Great Streets Small Business Grant Program:

Criminological Effects in Washington, D.C.'s Emerging Corridors

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Abstract

The Great Streets program in Washington, D.C. was initially designed in the mid-2000s to assist small business owners experiencing financial stress resulting from the city's transportation-related construction projects. The program has since evolved to support hundreds of small businesses in the city's emerging neighborhood corridors. While a causal connection between socioeconomic deprivation and criminal behavior has long been theorized, there are few studies analyzing the relationship between commercial revitalization and crime rates at the business level. Our research attempts to address the question: How does giving a small business a public retail revitalization grant affect crime rates in the immediate proximity of the store front? Using grantee and crime data from Open Data DC and demographic data from the United States Census Bureau, this study employs an innovative donut geospatial modeling technique to set treatment and control areas in concentric circles with equal square footage around each grantee. Because the two areas are equal, crime counts occurring in each could be directly compared. A difference-in-differences approach was used to analyze the impact of small business grants on crime in the immediate vicinity of grantees. Crime outcomes were evaluated for the District as a whole, then separated by corridor. Our results suggest that the effectiveness of the Great Streets program to reduce property crime is dependent on the demographic makeup and socioeconomic shifts of a neighborhood. This is consistent with contemporary criminological research which shows that as communities absorb higher-income residents, these residents are often more likely to report property crime. These results indicate promise for business development grants to curb certain types of crime in particular neighborhoods.

Executive Summary

Great Streets is a commercial revitalization initiative in Washington, D.C. administered by the Office of the Deputy Mayor for Planning and Economic Development (DMPED). It is designed to "support existing small businesses, attract new businesses, increase the District's tax base, create new job opportunities for District residents, and transform emerging corridors into thriving and inviting neighborhood centers" ("About Great Streets," n.d.). Our study evaluated the impact of the Great Streets program on crime rates immediately adjacent to grantee businesses for the District and for four of the program corridors. The treatment and control groups were created using a geospatial donut method that defined them as areas of concentric circles around each grantee. Because the circles were set so that the two areas were equal, crime counts in each could be directly compared. Using ArcMap, crime occurrences were counted and demographics were assigned to the treatment and control areas. A difference-in-differences analysis was used to evaluate the impact of the program on crime in the immediate vicinity of the grantees.

Figure 1. Changes in Crime Incidences Due to Great Streets and Changes in Poverty Rates

The results indicated grants led to a small increase in crime outcomes in corridors where poverty rates decreased and a reduction in crime outcomes in corridors where the poverty rate increased during the time period of the study (*see* figure 1). District-wide and in the Georgia Ave NW and H Street NE corridors, crime counts increased while the average poverty rate decreased. In the Martin Luther King Street NE corridor, crime counts decreased while the average poverty rate increased. Both crime counts and poverty rate remained relatively flat in the Rhode Island Ave NE corridor. These results are consistent with criminological research showing that as communities attract higher-income residents they are likely to experience an increase in reported property crimes. This suggests that neighborhood demographic shifts play an important role in predicting property crime reporting. The study also advances the use of donut geomasking in criminological research. While this method is new and mostly used in public health research, it has great potential for understanding crime trends using potentially sensitive data.

Background

As explained by Great Streets staff, the impetus for this commercial grant program was to respond to the frustration of small business owners who were experiencing financial interruptions as a result of the city's ongoing transportation-related construction projects (Kirk-Patrick, 2018). In response to the building of the DC Streetcar in the mid-2000s, the first Great Streets grants were directed at supporting small businesses along H Street NE. Since 2006, the grant program has grown to support hundreds of businesses in 13 corridors known as the Great Street Corridors (*see* figure 2).

DMPED accepts applications for its competitive Great Streets Small Business Retail Grants on an annual basis, and awards up to $50,000 to eligible small business owners who wish to improve their storefront ("RFA FY2019 Great Streets Retail Small Business Grant," n.d.). Grant eligibility dictates that a small business owner must have or plan to have a new or existing business in one of Great Street Corridors.[5] While program administrators prioritize funding small businesses in service deserts, as long as a small business owner demonstrates how they will impact the corridor and incentivize the community to patronize the business, then they are eligible for maximum funding (Cook & Kirk-Patrick, 2018).

Past grantees have used, and benefited from, their funds in diverse ways. A local journalist interviewed the owners of three Great Streets grantees of the Connecticut Avenue NW Corridor. They reported using their funds for equipment and an outdoor café (Bread Furst, 4434 Connecticut), interior and outdoor dining areas (Acacia Bistro, 4340 Connecticut), and improvements to interior dining areas and infrastructure repairs (Italian Pizza Kitchen, 4483 Connecticut) (Berlin, 2017). Over the years, grantees have reported improved foot traffic, better marketing products, upgraded equipment, and hiring additional staff. The awardees say all of these improvements contribute to increased revenue as each element allows them to attract more customers (Cook & Kirk-Patrick, 2018).

