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Need drugs, will travel?: The distances to crime of illegal drug buyers

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ABSTRACT

Purpose: This study examines distances to crime among illegal drug buyers while controlling for buyer, drug, and destination characteristics.
Methods: Geocoded arrests for drug buyers in an urban municipality, over a three year period, spatially identify major drug markets. Negative binomial regression is used to model compositional characteristics of drug arrestees and contextual effects of markets on distance to arrest ($n = 4{,}082$).
Results: Trip distance to drug purchase arrest varies by drug market. Being white, and having prior contact with the criminal justice system correlated with longer trip distances. Additional compositional effects vary by drug type.
Conclusions: In line with prior journey to crime research and crime pattern theory, illicit drug buyers are arrested in close proximity of their homes. Future research should consider the extent to which short aggregate market distances reflect policing differentials and close social ties.

Introduction

Work on journeys to offense locations for violent and property crimes dates back at least eight decades (White, 1932). The distance traveled from an offender's starting point to the offense location is known as the journey to crime (Rengert, 2004). Starting points, or origins typically reference the home location of the offender, while destinations refer to arrest locations. Researchers have described typical distances, origins and destinations of these journeys, examined the determinants of distance and direction, and argued about whether the distribution of journey distances does or does not follow a distance decay distribution (Rengert, Piquero, & Jones, 1999; Rengert & Wasilchick, 2000; Townsley & Sidebottom, 2010). Distance decay refers to the common research finding that most crimes tend to occur close to the homes of offenders, and therefore becomes less likely as distance from the home increases (see above citations).

Although property and violent crimes have received a considerable amount of empirical attention, much less is known regarding illicit drug purchases. Two studies investigating determinants of individual-level distance to crime for buying drugs found that the type of drug bought and characteristics of the buyer influence distance (Forsyth, Hammersley, Lavelle, & Murray, 1992; Pettiway, 1995). Limitations of both studies, however, preclude treating the observed correlates of distance to drug buying as definitive. A more recent study by Levine and Lee (2013) however, found that environmental features, position in the metropolitan area, and the interaction of age and gender matter in predicting trips to drug dealing. We build off of these findings to examine trip distances to drug *purchase* arrests.

A number of research voids are addressed in the current study as well. Most importantly, work to date on distance to drug buying has neglected destination features. That is, did the drug purchase occur within a recognized drug market, and if so, in which one? Market as compared to non-market destinations, and different specific markets, can attract different types of buyers. Consequently, it is not clear if offender correlates of longer distances to drug purchases persist after taking destination into account. Nor is it clear if drug type conditions travel distance. These questions are answered in the current inquiry.

In addition to taking the above considerations into account, the current work hopes to improve on prior studies on distance to drug buying in several ways. First, a complete population of drug buyers' distances to drug arrest in a municipality is investigated. Second, arrestees who purchased a range of different drugs are included. Third, this study does not dichotomize distance, and instead operationalizes it as the right-angle distance in miles from each arrestee's home to their arrest location. Finally, it controls for potentially confounding within-arrestee-between-trip distance variation from between-arrestee distance variation.

There are several implications of this research. First, understanding drug-arrestee journeys to crime may lend insight into how criminal justice actions affect illicit drug markets. Second, describing the drug arrestee journey may facilitate a discussion on intervening

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variables clarifying the drug market/violent crime relationship. Third, the methodological approach presented examines the proximity of drug buying arrest locations to each arrestee's home residence. It is possible, therefore, that drug-buying journeys can be placed within the larger theoretical context of crime pattern theory.

This paper begins by reviewing literature on the journey to crime and considers the recent controversy about whether distance to offense demonstrates a distance-decay pattern. It also considers the only three studies examining the determinants of drug offender trip distance and the limitations of each. It then acknowledges recent drug market research, concentrating on theories connecting markets and journeys to crime. This section is followed by a description of data and methodology. Next, findings on the journey to arrest are presented. Finally, we conclude with theoretical and policing implications.

Distance to crime beyond index crimes

Distance to crime findings support the notion that offenders adhere to the least effort principle (Zipf, 1949). In a study of Indianapolis homicides White (1932) found that homicide offenders travel a mean distance of .11 miles to the offense location. Longer—albeit still short—distances of under one mile have been reported by other studies (Bullock, 1955; Groff & McEwen, 2006). Offenses such as aggravated assault also link to short offender travel distances, generally less than on mile (Block, Galary, & Brice, 2007; Gabor & Gottheil, 1984; Phillips, 1980; White, 1932). Research generally reports lengthier travel patterns for robbery offenders, with aggregate distances of at least one mile (Normandreau, 1968).

