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Gender-based violence and urban economic activity

Vicki Norberg-Bohm White Paper

Abraham Holland

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Gender-based Violence and Urban Economic Activity

Vicki Norberg-Bohm White Paper

Abraham Holland*
Harvard Kennedy School of Government (HKS)

September 11, 2017

Abstract

While crime is a universal concern of every city government, the rapid urbanization of many developing countries places particular strain on law enforcement organizations. A growing body of research suggests women and men may have different responses to crime or perceived crime risk, particularly in the case of sexual violence. This paper adds to the literature by documenting gendered changes in economic activity following a report of sexual violence in Lusaka, Zambia. Using fixed-effects regression, I observe a temporary 30% average decrease in transaction activity at over-the-counter money transfer kiosks within the locality of the reported assault. This effect is more pronounced for women versus men, does not exist for other categories of reported crime, and appears to displace activity across time rather than a purely destructive effect. Surprisingly, female midday customer traffic is most strongly affected. While preliminary and hampered by a small sample, these correlational findings are consistent with sexual violence generating gendered economic consequences beyond the immediate victim. Further research is required to understand whether these responses are rational and the mechanism(s) underlying this potential externality.

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Introduction

While crime is a universal concern of every city government, the rapid urbanization of many developing countries places particular strain on law enforcement organizations. Zambia is urbanizing faster than the African average and is expected to be nearly 60% urban by 2050 (UN, 2015), making a deeper understanding of how crime may distort economic behavior an important policy-relevant question. Previous work by Rosenthal and Ross (2010) and Cullen and Levitt (1999) highlight spatial sorting (e.g. voting with their feet) as a way entrepreneurs and crime-sensitive families protect themselves. Financial constraints or other housing market frictions may limit this ability, making understanding the potential distributional consequences of crime for vulnerable populations even more important.

Even within a household, specific types of crime risk and the associated responses are likely heterogeneous. While reliable data is elusive, Africa has the highest rate of combined partner and non-partner sexual violence against women in the world (WHO, 2013). Other work by Janke, Propper, and Shields (2016) finds some local violent crimes and sensational crimes against women disproportionately reduce females physical mobility (walking). With these studies in mind, local sexual violence (LSV) in Zambia may be particularly prone to creating observable economic distortions for female consumers. As such, this paper focuses on testing whether female consumers shift their economic activity in response to LSV.

Literature Review

While a significant portion of the modern economics literature has focused on the causes of crime in a particular time and place, e.g. Becker (1968), Glaeser and Sacerdote (1999), O'Flaherty and Sethi (2010), Phillips and Sandler (2015), etc. A growing body of work has sought to understand the potential distortionary effect of crime (or fear of crime) on economic activity.

Linden and Rockoff (2008), Pope (2008), and Abadie and Dermisi (2008) focus on localized price movements and generally identify negative effects. Another strand of the literature focuses on explaining how crime may distort where particular economic activities occur. Perhaps the clearest examples of this are Rosenthal and Ross (2010) and Cullen and Levitt (1999). Both find evidence of spatial sorting (e.g. voting with their feet) as a way entrepreneurs and crime-sensitive families protect themselves.

At the individual level, Janke, Propper, and Shields (2016) identifies another type of distortion as a result of local violent crimes and sensational crimes against women, individuals reduce their non-leisure physical mobility (walking). While this effect is true for both British women and men, women appear to curtail their physical activities more than men. Interestingly, this is consistent with one of the few studies focused on individual behavioral responses and crime (and fear of crime) in the developing world. Braakmann (2012) finds women are more likely to change their mode of transportation their male counterparts. While Braakmann does not separate urban and rural effects, he also finds that individuals, men and women, alter their normal travel routes in response to both being victimized and fear of being victimized. These results are broadly consistent with subsequent work that has generally supported the view that gender may play an important role in understanding the individual distributional consequences of crime (Teixeira and Soeiro, 2013; Cheng and Smyth, 2015; Dustmann and Fasani, 2015; Powdthavee, 2005).

This work contributes to the literature by along two key dimensions. First, I provide suggestive evidence of both crime-related spatial and temporal economic displacement in a developing world context. Second, I depart of the general development economics literature in this domain by focusing on discrete responses to specific events. From a practice perspective, this work is a stepping stone toward estimating potential economic externalities associated with different types of crime.

Data

The main explanatory data source is drawn from administrative records of the Zambian Police Service (ZPS) in Lusaka city. This data spans February 2015 - July 2015 from 40 police locations and is a random 30 % sample of days within this period.[1] For a sampled day, I have the universe of reported incidents. Importantly, the ZPS maintains a reporting log and an investigation log. The reporting log, known as an Occurance Book (OB), is an exhaustive decentralized catalog of every incident reported to a given ZPS location. Incidents are recorded as they have been relayed by the public and are generally reported to the closest police location, making the OB the best available first proxy for the perceived local crime environment. The second log, known as the Crime Register (CR), is a centrally managed inventory of all active and completed investigations. As not all reported incidents are investigated, the CR is a strict subset of the OB. For the purposes of this analysis, all empirical specifications use data drawn from the OB, covering 3,442 incidents. Table 1 breaks down reported crimes by ZPS category. For the purposes of analysis, The main category of interest are those crimes described as Injurious to the Public (ItP). In this sample, ItP crimes (N=23) include rape, indecent assault, and defilement (sexual assault of a minor). Murders (N=2) are also generally included in the ItP category. While results are qualitatively unchanged, I have excluded murders purposes of this analysis. As such, I will describe this category and what effects I observe as being related to reports of sexual violence. As is immediately clear, only 23 reported sexual violence cases means my main explanatory variable almost certainly lacks sufficient variation for many types of sub-analyses. Other reported crimes such as murder, forgery/impersonation, and crimes against lawful authority also lack sufficient variation. Future data collection efforts may be able to address this shortcoming.