[5] Ineligible businesses, as outlined in the 2019 Request for Application, include: Adult Entertainment, Auto Body Shop, Bank, Bar, Construction/General Contracting, E-commerce Business, Financial Services, Home-Based Businesses, Hotels, Liquor Stores, Nightclubs, Phone Stores, Real Estate Development/Property Management Realtor, and previously awarded businesses.

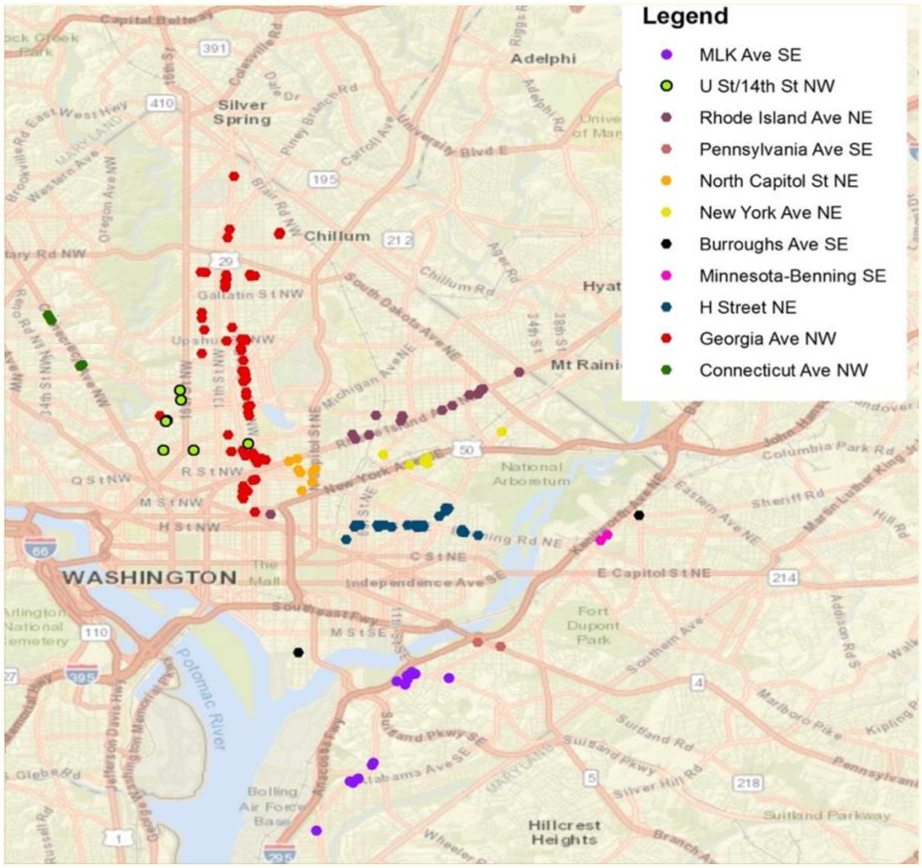


Figure 2*. Map of the Great Streets Corridors generated in ArcGIS as of December 2018.*

Accompanying the geographic expansion of the grant program is a richer development of the program's goals. The Great Streets Program Director, Sybongile Cook, explained that the contemporary goals of the program are to increase tax bases, create jobs, and spread capital improvement dollars. Director Cook's ultimate hope is to transform historically lower socioeconomic areas into "livable, walkable, and shoppable areas" (Cook & Kirk-Patrick, personal communication, December 7, 2018). With an eye towards creating equitable access, Director Cook emphasized neighborhood stability as one of the program's foundational goals. While crime reduction was not an explicit consideration of the program's original concept, it has become a part of recent conversations. DMPED staff have discussed the possibility of infusing money into high-crime areas in an attempt to hinder criminal activity; "if you give people jobs, there will be less crime" (Cook & Kirk-Patrick, personal communication, December 7, 2018).

Literature review

Criminologists have long theorized a relationship between socioeconomic deprivation and criminal behavior. However, few researchers have examined the relationship between commercial revitalization initiatives and crime rates. Perhaps the most relevant studies examine the impact of Business Improvement Districts (BIDs) on crime rates (e.g. Brooks, 2008; Hoyt, 2004; Cook & MacDonald, 2011). These studies suggest that BIDs act as mediators of crime reduction by strengthening neighborhood collective efficacy as a means of reinforcing social control. As BIDs typically assess a voluntary tax on local businesses to fund auxiliary neighborhood services like security, sanitation, and urban planning, scholars have described them as the privatization of public safety in urban neighborhoods (MacDonald, Grunwald, Stokes & Bluthenthal, 2013). BIDs operate at the neighborhood-level, which means BIDs research is limited to neighborhood effects. Few studies have drilled down to the structural level (i.e. a business storefront), to investigate the individual effects of community revitalization initiatives on crime.

