robbery, noted by Chong's (2015) study on the public nature of museums and galleries. Since it seems clear that museums already face security problems due to their public nature, one would think that more protective measures would be put in place. However, security measures put in place around museums and in front of works may actually take away from the experience of a viewer, a problem that Seaton (2014) discusses in her study. Another reason is the belief that high security measures may actually signal to a thief that there are highly valuable pieces within the museum, a counter-intuitive effect Nicita and Rizzoli (2010) find in their analysis of how museums can protect themselves from theft. In this case security would do the opposite of protecting art, rather signaling to thieves that this a place worth robbing.

b. Museums Lack of Prevention Against Art Theft

Museums' collections of highly famous and well-known works of art may actually give them the belief that they are safe from theft. Masterpieces, despite their astonishing market value, are usually not a target for thieves. Thieves are more likely to go for a piece

sales. Coomber (2013) found that in some, but not all cases, auction results from five years after a theft were higher for artists who suffered a theft compared to five years before were higher. While the effect on museums as a whole is left to be explored, previous literature has examined the specific case study of how the Isabella Stewart Gardner Museum was able to turn their loss into profit. The theft resulted in an increase in membership, donations, attendance, and an overall financially solvent institution that had not existed before.

4. Data

To understand the impact of art theft on museums I will use an empirical model with data from major art institutions in the United States. This data comes from the museums' tax forms, and since they are non-profit institutions their tax forms are available for public reading online at Non-Profit Explorer[3]. The tax forms provide each institution's total revenue, as well as the percent of this that comes from contributions, and in varying cases admissions revenue, membership revenue, fundraising revenue, and insurance for each fiscal year from around the past ten years. With this information I will be able to examine it[4]. In addition, I will include population density for each city, obtained from the US Census, which could influence how many members or visitors a museum has[5]. I will also include the property crime rate for each city, obtained from the FBI, as this would affect a museum's purchase of insurance which I also plan on observing[6]. Another control is the region code for each area that the museum is located in given by the US Census[7]. I also include the number of total works that each of the treatment museums have by the stolen artist as a control, which was found by searching each museum's online collection. All variables measured in dollars have been adjusted to 2017 dollars with the CPI.

The majority of notorious art thefts that have occurred in the 2000s have taken place in Europe. It is much harder to find this kind of data for these private European museums, so I will examine how American institutions are affected by an art theft abroad. The effect will not be as obvious as if I was looking atf data folook .0he 444.42 5:t.-ETQq0.0000092rk(<01764<016F015D01

Picasso, Matisse, Gauguin, de Haan, and Freud. This theft will be the one I use as my case study, as the theft was large enough and featured multiple high-profile artists to have vast news coverage. It is also the biggest art theft in the time frame where these museums have tax forms available. I will compare varying revenues and insurance payments of ten American museums that feature at least three of the artists whose works were stolen with ten American museums who do not have works by any of the stolen artists. The museums who do feature work by the stolen artists include the MFA Boston, MFA Houston, Guggenheim, Metropolitan Museum of Art, Philadelphia Museum of Art, Cleveland Museum of Art, Art Institute of Chicago, Detroit Institute of Art, Toledo Museum of Art, and Indianapolis Museum of Art. The ten museums who do not are the ICA Boston, New Britain Museum of American Art, Kemper Museum of Contemporary Art, MCA Chicago, American Folk-Art Museum, MOCA Los Angeles, Museum of Contemporary Art San Diego, Madison Museum of Contemporary Art, Whitney Museum of American Art, and the Minnesota Museum of American Art. For both groups I will examine the museums' admissions revenue, membership revenue, fundraising revenue, and insurance in the pre period, 6 years before the theft, and the post period, 5 years after the theft.

A limitation of this paper is that it exhibits sample selection bias. Since museums who have suffered thefts in recent years do not have public data available I instead had to choose a representative group of museums that feature artwork by the artists who were stolen from as the treatment group. The theft that I am examining as the shock had work stolen from major artists who are very famous, and because of this the treatment group of museums are larger, more well-known institutions. The control group includes museums who do not feature artwork by these famous artists and for that reason they are much smaller, less known, and consequently poorer. The impact of this is that the treatment group will have larger fundraising revenue, membership revenue, admission revenue, and insurance payments simply because they are larger and more well-known institutions.