The primary dependent variables are drawn from the administrative data of a domestic electronic payments provider, Zoona. As Zoona conducts all transactions over-the-counter,

[1] For confidentiality reasons, the research team collected only sufficient details to enable the local ZPS authorities to categorize the reported incidents into broad categories according to the Zambian criminal code. Furthermore, the particular sampling method, providing each day an equal 30% probability of being sampled, is highly likely to have induced attenuation bias via a classic random errors in variables problem.

Table 1: **Summary Statistics: Weekly Reported Crime (OB)**

Category	**Average**	**Min**	**Max**	**Total**
Overall Crime Count	6	1	40	3442
Public Order	0	0	3	62
Lawful Authority	0	0	0	0
Sexual Violence	0	0	2	23
Murder	0	0	1	2
Against Persons	2	0	22	1199
Relating to Property	3	0	22	1732
Injury to Property	0	0	4	181
Forgery / Impersonation	0	0	2	3
Other	0	0	8	240

sending (receiving) money requires the sender (receiver) to be physically present at one of the many Zoona kiosk locations. As every kiosk can send and receive, the choice of where to transact within Zoona's network is entirely driven by the customer's preferences. To date, there are more than 300 kiosks within/around Lusaka. Each transaction includes the date, location, amount, and gender of the sender/receiver.[2] As such, it is possible to aggregate transactions to the kiosk-level, as well as conduct robustness tests by restricting analyses to those customers with a history of operating within Lusaka. For confidentiality reasons, it is not possible to recover the identities of specific consumers. All analyses include all transactions conducted at kiosks within the sampled areas. Table 2 provides a brief summary of weekly kiosk-level activity (N= 588 kiosk-weeks) for the 36 kiosks identified as being nearest to a sampled police location. The average kiosk engages in 145 pick up transactions per week (approximately 30 USD/transaction). Customers tend to be slightly more female (55%) and have generally used Zoona at least once before (81%). Interestingly, the majority of transactions (76%) are by those whom conduct least 75% of their activity in Lusaka (a 'Lusaka Resident') and nearly half of customers (45%) have previously conducted business at that specific kiosk. Lastly, it appears that a typical (modal) hour of operation sees approximately 10 female customers and 8 male customers.

[2] In some cases the gender of the customer is recorded differently across time. I have assumed that if you are ever coded as a woman that the customer is actually female. Leaving the data unchanged does not qualitatively change the nature of my findings or affect the statistical significance of my findings.

Table 2: Nearest Kiosk Weekly Summary Statistics

Variable	Mean	Standard Deviation
Total Pick Up Amounts (ZMW)	43,719	40,696
Total Pick Up Transactions	144	115
Number Female Customers	80	66
Number First-time Transactions	27	21
Number Experienced-Customer Transactions	117	95
Number Transactions by Lusaka Resident	109	89
Number Returning Customers	65	61
Modal Hourly Female Activity	10	
Modal Hourly Male Activity	8	

I connect these two datasets by creating non-overlapping Thiessen polygon catchment areas for each police location within Lusaka (average area, 4.7 km, example in appendix Figure A1), and then indexing each kiosk to the nearest police location, catchment area, or neighboring region.[3] The average distance between the nearest kiosk and the police location is 770 meters. In some cases (N=4), a single kiosk may be the closest Zoona location to more than one police post/station. While only 1 pair both report an sexual violence incident (1 week apart), the least contentious approach appears to be simply dropping the pair from the sample.[4] I have attempted to address other potential concerns by first Winsorizing dependent variables at 1%. Second, I have included week and police location fixed effects. Finally, I have reported multiple types of standard errors, including those clustered at the police location level. While I understand that these solutions can only partially address empirical concerns, further work with a larger sample will be required to adopt other methods.

Analytic Approach

In the spirit of Linden and Rockoff (2008) and others, this paper takes an explicitly spatial view on how crime risk may affect economic outcomes. Consistent with previous literature, I view crime (or perceived crime risk) as a negative local amenity. As such, there are four key identifying assumptions: (i) reported crime(s) must reflect actual perceived crime(s) for a given location, (ii) reported crime(s) must not already be 'baked in' to individuals' behavior, (iii) the observed economic activity is generally conducted by individuals with an awareness of local crime, and (iv) observed individuals have the ability to alter their behavior in response to perceived changes in crime/crime risk. Given data limitations, I cannot assess whether any observed behavior changes are rational. I will leave those determinations for future studies.

[3]The catchment area and neighboring region analyses impose a somewhat stricter form of closeness, as a kiosk must be within the polygon catchment area. Police locations without a kiosk in their catchment area are dropped from this analysis, making comparisons between the nearest kiosk and these analyses more difficult.

[4]Leaving the pair in results in qualitatively similar findings, although the statistical significance of the sexual violence coefficient in Table 7 Column 5 is slightly weaker.

Considering the first assumption, Zambian police guidelines generally require crimes be reported in the area they occurred. Beyond the statutory requirement, informal Zambian consumer surveys generally indicate an awareness and practice of reporting perceived crime(s) to the nearest location. Notably, this ignores the shadow crime rate, the difference between reported and actual crime. As in many developing nations, non-reporting rates are likely to be rather high and sensitive to local conditions. As such, extreme care should be used when considering the external validity of this study beyond the Zambian environment.

In terms of the second assumption, Rosenthal and Ross (2010)'s work clearly suggests crime and crime risk can be 'baked in' to the local structure of economic activity. In its strongest form, (ii) clearly fails and reported crimes should have little/no effects on the level of observed economic activity. A slightly weaker formulation suggests observable results reflect the residual inability to adapt to the local criminal environment (market failure) or the partial equilibrium effect of a changing criminal environment. As preventive measures and the relative vulnerability of populations may vary, heterogeneous effects by crime type is also possible. Consumer-level papers such as Janke, Propper, and Shields (2016) and this study makes the most sense in this context. Table 3 highlights this idea with an exploratory regression of the number of weekly reports by crime category on the log-transformed weekly number of customers picking up funds from a kiosk in the same week. Notably, only sexual violence reports appear to have a significant relationship with female consumers.