Literature that addresses the interplay of neighborhood economics and crime at the structural level primarily focuses on vacant lots (e.g. Branas, et al., 2011) and foreclosed homes (e.g. Cui & Walsh, 2014). Branas and colleagues (2011) found that the greening of vacant lots in Philadelphia was associated with a reduction of violent crimes citywide, but varied for other crimes by event type and geography. Operating in a social disorganization theory framework, Branas and colleagues posit that community interest in maintaining a newly greened lot may have increased police calls resulting in an increase in reported property crimes. Cui and Walsh (2014) studied the impact of home foreclosures on crime and found contrasting results. Rather, they found that violent crime rates rose once foreclosed homes became vacant while property crime rates were unchanged. Cui and Walsh defend their results by arguing that to the extent squatters or drug dealers are frequenting vacant properties, such individuals would be less likely to report property crime than violent crime. Despite their contrasting findings, Branas and colleagues (2011) and Cui and Walsh (2014) construct a thematically similar defense: demographic shifts of a neighborhood may impact the frequency with which property crime is reported.

Theoretical framework

The Great Streets grant program's encouragement of commercial improvement in historically socio-economically depressed neighborhoods effectively mirrors the theoretical framework for previous research on mixed-income developments and suggests similar mechanisms at play.
Shaw & McKay's (1942/2016) social disorganization theory hypothesizes that community structural characteristics tied to social disorganization (i.e. mobility, poverty, and racial heterogeneity) lead to weak social ties that result in increased crime. Premised on the assumption that affluent communities have strong social ties because of shared values, social disorganization posits that non-affluent communities have weak social ties and thus promote crime-positive values. Modern criminologists have extended social disorganization theory by advancing the notion of collective efficacy, or the idea that social ties serve as a barometer of social cohesion and trust (Sampson, Raudenbush & Earls, 1997/2016). Much like Samspon, Raudenbush, and Earls, most scholars interpret social control to implicate *informal* mechanisms of control. Meaning, the willingness of neighbors to intervene if they see wrongdoing (Kubrin & Weitzer, 2003). Shaw and McKay concluded that when social ties are strong, a neighborhood is socially organized and less prone to crime.

As exhibited in the BIDs research, some scholars have supplemented social disorganization analysis with aspects of social control. Exploring social control and 'positive' gentrification, Chaskin and Joseph (2013) explain that mixed-income developments allow for the establishment of a diverse social network which bridges social capital and strengthens social ties. It is expected that higher-income residents will maintain order and safety in their neighborhood through normative notions of law enforcement to protect their investment, resulting in more residents feeling empowered to enforce *formal* mechanisms of control by calling the police to report property crimes.

Research question

Couched in citywide crime trends, our research attempts to address the question: How does giving a small business a public retail revitalization grant affect crime rates in the immediate proximity of the store front? According to social disorganization theory purists:

Hypothesis: Small businesses that benefit from a retail revitalization grant are likely to experience less crime in the immediate proximity of their store fronts as social ties and community social controls are strengthened through improved structural characteristics.

However, according to social control critiques of social disorganization, it is possible that the interaction of collective efficacy and bridging of social capital may mitigate or negate these effects, resulting in increased property crimes.

Methodology

Data

Open Data DC provided the Great Streets Grantees and crime datasets. The Great Streets dataset included the business name, census tract number, DC ward number, and the latitude and longitude coordinates of businesses that received the grants. Our study sample consisted of 175 businesses spread over eleven corridors that received grants from 2014 to 2016 (*see* figures 2 and 3). The publicly available crime dataset included total crime, burglary, robbery with a weapon, theft from automobiles, and other theft. These were downloaded for years 2013 to 2016.

Census tract level demographic data from 2013 to 2016 was obtained from the United States Census Bureau. Consistent with criminology research, the controlling demographic variables used in this study included median age, high school graduation rate, poverty rates, and percent of residents who are African American or Hispanic.

Study design

This paper employed geospatial techniques and difference-in-differences modeling to analyze the impact of a small business receiving a Great Streets grant on crime in the immediate vicinity of the grant awardee. Crime outcomes were evaluated for the District as a whole and then separated for each of the corridors.

The difference-in-differences method attempts to measure the effect of a treatment on an outcome variable by comparing a group of those receiving the treatment to a control group not receiving the treatment. Both groups are studied over the same time period which begins before the treatment starts and ends after the treatment is completed. The difference in the outcome variable between the change in the treatment group and the change in the control group is the difference-in-differences estimate and suggests a causal relationship attributable to the treatment. This method controls for extraneous effects that have an influence on the outcome variable not related to the treatment.