5. Empirical Analysis

The coefficient of interest is β3, the coefficient on the interaction term, as it reveals the marginal effect on the treatment group following the theft. Here the Y, the dependent variable, represents the museum's attendance revenue, membership revenue, fundraising revenue, and insurance payments in each respective regression. The controls will include the GDP per capita of the city of each museum, the population density of each city, the property crime rate for each city, the number of works each museum features by the artists who were stolen from, and dummy variables for the regions given by the US Census, the region 4 dummy is left out of the regression. My hypothesis as discussed before is:

1. β3 will be positive and statistically significant for attendance revenue, membership revenue, and fundraising revenue and I will be able to reject the null that β3=0 when y=attendance revenue, membership revenue, or fundraising revenue.
2. β3 will equal 0 for insurance payments and that I will fail to reject the null that β3=0 when y=insurance payments.

6. Regression Results

My regression results reveal that the coefficient on the interaction term is not statistically significant for any of the regressions, whether the dependent variable is admission revenue, fundraising revenue, membership revenue, or insurance. In Table 2 and Table 3 we see the regression results for membership revenue, fundraising revenue, attendance revenue, and insurance as the respective dependent variables. My first hypothesis, that β3 will be positive and statistically significant for attendance revenue, membership revenue, and fundraising revenue was proved wrong by my results. In all four regressions I failed to reject the null hypothesis that $\beta3=0$ at the 1%, 5%, and 10% significance levels.

In the first column of Table 1 where fundraising revenue is the dependent variable the theft was not statistically significant at the 1%, 5%, or 10% level. The coefficient here reveals that if the results were significant the treatment group of museums would have seen a $268,999 increase in fundraising revenue, holding all other independent variables constant, which would have supported my initial idea. The standard deviation of fundraising revenue is $4,655,895.82, found in the overall descriptive statistics in Table 6, so the coefficient is not economically significant.

In the second regression, on admission fees revenue, the theft has no statistical effect on the treatment group of museums at the 1%, 5%, or 10% level. In this case the coefficient shows that had the results been significant the treatment group of museums would have lost $1,302,699 in admission revenue following the theft, holding all other independent variables constant, which does not support what I expected to find. The standard deviation of admission fees revenue is $5,981,790.11 and the mean is $3,953,492.87 so this coefficient is not economically significant.

In the third column on membership dues the coefficient of significance, the interaction term, is not statistically significant at the 1%, 5%, or 10% level. Had the results been significant the coefficient would have indicated that after the theft museums who featured artwork by the stolen artists had an increase in membership dues of $842,602, compared to museums who did not, holding all other independent variables constant. This result is what

fees, and spend more on insurance payments. To control for this I ran another regression, in Table 3 and Table 4 respectively, where I dropped the two treatment groups with the largest amount of works by the artists who were stolen from. In these results the number of works were no longer statistically significant for fundraising reves6(u)4(n)4(d)4(r)-4(ais)-3(in)5(g)-7( )-2(r)-4