Table 3: Weekly Crime Reports By Type, Log Number of Customers by Gender

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sexual Violence (F)	-0.294*						
	(0.154)						
Sexual Violence (M)	-0.171						
	(0.131)						
Public Order (F)		0.027					
		(0.066)					
Public Order (M)		-0.004					
		(0.046)					
Against Persons (F)			0.003				
			(0.008)				
Against Persons (M)			-0.003				
			(0.008)				
Relating to Property (F)				-0.005			
				(0.005)			
Relating to Property (M)				-0.005			
				(0.006)			
Injury to Property (F)					0.024		
					(0.018)		
Injury to Property (M)					0.006		
					(0.017)		
Aggregate Crime (F)							-0.000
							(0.003)
Aggregate Crime (M)							-0.002
							(0.004)
DV Mean (F)	3.931	3.931	3.931	3.931	3.931	3.931	3.931
DV Mean (M)	3.773	3.773	3.773	3.773	3.773	3.773	3.773
R-squared (F)	0.889	0.886	0.886	0.886	0.886	0.887	0.886
R-squared (M)	0.866	0.865	0.865	0.865	0.865	0.865	0.865
N	588	588	588	588	588	588	588

Clustered standard errors in parentheses, Data winsorized at the 1% level

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Shifting to the customer side, the third and fourth assumptions are satisfied in a more probabilistic fashion. Zoona is an over-the-counter electronic money transfer service, as such each side generally has a distinct sender and a receiver. Each transfer can be picked up to a year after it has been sent, and there are no additional Zoona-imposed fees, penalties, or incentives to influence the pick up decision. I focus on receivers, those picking up funds, as both the need and timing of the pick up decision are more likely driven by local factors versus the decision of when and where to send money through Zoona's network. While the analysis here employs the universe of Zoona customers and transactions within the study catchment area, I have replicated the analysis with only those customers that have conducted the vast majority (75%) of their activity within Lusaka. As in the primary analysis, the observed effects appear to be concentrated amongst the Lusaka resident females. As it is not central, I have included this analysis in the appendix. *Prima facie*, Table 2's summary statistics, in particular significant shares of experienced and returning customers, is consistent with the notion of locally-savvy customers engaging in economic activity. In terms of the final assumption, Zoona's kiosks are ubiquitous across Lusaka. There are over 300 kiosks throughout the city and 63 within the areas covered by this study. The modal police catchment area has 2 kiosks (Mean: 1.96) and may have up to 5 Zoona locations. Customers clearly have the ability to choose where to pick up funds from Zoona's network.

Empirical Implementation

I now turn to a more detailed examination of the changes in transaction activity associated with a sexual violence report at a given police location (l) in a particular week (w). Each set of log-linear specifications in the following tables take a similar general form:

$$Y_{lw} = ItP_{lw} + W_w + L_l + \epsilon_{lw}$$

In each of the following Tables 4 - 7, I present analyses at 3 levels of aggregation. The dependent variable in Column 1 is the transaction activity at the nearest kiosk. Column 2 investigates the effects of a reported sexual violence on activity at the catchment area level (all Zoona kiosks within a reporting region). Column 3 is a test for economic activity displacement, the dependent variable is the aggregation of activity for all the neighboring police precincts. Columns 4 and 5 attempt to address a clear concern with the primary specification, the error term is likely handled incorrectly. I modify my standard errors and report Huber-White heteroskedasticity-robust errors in Column 4 and police catchment area clustered errors in Column 5.

In each case, a similar general pattern emerges. Statistically significant nearly 30% declines in activity at the kiosk located closest to the police station: weekly pick up value, transaction volume, and number of female or male customers. Negative, but statistically insignificant estimates at the catchment-area level and positive but insignificant effects in the neighboring regions. The point estimates for male consumers are generally smaller, but statistically indistinguishable from the female estimates. While not conclusive, these findings are at least consistent with a gendered partial spatial displacement of economic activity away from the location of a reported incident. The relative lack of sexual violence reports is also clearly an issue, columns 4 and 5 are either barely significant or statistically indistinguishable from zero. Given empirical concerns, Column 5 is the more credible specification I am current able to estimate.

Table 4: Weekly Injurious to the Public Crime Reports, Log Female Transaction Volume

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Sexual Violence	-0.294***	-0.108*	0.018	-0.294	-0.294*
(Weekly)	(0.085)	(0.065)	(0.022)	(0.179)	(0.154)
DV Mean	3.931	4.429	6.148	3.931	3.931
R-squared	0.889	0.932	0.945	0.889	0.889
N	588	484	584	588	588
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Weekly Injurious to the Public Crime Reports, Log Male Transaction Volume

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Sexual Violence	-0.171**	-0.052	0.034	-0.171	-0.171
(Weekly)	(0.085)	(0.069)	(0.023)	(0.172)	(0.131)
DV Mean	3.773	4.342	6.029	3.773	3.773
R-squared	0.866	0.935	0.965	0.866	0.866
N	588	484	584	588	588
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Weekly Injurious to the Public Crime Reports, Log Weekly Transaction Volume

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Sexual Violence	-0.267***	-0.091	0.026	-0.267	-0.267*
(Weekly)	(0.085)	(0.062)	(0.020)	(0.189)	(0.157)
DV Mean	4.551	5.091	6.798	4.551	4.551
R-squared	0.879	0.943	0.958	0.879	0.879
N	588	484	584	588	588
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Weekly Injurious to the Public Crime Reports, Log Weekly Pick Up Value