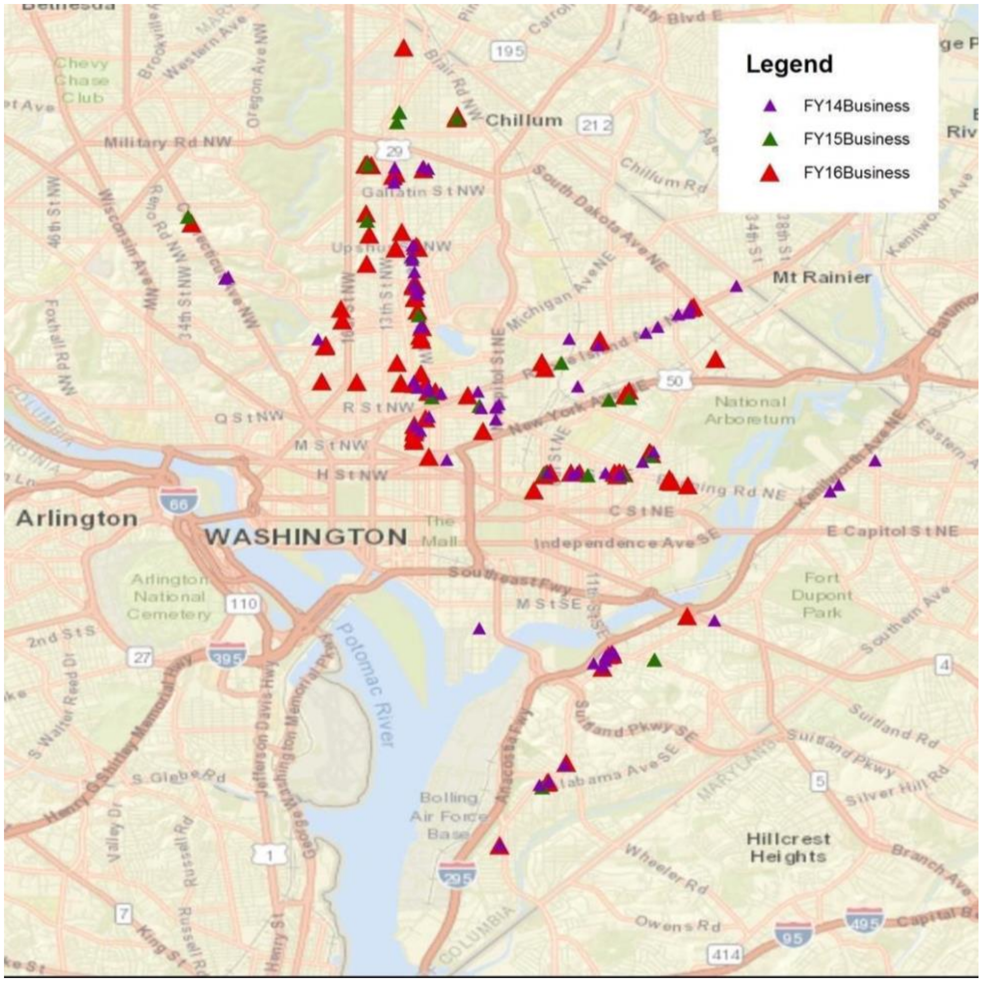
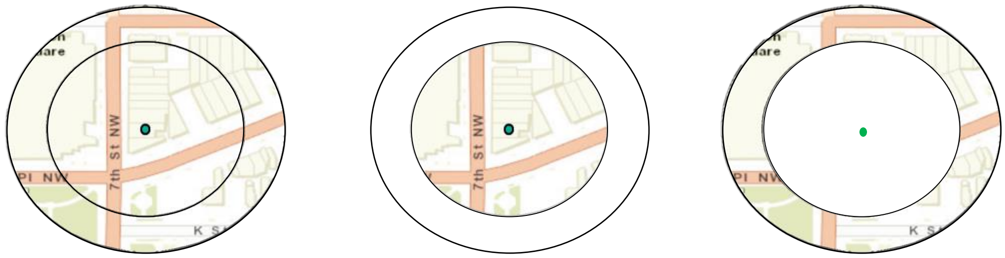


Figure 3. *Map of the Great Streets FY 14, 15, 16 grant awardees generated in ArcGIS.*

The treatment and control groups were created using a geospatial donut method based on its use in a paper by Branas, et al. (2011). The treatment and control groups were defined as the areas of concentric circles around each business grantee. The treatment area was a circle with a 250-foot radius around the treated business, and the control area was a ring around the treatment area with an inner radius of 250 feet and outer radius of 353 feet (*see* figure 4). These distances were selected to capture crime at the individual business level and to ensure both the treatment and control areas had the same square footage. Because the areas are the same size, counts of the crimes occurring in the treatment area and the control area can be directly compared. The crime data was joined to the treatment and control areas using ArcMap (*see* figure 5). ArcMap then counted the crime occurrences in each of the two areas by year.