Figures

Figure 1a. Non-Profit Museums Optimization

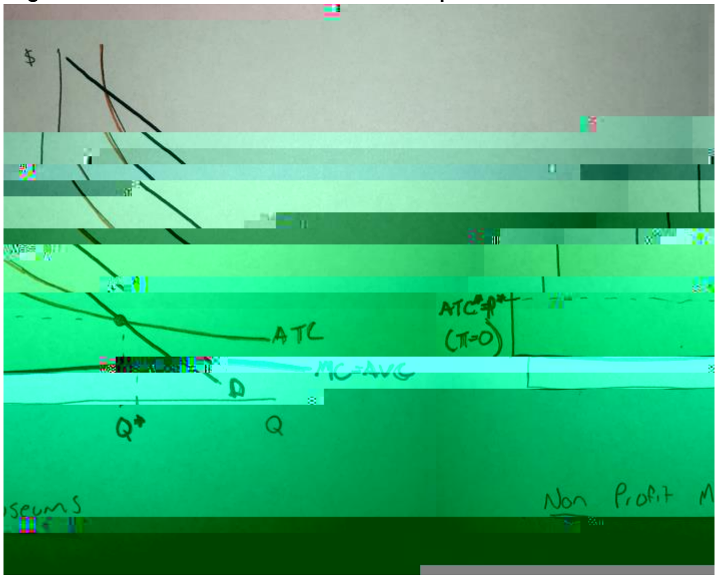

Figure 1b. Non-Profit Museums after a theft

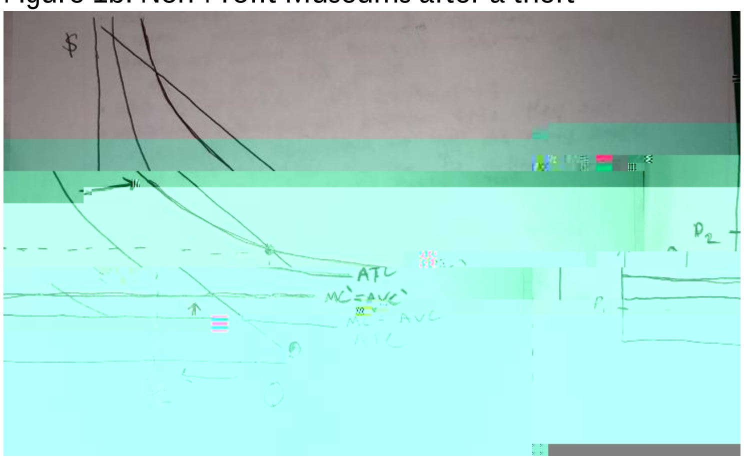

Figure 1c. Museums who Receive Donations Following a Theft

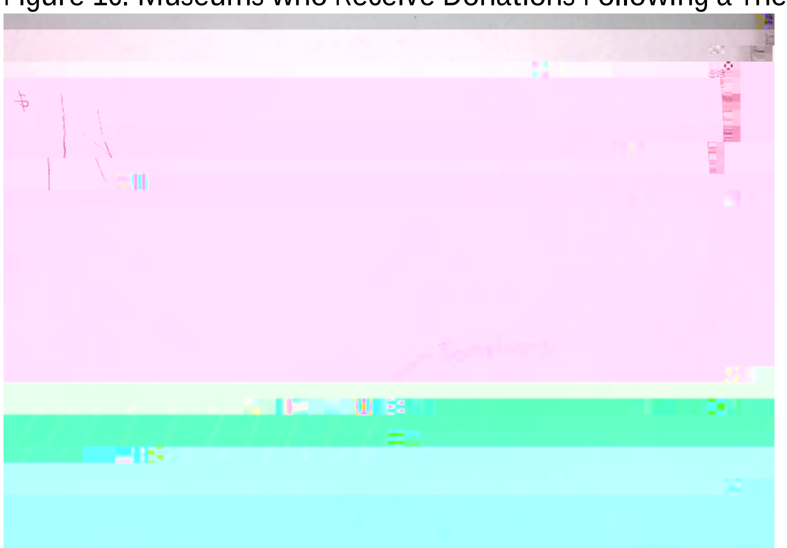

Figure 2a. Fundraising Revenue Before and After the Theft in 2012

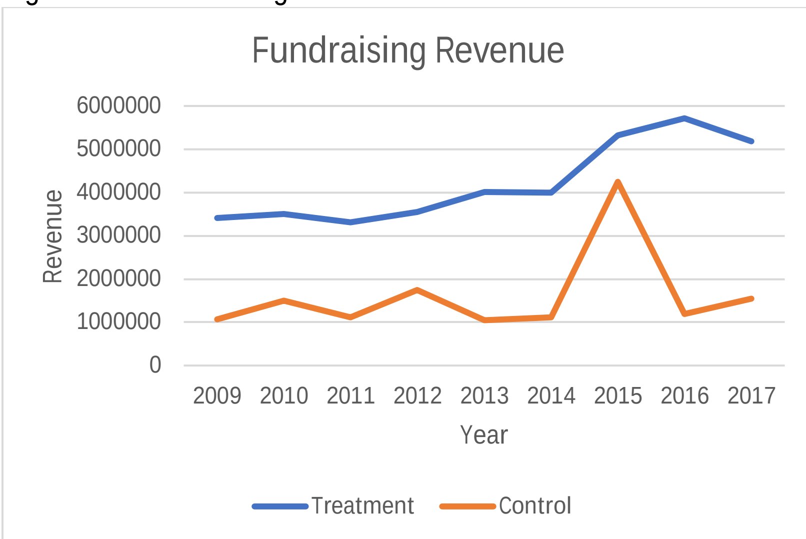

Figure 2b. Membership Revenue Before and After the Theft in 2012

Figure 2c. Attendance Revenue Before and After the Theft in 2012

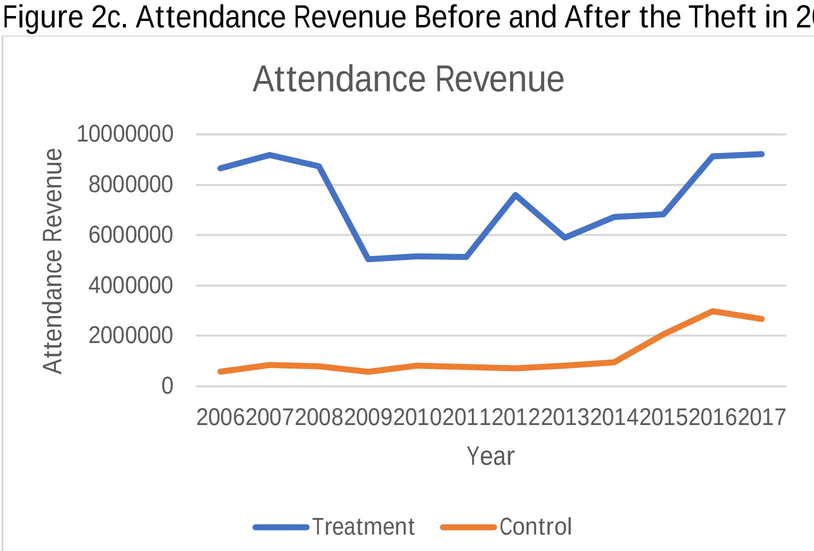

Table 1a. Summary Statistics for Control Group before Theft

Table 1d. Summary Statistics for Treatment Group After Theft

Variable	Obs	Mean	Std. Dev.	Min	Max
fundraising	33	4900850	6509612	19278.68	2.18e+07
membership	49	7329639	8610202	545776.2	3.09e+07
admission	34	7609853	7106317	528165.6	2.19e+07
contribution	50	8.50e+07	1.11e+08	6946955	6.11e+08
insurance	50	1025074	673960.3	244018.9	2755614
gdppercapita	50	63164.01	9002.679	46880	79060.53
propertycr	50	2322.158	722.3811	1308.5	3540
popdens	50	1341.241	855.4298	328.8889	2891.398
totalrevenue	50	2.83e+08	8.79e+08	1.97e+07	6.26e+09
n_works	50	335.8	293.9134	37	835

Table 2. Regression Results for Fundraising Revenue, Membership Revenue, Admissions Revenue

	1	2	3
VARIABLES	fundraisingrevenue	admissionfeesincome	membershipdues

Table 3. Regression Results for Insurance

VARIABLES	(1) insurance
treatment	522,555.600***
	(91,768.269)
post2	139,130.440*
	(81,879.459)
treatxpost2	-210,398.715
	(139,272.192)
n_works	1,685.648***
	(294.402)
Constant	2029237.596***
	(491,242.140)
Observations	208
R-squared	0.682