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Sexual Violence	-0.289***	-0.032	0.001	-0.289	-0.289*
(Weekly)	(0.094)	(0.070)	(0.022)	(0.210)	(0.169)
DV Mean	10.164	10.750	12.506	10.164	10.164
R-squared	0.884	0.948	0.969	0.884	0.884
N	588	484	584	588	588
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

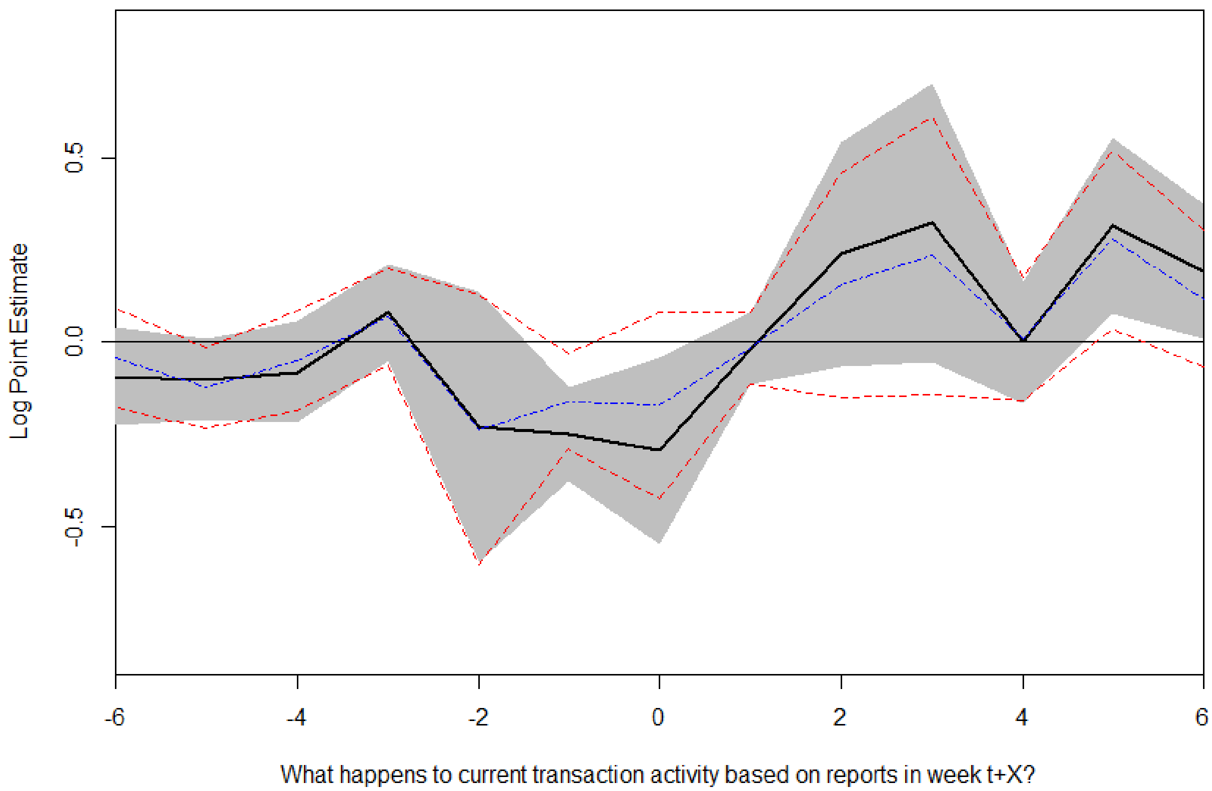
Figure 1: Hourly Transaction Activity by Gender

Space is not the only potential dimension of distortion, if a customer prefers to transaction at a given kiosk, they may simply shift their transaction activity to a different time of day or delay a transaction until they can find out more about the post-report crime environment. Figure 1 examines this first question by regressing consumer traffic by gender on LSV reports by each business hour (08:00 - 17:00). Female activity is described by the solid line and the grey-shaded region represents the 90% confidence interval with standard errors clustered at the police location level. Similarly, the blue dashed line represents male activity and the red dashed lines are the 90% confidence intervals. While statistically significant declines in female customer traffic are confined to the hours between noon and 14:00, the female point estimates are almost universally negative and economically meaningful (10-20% declines in traffic relative to a typical business hour). The male pattern is less pronounced and only occasionally significant.

Considering the question of longer term temporal displacement, one potential approach of this phenomenon is to test for effects of sexual violence reports on past and future economic activity. While the tables are included in the appendix (Tables A4.1-12), Figure 2 uses the same graphic scheme as Figure 1 and plots the point estimate of lagged and lead sexual violence reporting over a 6-week window on nearest-kiosk log weekly female and male transaction volume (number of customers) in week w. While the relatively small number of reported sexual violence incidents is clearly still an issue, the observed J-shaped pattern is consistent with reporting delays, citizens learning of the event through non-police channels prior to the report, and a temporary temporal displacement of activity. Anecdotal conversation(s) with ZPS officers responsible for investigating sexual violence cases confirm that it is not uncommon for a citizen to delay reporting a crime.[5] Interestingly, a different plausible explanation for this local rebound effect is that once the crime is reported, the ZPS's response restores local confidence and economic activity returns. Another potential concern is that the observed trends are simply part of a broader 'crime wave'. While I can only test whether this may be true for reported crime, it does not appear to be the case. I replicate the Figure 2 analysis for lead and lagged sexual violence reports on the two types of crime remaining with a significant number of observations, crimes against persons and relating to property. I have reported these figures in the appendix (Figures A2a and A2b).

[5]Further research on when and how individual citizens learn of local crimes is still pending.