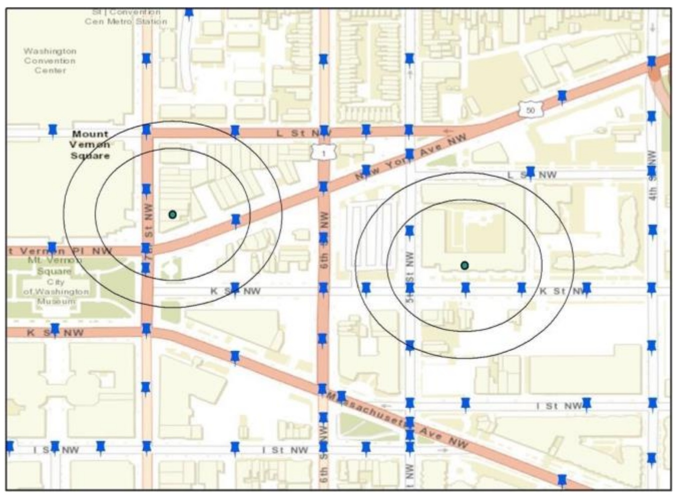


Figure 5: *Crime Counts in Treatment and Control Areas*

For the census information, the demographic data was joined to the treatment and control areas in ArcMap by census tract. The center point of the circles was used to assign demographic values to the treatment and control areas. The treatment and control area for a specific grantee share identical demographic values, however, those demographic values change within each area over time.

Each grantee was in the pre-period for the years before they received the grant, and in the post-period for the year they received the grant and after. In 2013, all of the grantees were in the pre-period. In 2014, 68 businesses received grants and were in the post-period. In 2015, 19 additional businesses received the grants and were in the post-period. In 2016, the remaining 88 businesses received the grant, and all 175 businesses were in the post-period. Table 1 shows how the businesses moved through the pre- and post-periods throughout the study. Tables 1 through 4 summarize the relevant statistics used in the study.

Table 1: Pre- and Post-Periods by Year

Year	Number of Grants Awarded	Number in Pre- and Post-Periods	
		Pre-period	*Post-period*
2013	-	175	0

2014	68	107	68
2015	19	88	87
2016	88	0	175

Table 2: Summary Statistics of Crime Variables

	Treatment Group					Control Group				
	N	**Mean**	**SD**	**Min**	**Max**	**N**	**Mean**	**SD**	**Min**	**Max**
	Total Crime – Counts per Treatment or Control Area									
Pre-Period	370	21.13	17.10	1	119	370	13.78	14.53	0	98
Post-Period	330	23.74	20.27	0	119	330	14.13	16.53	0	108
	Burglary – Counts per Treatment or Control Area									
Pre-Period	370	1.20	1.70	0	13	370	0.82	1.31	0	6
Post-Period	330	0.93	1.03	0	5	330	0.62	1.04	0	5
	Robbery with a Weapon – Counts per Treatment or Control Area									
Pre-Period	370	2.37	2.54	0	15	370	1.52	1.56	0	9
Post-Period	330	2.25	1.95	0	9	330	1.17	1.56	0	8
	Theft from Auto – Counts per Treatment or Control Area									
Pre-Period	370	5.94	6.36	0	40	370	4.99	6.16	0	33
Post-Period	330	7.90	10.42	0	69	330	5.48	8.11	0	56
	Theft Other – Counts per Treatment or Control Area									
Pre-Period	370	9.17	10.76	0	69	370	4.83	7.41	0	61
Post-Period	330	9.95	11.78	0	64	330	5.23	8.60	0	69

Table 3: Summary Statistics of District-Wide Demographic Variables

	N	**Mean**	**SD**	**Min**	**Max**
Median *Age*					
2013	175	35.15	5.76	22.0	48.4
2014	175	34.71	5.56	21.4	47.7
2015	175	34.74	5.24	22.3	45.2
2016	175	34.55	5.22	21.5	45.3
Percent of Residents *African American*					
2013	175	60.11	25.16	4.5	99.4
2014	175	59.12	24.40	4.4	97.9
2015	175	56.96	25.26	6.3	97.4
2016	175	55.06	25.42	6.2	96.9
Percent of Residents *Hispanic*					
2013	175	12.26	10.58	0.0	38.2
2014	175	12.17	10.52	0.4	41.5
2015	175	12.65	10.83	0.3	43.0
2016	175	12.25	9.81	0.6	38.0
Percent of Residents *High School Graduate From*					
2013	175	85.05	6.25	70.6	100.0
2014	175	85.39	6.04	70.6	99.5
2015	175	85.97	6.06	74.0	99.2