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Results from estimating equation (1) by OLS using data from 2006-2017. Post=1 after 2012. Regressions also include controls for GDP per capita, property crime, population density, and region code.

Table 4. Regression Results for Fundraising Revenue, Membership Revenue, Admissions Revenue with Two Treatment Museums Dropped

	1	2	3
VARIABLES	fundraisingrevenue	admissionfeesincome	membershipdues
treatment	314,603.956	8147922.488***	441,848.022
	(579,920.420)	(1210881.793)	(306,190.937)
post	1179308.291	597,500.291	201,046.395
	(1359034.392)	(846,783.251)	(326,105.990)
treatxpost	311,959.415	-496,070.986	-499,462.840
	(681,482.725)	(1127982.868)	(385,509.164)
n_works	-1,334.495	-11,886.239***	14,602.130***
	(2,447.780)	(2,751.862)	(918.267)
Constant	-9547417.148	45,921.550	-2008563.831**
	(6900646.457)	(3477276.551)	(950,198.194)
Observations	101	133	182
R-squared	0.243	0.664	0.783

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Results from estimating equation (1) by OBDC qDC qDC q[

Table 5. Regression Results for Insurance Payments with Two Treatment Museums Dropped

VARIABLES	(1) insurance
treatment	600,138.553***
	(80,604.702)
post	163,149.438**
	(64,055.859)
treatxpost	5,684.175
	(81,332.491)
n_works	435.665***
	(160.404)
Constant	1911538.430***
	(332,561.095)
Observations	186
R-squared	0.712

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Results from estimating equation (1) by OLS using data from 2006-2017. Post=1 after 2012. Regressions also include controls for GDP per capita, property crime, population density, and region code.

Table 5.

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