Figure 2: Lead and Lagged Sexual Violence Reports on Log Weekly Transactions



Conclusion

While this paper is best understood in the context of a preliminary correlational analysis, it does highlight several potentially important stylized facts. First, it appears changes local Zoona transaction activity are only correlated to reports of sexual violence. Other types of reported crime does not appear to affect this type of economic behavior. Second, there does appear to be a temporary significant negative effect on female transaction activity at the hyper-local (nearest kiosk) level. Findings at the police catchment area and neighboring regions level are statistically insignificant, but the direction of each finding is consistent with a spatial response (e.g. avoidance) to a negative local amenity. Finally, the temporal pattern of economic activity and sexual violence reports suggest(s) a generalized decline in female patronage across most hours of the day. Over the course of weeks, my results suggest a delay in reporting and local awareness of the incident, as economic responses begin *before* an incident is reported. While economic activity appears to recover post-report, it is unclear if this is due to a natural consumer updating of local safety or the response from the local ZPS officers. More broadly, these sexual violence incidents do not appear to be part of a generalized change in reported criminal activity.

As this is a preliminary study, future research could certainly change/improve these findings. As it is not immediately obvious how to appropriately handle standard errors in this case, additional robustness exercises on the existing small sample, such as the nonparametric permutation test developed in Chetty, Looney, and Kroft (2009), may improve confidence in these results. Similarly, an alternative empirical specification that replicates the above analysis with daily, rather than weekly, activity with day and end-of-month fixed effects could use less degrees of freedom and provide a marginal power gain. More data, qualitative and quantitative is also necessary to both improve precision and uncover potential mechanisms underlying these observed responses.