2016	175	87.11	6.13	74.6	99.1
Percent of Residents *Living Below the Poverty Line*					
2013	175	19.06	10.69	3.1	52.2
2014	175	19.16	11.50	2.5	53.2
2015	175	18.25	11.55	3.8	51.8
2016	175	17.63	10.93	3.6	52.0

Table 4: Summary Statistics of Demographic Variables by Corridor

	2013	**2014**	**2015**	**2016**	**2013**	**2014**	**2015**	**2016**
	Georgia Ave NW (N = 76)				**H Street NE (N = 31)**			
Median Age	35.17	34.91	35.19	34.72	35.08	34.82	34.59	34.42
Percent of Residents *African American*	50.56	49.82	47.87	46.32	58.41	56.79	51.82	47.69
Percent of Residents *Hispanic*	19.56	20.26	20.78	19.56	6.50	4.43	4.99	5.75
Percent of Residents *High School Graduate From*	84.61	84.76	84.88	85.88	86.69	87.65	89.34	90.40
Percent of Residents *Living Below the Poverty Line*	15.71	14.99	13.30	13.15	17.56	18.07	16.74	15.26
	Martin Luther King Ave SE (N = 18)				**Rhode Island Ave NE (N = 19)**			
Median Age	32.73	31.73	31.54	32.44	38.68	37.71	38.04	38.59
Percent of Residents *African American*	96.45	95.21	94.20	93.16	77.52	75.83	75.47	73.72
Percent of Residents *Hispanic*	0.26	1.34	1.67	2.05	8.23	7.68	7.35	7.51
Percent of Residents *High School Graduate From*	82.04	83.3	84.31	85.40	84.84	83.98	84.41	85.55
Percent of Residents *Living Below the Poverty Line*	33.36	37.77	38.22	35.90	17.14	17.14	17.85	17.40

Using the difference-in-differences method allowed us to isolate the impact of the grants on crime outcomes in the District between 2013 and 2016. The theoretical regression specification for the difference-in-differences analysis was:

$CrimeOutcome_i = \beta_0 + \beta_1 TreatmentDummy_i + \beta_2 TimeDummy + \beta_3 TreatmentTime + \beta_4 MedianAge_i + \beta_5 PercentBlack_i + \beta_6 PercentHispanic_i + \beta_7 PercentHighSchool_i + \beta_8 PercentPoverty_i + \sum_i$

Where: CrimeOutcome = Total Crime, Burglary, Robbery, Theft from Auto, or Theft Other

TreatmentDummy = 0 for the Control Group and 1 for the Treatment Group,

TimeDummy = 0 for the pre-period and 1 for the post-period,

β_3 = the difference-in-differences coefficient

TreatmentTime = the difference-in-differences interaction term TreatmentDummy * TimeDummy, and

$\sum$ = error term

Difference-in-Differences Results

The difference-in-differences equation was analyzed for total crime, burglary, robbery, theft from auto, and other theft for the District as a whole and for four of the eleven corridors in the Great Streets Program that had more than ten businesses receiving grants from 2014 to 2016. The results are presented in Tables 5 and 6. The remaining seven corridors were not included because the sample size was too small for conclusive results.

Table 5: Output for Crime Outcomes District-Wide

VARIABLES	Total Crime	Burglary	Robbery	Theft from Auto	Theft Other
TreatmentDummy	7.349***	0.386***	0.862***	0.959**	4.373***
	(1.574)	(0.117)	(0.183)	(0.467)	(0.987)
TimeDummy	0.783	-0.181*	-0.324***	0.877**	0.455
	(1.013)	(0.0935)	(0.110)	(0.417)	(0.585)
TreatmentTime	2.263	-0.0774	0.214	1.462***	0.354
	(1.416)	(0.134)	(0.186)	(0.512)	(0.983)
MedianAge	-0.604***	-0.0144	-0.0243	-0.441***	-0.117
	(0.173)	(0.00890)	(0.0177)	(0.0899)	(0.106)
Black	-0.161***	-0.00694***	0.000117	-0.0802***	-0.0690**
	(0.0501)	(0.00240)	(0.00555)	(0.0250)	(0.0279)
Hispanic	-0.249**	-0.0262***	-0.00937	-0.0582	-0.108
	(0.122)	(0.00520)	(0.0138)	(0.0497)	(0.0667)
HighSchoolGrad	-0.478**	-0.0380***	-0.0250	-0.283***	-0.0829
	(0.195)	(0.0111)	(0.0238)	(0.0823)	(0.106)
Poverty	-0.350***	-0.0138**	-0.0162	-0.201***	-0.103
	(0.114)	(0.00568)	(0.0127)	(0.0457)	(0.0639)
Constant	94.48***	5.559***	4.908*	53.53***	23.20*
	(20.95)	(1.066)	(2.508)	(8.423)	(12.13)
N	1,400	1,400	1,400	1,400	1,400
R-squared	0.156	0.050	0.063	0.207	0.095