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Appendix

Figure A1: Thiessen Polygon Example, ZPS Locations and Lusaka City

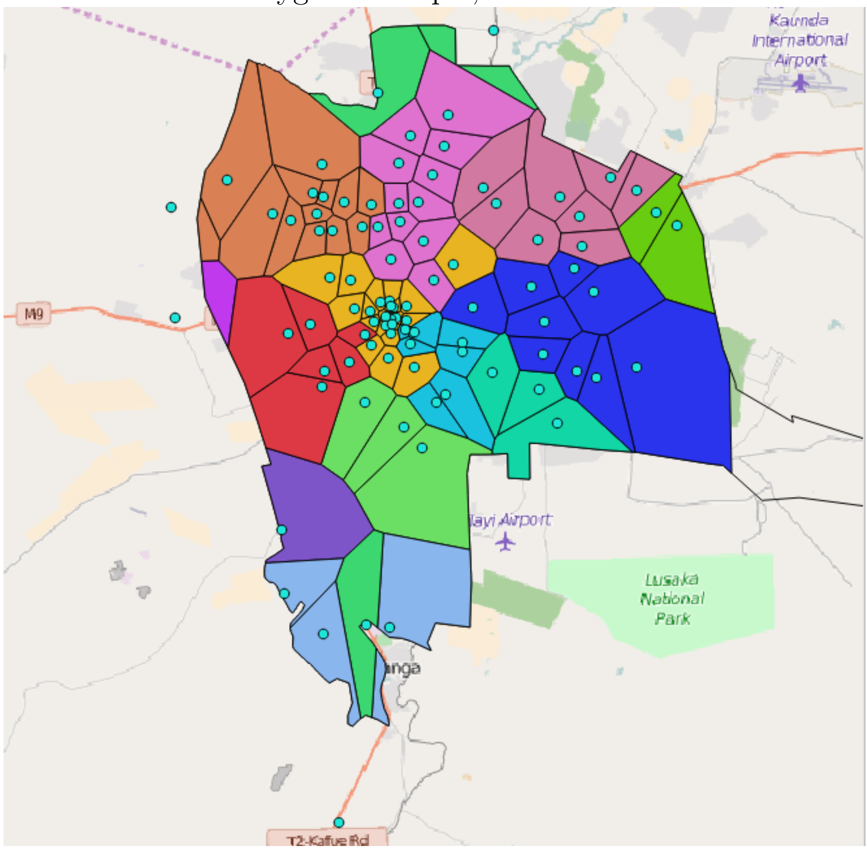

Figure A2a: Lead and Lagged ItP Reports on Log Crimes Against Persons

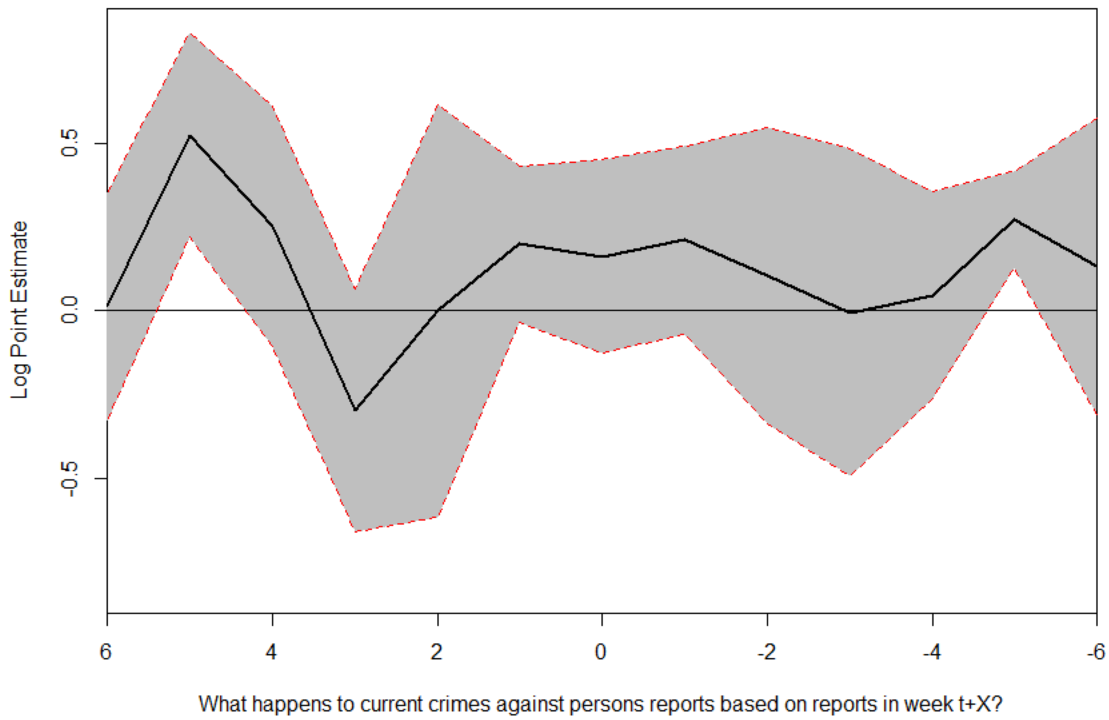

Figure A2b: Lead and Lagged ItP Reports on Log Crimes Relating to Property

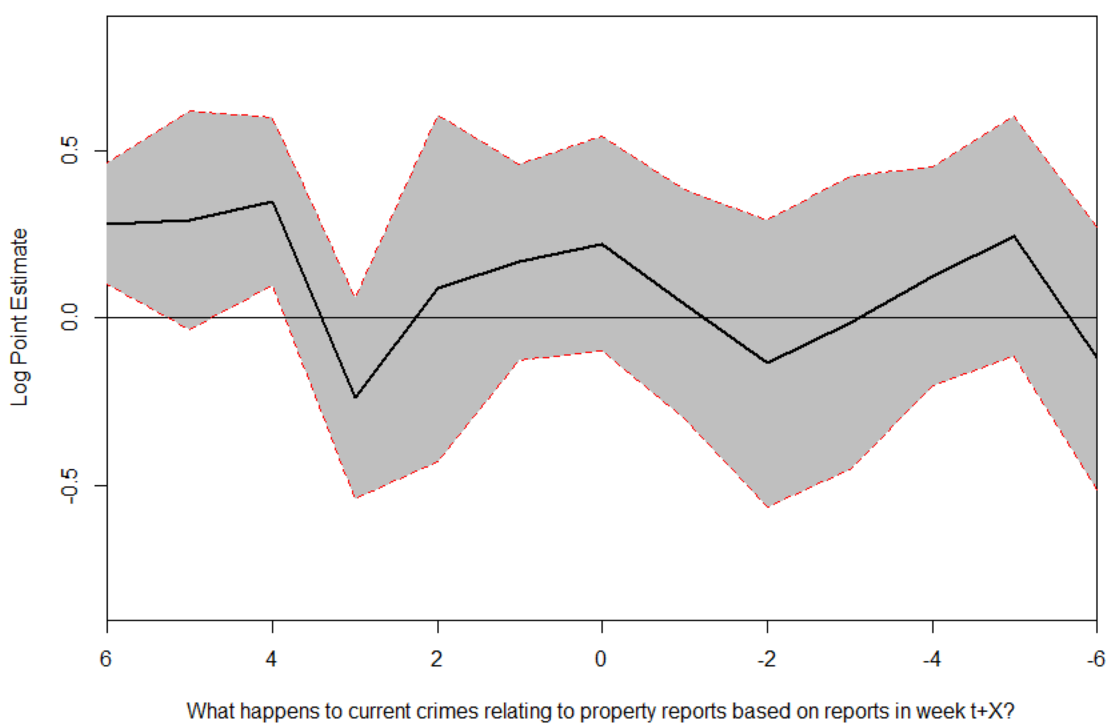

Table A4.1: Weekly Injurious to the Public Crime Reports (1 Wk Lead), Weekly Send Amounts

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Lead Wkly ItP (1 Wk)	-0.188*	-0.089	0.037	-0.188**	-0.188***
	(0.102)	(0.079)	(0.027)	(0.077)	(0.053)
DV Mean	10.191	10.796	12.489	10.191	10.191
R-squared	0.899	0.953	0.966	0.899	0.899
N	439	356	438	439	439
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4.2: Weekly Injurious to the Public Crime Reports (2 Wk Lead), Weekly Send Amounts

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Lead Wkly ItP (2 Wk)	-0.247**	-0.044	0.026	-0.247	-0.247
	(0.102)	(0.070)	(0.028)	(0.166)	(0.219)
DV Mean	10.208	10.843	12.490	10.208	10.208
R-squared	0.908	0.961	0.967	0.908	0.908
N	410	333	410	410	410
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4.3: Weekly Injurious to the Public Crime Reports (3 Wk Lead), Weekly Send Amounts

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Lead Wkly ItP (3 Wk)	0.132	0.139*	-0.008	0.132	0.132
	(0.113)	(0.079)	(0.030)	(0.097)	(0.083)
DV Mean	10.236	10.862	12.503	10.236	10.236
R-squared	0.903	0.961	0.969	0.903	0.903
N	388	316	388	388	388
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4.4: Weekly Injurious to the Public Crime Reports (4 Wk Lead), Weekly Send Amounts

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Lead Wkly ItP (4 Wk)	-0.073	-0.029	-0.045*	-0.073	-0.073
	(0.084)	(0.056)	(0.024)	(0.123)	(0.053)
DV Mean	10.255	10.864	12.497	10.255	10.255
R-squared	0.920	0.970	0.969	0.920	0.920
N	364	296	364	364	364
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4.5: Weekly Injurious to the Public Crime Reports (5 Wk Lead), Weekly Send Amounts

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Lead Wkly ItP (5 Wk)	0.016	-0.088	-0.027	0.016	0.016
	(0.086)	(0.058)	(0.024)	(0.096)	(0.097)
DV Mean	10.271	10.878	12.501	10.271	10.271
R-squared	0.914	0.968	0.969	0.914	0.914
N	336	273	336	336	336
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4.6: Weekly Injurious to the Public Crime Reports (6 Wk Lead), Weekly Send Amounts

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Lead Wkly ItP (6 Wk)	-0.150*	-0.087	-0.001	-0.150	-0.150
	(0.087)	(0.067)	(0.025)	(0.110)	(0.105)
DV Mean	10.273	10.871	12.502	10.273	10.273
R-squared	0.917	0.960	0.971	0.917	0.917
N	316	259	316	316	316
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4.7: Weekly Injurious to the Public Crime Reports (1 Wk Lag), Weekly Send Amounts

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Lag Wkly SV (1 Wk)	-0.001	-0.021	0.007	-0.001	-0.001
	(0.095)	(0.073)	(0.026)	(0.126)	(0.053)
DV Mean	10.205	10.791	12.493	10.205	10.205
R-squared	0.906	0.952	0.967	0.906	0.906
N	439	356	438	439	439
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4.8: Weekly Injurious to the Public Crime Reports (2 Wk Lag), Weekly Send Amounts

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Lag Wkly ItP (2 Wk)	0.322***	0.064	0.025	0.322*	0.322
	(0.102)	(0.077)	(0.025)	(0.166)	(0.222)
DV Mean	10.202	10.824	12.501	10.202	10.202
R-squared	0.889	0.947	0.968	0.889	0.889
N	410	333	410	410	410
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4.9: Weekly Injurious to the Public Crime Reports (3 Wk Lag), Weekly Send Amounts

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Lag Wkly ItP (3 Wk)	0.305***	0.114	0.017	0.305**	0.305
	(0.111)	(0.081)	(0.026)	(0.155)	(0.219)
DV Mean	10.232	10.855	12.514	10.232	10.232
R-squared	0.883	0.947	0.970	0.883	0.883
N	387	315	387	387	387
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4.10: Weekly Injurious to the Public Crime Reports (4 Wk Lag), Weekly Send Amounts

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Lag Wkly ItP (4 Wk)	0.046	0.067	0.022	0.046	0.046
	(0.107)	(0.076)	(0.025)	(0.259)	(0.099)
DV Mean	10.235	10.855	12.513	10.235	10.235
R-squared	0.896	0.956	0.971	0.896	0.896
N	363	295	363	363	363
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4.11: Weekly Injurious to the Public Crime Reports (5 Wk Lag), Weekly Send Amounts

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Lag Wkly ItP (5 Wk)	0.322***	0.020	0.026	0.322	0.322
	(0.109)	(0.075)	(0.027)	(0.208)	(0.204)
DV Mean	10.250	10.872	12.518	10.250	10.250
R-squared	0.902	0.961	0.970	0.902	0.902
N	335	272	335	335	335
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4.12: Weekly Injurious to the Public Crime Reports (6 Wk Lag), Weekly Send Amounts

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Lag Wkly ItP (6 Wk)	0.122	0.067	0.018	0.122	0.122
	(0.120)	(0.086)	(0.029)	(0.216)	(0.124)
DV Mean	10.283	10.884	12.536	10.283	10.283
R-squared	0.899	0.957	0.972	0.899	0.899
N	316	259	316	316	316
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Analysis using Lusaka Residents Only

Table A3 (Lusaka Residents): Weekly Crime Reports By Type, Weekly Send Amounts

	(1) est1	(2) est2	(3) est3	(4) est4	(5) est5	(6) est6	(7) est7
ItP (Weekly)	-0.272***						
	(0.098)						
PO Weekly		0.055					
		(0.056)					
AP Weekly			0.006				
			(0.009)				
RTProp Weekly				-0.007			
				(0.007)			
ITProp Weekly					0.012		
					(0.033)		
Other Weekly						-0.006	
						(0.026)	
Agg Crime Weekly							-0.001
							(0.004)
DV Mean	9.889	9.889	9.889	9.889	9.889	9.889	9.889
R-squared	0.863	0.861	0.861	0.861	0.861	0.861	0.861
N	620	620	620	620	620	620	620

Standard errors in parentheses, Data winsorized at the 1% level

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4 (Lusaka Residents): Weekly Injurious to the Public Crime Reports, Log Weekly Pick Up Value

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
ItP (Weekly)	-0.272***	-0.058	0.013	-0.272	-0.272
	(0.098)	(0.077)	(0.023)	(0.219)	(0.175)
DV Mean	9.889	10.466	12.158	9.889	9.889
R-squared	0.863	0.932	0.973	0.863	0.863
N	620	496	616	620	620
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A5 (Lusaka Residents): Weekly Injurious to the Public Crime Reports, Log Weekly Transaction Volume

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
ItP (Weekly)	-0.268***	-0.105	0.032	-0.268	-0.268
	(0.089)	(0.074)	(0.020)	(0.196)	(0.170)
DV Mean	4.282	4.801	6.456	4.282	4.282
R-squared	0.857	0.912	0.965	0.857	0.857
N	620	496	616	620	620
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A6 (Lusaka Residents): Weekly Injurious to the Public Crime Reports, Log Female Transaction Volume

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
ItP (Weekly)	-0.282***	-0.107	0.022	-0.282	-0.282*
	(0.085)	(0.073)	(0.023)	(0.176)	(0.152)
DV Mean	3.672	4.140	5.805	3.672	3.672
R-squared	0.876	0.905	0.949	0.876	0.876
N	620	496	616	620	620
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A6a (Lusaka Residents): Weekly Injurious to the Public Crime Reports, Male Transactions

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
ItP (Weekly)	-0.133	-0.057	0.043*	-0.133	-0.133
	(0.084)	(0.075)	(0.023)	(0.151)	(0.120)
DV Mean	3.513	4.059	5.681	3.513	3.513
R-squared	0.849	0.917	0.971	0.849	0.849
N	620	496	616	620	620
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4.1 (Lusaka Residents): Weekly Injurious to the Public Crime Reports (1 Wk Lead), Weekly Send Amounts