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

The coefficient on the TreatmentTime variable, β_3, is the difference-in-differences estimator, or the expected impact of the grants on the crime outcomes. For the district-wide evaluation, it shows the impact of the Great Streets program was an estimated increase of 2.26 counts of total crime within the treatment area relative to the control area, holding the demographic covariates constant. The increase was not statistically significant (p-value = 0.112), and it was a small effect of about 11 percent of a standard deviation. Burglary showed a small effect size decrease, while robbery and other theft showed small increases, but these were not statistically significant. Theft from automobiles was the only crime outcome that had a statistically significant change district-wide, and it was significant at the 99 percent level. The estimated increase of 1.46 counts within the treatment area was a small effect size of about 14 percent of a standard deviation.

Table 6: Difference-in-Differences Estimates of the Impact of the Great Streets Program on Crime Outcomes in Washington, DC

	District-Wide			**Georgia Ave NW**			**H Street NE**		
Outcome (Crime Counts)	β	**SE**	$\mathbf{R^2}$	β	**SE**	$\mathbf{R^2}$	β	**SE**	$\mathbf{R^2}$
Total Crime	2.263	1.416	0.156	3.919	2.489	0.231	3.775	3.945	0.144
Burglary	-0.0774	0.134	0.050	0.0980	0.192	0.056	0.273	0.384	0.207
Robbery	0.214	0.186	0.063	0.0602	0.277	0.058	0.0941	0.539	0.117
Theft From Auto	1.462***	0.512	0.207	2.725**	1.402	0.287	0.116	0.794	0.223
Theft Other	0.354	0.983	0.095	0.907	1.746	0.107	1.719	2.982	0.174
	Martin Luther King Ave SE			**Rhode Island Ave NE**					
	β	**SE**	$\mathbf{R^2}$	β	**SE**	$\mathbf{R^2}$			
Total Crime	-6.75***	2.512	0.422	-0.211	3.832	0.218			
Burglary	-1.528***	0.453	0.208	0.311	0.299	0.164			
Robbery	-0.0278	0.625	0.335	-0.293	0.377	0.227			
Theft From Auto	-0.472	0.678	0.215	0.346	1.404	0.089			
Theft Other	-3.167*	1.725	0.345	-0.791	2.251	0.227			

SE = Robust standard errors
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

To understand neighborhood-level impacts, a similar regression analysis was used to explore the results by corridor. Each corridor displayed varying outcomes by crime type.
The Georgia Avenue NW corridor was the most similar to the district-wide results, with only theft from automobiles having a statistically significant change in crime counts. The increase of 2.72 incidences in the treatment area relative to the control area was a small to moderate effect size of about 26 percent of a standard deviation at the 95 percent significance level. Total crime, burglary, robbery and other theft all showed small size increases that were not significant.

The Martin Luther King SE corridor saw decreases in all crime outcomes, with the decrease in Burglary significant at the 99 percent level, the decrease in total crime significant at the 95 percent level, and the decrease in other theft significant at the 90 percent level. The total crime decrease of 6.75 incidences in the treatment area was a small to moderate effect size of about 33 percent of a standard deviation. The decrease in burglary of 1.53 incidences was a large effect size of 148 percent of a standard deviation. Other theft showed a small to moderate decrease of 3.17 incidences or about 27 percent of a standard deviation. Robbery and theft from auto both showed small, statistically insignificant decreases. Both the Rhode Island NE and H Street NE corridors had statistically insignificant results. The Rhode Island NE corridor had small effect size changes for all crime output variables and the H Street NE corridor had small effect size increases for all crime outcomes.

For all of the above regressions, robust and clustered standard errors were used. Robust standard errors were used to correct for heteroskedasticity, and standard errors were clustered over the panel variable Business Name to correct for likely serial correlation.

Discussion

Our hypothesis was rejected and affirmed in part, dependent on geography and crime type. The grants are associated with a decrease in crime in the MLK corridor, with significance at the 90 percent level for total crime, burglary, and other theft. The analyses also indicated that business improvements were associated with a small increase in crime outcomes district-wide and in the Georgia Ave NW and H Street NE corridors. They suggested no impact in the Rhode Island Ave NE corridor and a significant reduction in total crime in the Martin Luther King Ave SE (MLK) corridor. In terms of crime type, theft from automobiles showed a small yet significant increase district-wide and in the Georgia Ave NW corridor but was unchanged in the remaining corridors. While these results are inconsistent, they indicate promise of business development to curb certain types of crime in particular neighborhoods.