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Lead Wkly ItP (1 Wk)	-0.203*	-0.068	0.048	-0.203*	-0.203***
	(0.117)	(0.095)	(0.029)	(0.105)	(0.068)
DV Mean	9.914	10.509	12.146	9.914	9.914
R-squared	0.871	0.931	0.971	0.871	0.871
N	462	365	461	462	462
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4.2 (Lusaka Residents): Weekly Injurious to the Public Crime Reports (2 Wk Lead), Weekly Send Amounts

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Lead Wkly ItP (2 Wk)	-0.183*	0.031	0.039	-0.183	-0.183
	(0.107)	(0.082)	(0.028)	(0.172)	(0.217)
DV Mean	9.930	10.554	12.136	9.930	9.930
R-squared	0.884	0.941	0.973	0.884	0.884
N	433	341	433	433	433
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4.3 (Lusaka Residents): Weekly Injurious to the Public Crime Reports (3 Wk Lead), Weekly Send Amounts

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Lead Wkly ItP (3 Wk)	0.193*	0.177**	0.030	0.193**	0.193**
	(0.109)	(0.079)	(0.031)	(0.090)	(0.078)
DV Mean	9.965	10.583	12.149	9.965	9.965
R-squared	0.892	0.955	0.973	0.892	0.892
N	409	323	409	409	409
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4.4 (Lusaka Residents): Weekly Injurious to the Public Crime Reports (4 Wk Lead), Weekly Send Amounts

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Lead Wkly ItP (4 Wk)	-0.061	-0.089	-0.036	-0.061	-0.061
	(0.084)	(0.058)	(0.027)	(0.113)	(0.043)
DV Mean	9.977	10.579	12.142	9.977	9.977
R-squared	0.916	0.966	0.975	0.916	0.916
N	383	301	383	383	383
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4.5 (Lusaka Residents): Weekly Injurious to the Public Crime Reports (5 Wk Lead), Weekly Send Amounts

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Lead Wkly ItP (5 Wk)	-0.132	-0.146**	-0.019	-0.132	-0.132
	(0.093)	(0.069)	(0.026)	(0.146)	(0.142)
DV Mean	9.993	10.595	12.146	9.993	9.993
R-squared	0.899	0.951	0.975	0.899	0.899
N	353	277	353	353	353
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4.6 (Lusaka Residents): Weekly Injurious to the Public Crime Reports (6 Wk Lead), Weekly Send Amounts

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Lead Wkly ItP (6 Wk)	-0.140	-0.179**	0.005	-0.140	-0.140
	(0.097)	(0.085)	(0.027)	(0.179)	(0.188)
DV Mean	9.992	10.583	12.150	9.992	9.992
R-squared	0.895	0.934	0.975	0.895	0.895
N	331	262	331	331	331
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4.7 (Lusaka Residents): Weekly Injurious to the Public Crime Reports (1 Wk Lag), Weekly Send Amounts

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Lag Wkly ItP (1 Wk)	0.059	-0.010	-0.010	0.059	0.059
	(0.099)	(0.082)	(0.028)	(0.118)	(0.036)
DV Mean	9.935	10.511	12.151	9.935	9.935
R-squared	0.887	0.937	0.970	0.887	0.887
N	462	365	461	462	462
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4.8 (Lusaka Residents): Weekly Injurious to the Public Crime Reports (2 Wk Lag), Weekly Send Amounts

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Lag Wkly ItP (2 Wk)	0.315***	0.039	0.015	0.315*	0.315
	(0.109)	(0.084)	(0.027)	(0.178)	(0.238)
DV Mean	9.928	10.539	12.150	9.928	9.928
R-squared	0.872	0.934	0.972	0.872	0.872
N	433	341	433	433	433
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4.9 (Lusaka Residents): Weekly Injurious to the Public Crime Reports (3 Wk Lag), Weekly Send Amounts

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Lag Wkly ItP (3 Wk)	0.301**	0.125	0.009	0.301*	0.301
	(0.119)	(0.092)	(0.027)	(0.161)	(0.224)
DV Mean	9.958	10.571	12.164	9.958	9.958
R-squared	0.858	0.930	0.976	0.858	0.858
N	408	322	408	408	408
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4.10 (Lusaka Residents): Weekly Injurious to the Public Crime Reports (4 Wk Lag), Weekly Send Amounts

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Lag Wkly ItP (4 Wk)	0.056	0.074	-0.006	0.056	0.056
	(0.121)	(0.091)	(0.028)	(0.281)	(0.113)
DV Mean	9.959	10.574	12.163	9.959	9.959
R-squared	0.868	0.935	0.975	0.868	0.868
N	382	300	382	382	382
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4.11 (Lusaka Residents): Weekly Injurious to the Public Crime Reports (5 Wk Lag), Weekly Send Amounts

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Lag Wkly ItP (5 Wk)	0.287**	0.061	0.013	0.287	0.287
	(0.120)	(0.092)	(0.030)	(0.227)	(0.189)
DV Mean	9.969	10.584	12.169	9.969	9.969
R-squared	0.872	0.940	0.972	0.872	0.872
N	352	276	352	352	352
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4.12 (Lusaka Residents): Weekly Injurious to the Public Crime Reports (6 Wk Lag), Weekly Send Amounts

	(1) Nearest Kiosk	(2) Catchment	(3) Neighbor	(4) Nearest Kiosk	(5) Nearest Kiosk
Lag Wkly ItP (6 Wk)	0.113	0.060	0.028	0.113	0.113
	(0.133)	(0.103)	(0.033)	(0.221)	(0.151)
DV Mean	9.999	10.595	12.189	9.999	9.999
R-squared	0.877	0.939	0.975	0.877	0.877
N	331	262	331	331	331
Standard Errors				Robust	Clustered

Standard errors in parentheses, Data winsorized at the 1% level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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