Differences in results may be driven by differences in corridor demographics. The demographics of the MLK corridor showed significantly higher rates of poverty and racial minorities. MLK corridor's poverty rate is 33-36 percent, which is more than twice that of the District and the other corridors studied. The corridor's poverty rate also increased during the time period of the study. District-wide and in the H Street NE and Georgia Ave NW corridors, poverty rates decreased, and in the Rhode Island NE corridor they remained steady. The number of African American residents decreased by about four percentage points district-wide and all corridors except for H Street, where it decreased by about 11 percentage points.

Consistent with Chaskin and Joseph's (2013) mixed-income development research, communities that experience a shift from socioeconomic homogeneity to socioeconomic heterogeneity are likely to experience an increase in reported property crime. This is especially true when communities absorb higher-income persons, as these new residents often expect to maintain order and protect their investment in the new neighborhood through normative notions of law enforcement. The logic being, as more residents feel empowered to enforce *formal* mechanisms of control they are more likely to report crime. This was consistent with findings from H Street NE and George Ave NW corridors, both of which experienced a decrease in poverty rates but an increase in property theft crimes. However, the MLK corridor remained relatively unchanged demographically and alternatively showed significantly less property crime for the treatment group. Rather than concluding that the Great Streets grant program is ineffective at reducing crime, this suggests that the demographic makeup of a neighborhood plays an important role in the reporting of property crime.

Limitations

In this study, the treatment area captured activity along the main streets where the businesses were located. The control area of the ring around the treatment area captured activity partially on the smaller streets off of the main corridor. It is possible that the control areas picked up different levels of crime due to different levels of pedestrian and vehicular traffic on the main corridors versus the smaller side streets. This could have caused the control areas to not be equal in expectation to the treatment areas. It also appears that crimes were geocoded as occurring at the center of the street and block, rather than the exact location, for privacy reasons. This may have led to a potential overcount of crime incidences for businesses on a corner or in the middle of a block, and a potential undercount for other businesses.

A different control group technique may have improved the analysis by better capturing the crime incidences. Due to legal concerns, the Great Streets program was unable to share the list of businesses who were eligible and applied for the grant but were denied. This group of businesses would have made a more suitable control group. In lieu of this, a future study may want to consider creating a control group of businesses that would be eligible for the grants but did not apply. This control group could be matched one-to-one based on similar characteristics to the treatment group of businesses that received the grants. The control businesses would also be on the main corridors in the Great Streets program, and thus the radius around them would be more likely to be equal in expectation to the treatment group areas. However, in absence of this information and in consultation of the geospatial criminology literature, we employed the recognized donut method to create an artificial control group.

The crime data available to conduct this research was not ideal. We had to use felony crime data, as that is what the Metropolitan Police Department collects and publicly releases. Arguably, as is consistent in comparable literature (e.g. Branas et al), more appropriate crime data would be inclusive of nuisance crimes like public intoxication or disturbing the peace. Future research on this topic should attempt to seek data that is inclusive of misdemeanor crimes. Moreover, given the theoretical support for our findings, additional research should be performed to confirm that an increase in crime correlates with an increase in calls to law enforcement.

Conclusion

Our study expands on existing literature in two ways. First, literature investigating the effects of community revitalization initiatives on crime is limited, as contemporary studies concerning the relationship of neighborhood economics and crime at the structural level primarily focus on vacant lots and foreclosed homes. Our attempt to understand the impact of structural improvements to small businesses on the prevalence of crime is unchartered territory and thus adds to this severely understudied field.

Second, it adds to the general literature of geospatial criminology. While there are current limitations to the donut technique, this fairly new spatial method holds great promise for better understanding crime patterns and trends. The adaptive method of donut geomasking is already being praised for its improved privacy protection in mapping health data (Hampton et al., 2010). Given similar privacy concerns in mapping sensitive crime data, such as the location of sex offenses or offenses involving minors, advancing donut-style methods is vital to unlocking the potential of using geospatial technology to further criminological research.

As each corridor in the program has different demographics, the services desired by each corridors' residents reflect those differences. When asked about the future vision of the grant program, Great Streets Director Cook highlighted an aspiration to ensure the annual Request for Applications meets the diverse needs of the city (Cook & Kirk-Patrick, personal communication, December 7, 2018). Early conversations around crime reduction included fleshing out strategies to incentivize ways to encourage small business owners to locate to high-crime police service area boundaries. This literature would benefit from additional research exploring the data that results from this crime prevention-based expansion of the Great Streets program.

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