Although residential burglary tends to be a more calculated crime, such offenders also generally travel short distances (Wiles & Costello, 2000). Bernasco and Block (2009) found that Chicago burglars are 822 times more likely to burglarize a home within their residence census tract and 99 times more likely to burglarize one in an adjacent census tract than one five census tracts away. Additional research has found that burglars generally travel between one and 1.75 miles (Phillips, 1980; Rhodes & Conly, 1981; Snook, 2004; White, 1932), with the exception of one study reporting findings of one half a mile (Reppetto, 1976).

Turning to demographic correlates, across multiple crime types, older offenders travel farther than younger ones (Gabor & Gottheil, 1984; Groff & McEwen, 2005; Nichols, 1980; Snook, 2004; Warren et al., 1998), and males travel farther than females (Gabor & Gottheil, 1984; Groff, Wartell, & McEwen, 2001; Nichols, 1980; Pettiway, 1995). Lastly, whites travel farther than racial minorities to offend (Carter & Hill, 1979; Nichols, 1980; Pettiway, 1982, 1995; Warren et al., 1998; Wiles & Costello, 2000).

More recent work has considered the role of environmental factors in shaping the criminal distance to crime. Not only do offenders prefer crime locations close to their current residences, but they also demonstrate an affinity with former residences. Length of time spent in former residence, the amount of time passed since leaving a former residence, spatial proximity, and time settled in current residence also influence the selection of offense locations (Bernasco, 2010). Although considerable work remains on determining the process underpinning the demographic and property/violent distance connections, at least the work has provided consistent correlates.

In terms of distances to drug crime, three studies are relevant. Forsyth et al. (1992) sought to learn more about travel to drug markets among new drug users residing in relatively drug free sections of Glasgow (Scotland). Snowball sampling identified 175 relatively new drug users. Respondents were asked if for each of 11 drug types “they could name places where they could score various drugs” (Forsyth et al., 1992, p. 295). A multiple regression model predicting distance found longer distances associated with more expensive drugs, and purchasers residing in a non-disadvantaged area purchasing drugs in a disadvantaged area.

Where Forsyth et al. (1992) asked respondents about all types of drugs, Pettiway (1995) concentrated on distances of just those purchasing crack cocaine in Philadelphia. Respondents were recruited via snowball sampling. In this project, for individual trips, Pettiway (1995) looked at the average distance ($n = 802$ trips) to purchase crack traveled by active users ($n = 160$) over several days, and separated users into shorter average distance users (average distance $<$ .50 miles) and longer distance users (average distance $>$ .50 miles). A discriminant function analysis revealed that gender (males were more likely to make longer average trips) and more children in the household were the only significant demographic correlates.

The third study examined travel patterns for multiple offense types, including drug dealing, in Manchester, UK (Levine & Lee, 2013). A negative binomial model was used estimate trip distance for 7,762 crime incidents. Considering offender correlates, longer trip distances were associated with Asian offenders, while African Caribbeans did not travel significantly longer distances than the intercept group.[1] Although gender alone proved statistically irrelevant, juvenile males traveled significantly shorter distances to arrest for drug dealing, as did those with an offense history. Additionally, drug dealing arrestees with co-offenders linked with longer distances.

Unique to the Levine and Lee (2013) study is the consideration of environmental effects. Arrestees who sold drugs in residential areas traveled shorter distances than the intercept group, while those who sold along transportation nodes traveled longer distances to arrest. Intra-metropolitan position also mattered. Offenders who sold in the city center and well as surrounding town centers commuted longer distances to arrest. Furthermore, there was a positive relationship between offender residence distance from downtown Manchester and distance to arrest location.

Significant methodological and statistical limitations of some of these drug studies include the following. First, because the Pettiway and Forsythe studies used snowball sampling, it was not possible to obtain population parameter estimates for the correlates of longer distances to buy illegal drugs. Second, Townsley and Sidebottom's (2010) separation of within-offender from between-offender sources of distance variation for burglars is extremely helpful. Their finding that only *some* offenders’ trip sets mimic the distance decay function is intriguing, as are their suggestions about what may be underlying the relationships between distance properties at within-offender vs. between-offender levels (for additional commentary see www.rbtaylor.net/distance_appendix.pdf). Following up on their point, neither of the first two studies clearly separated intra- from inter-offender distance variation. Moreover, neither of the first two studies investigated distance separately for other minority groups (i.e. Hispanics). We see this omission as problematic considering that other social science research has distinguished Hispanics from other minorities on social phenomena such as homicide patterns (Martínez, 2002) and residential segregation (Charles, 2003; Massey & Denton, 1993).

The Levine and Lee (2013) study, on the other hand, controls for ethnicity and the presence of multiple trips within the data. Their study, however, does not differentiate trips by drug type. That aside, their work does provide a first look at travel distances to drug selling. Focusing on drug *buying*, our study builds on the work of Levine and Lee by separately modeling travel distance to drug purchase arrests for marijuana, cocaine, and heroin. Additionally, it considers the extent to which being arrested in an area with a high spatial concentration of drug crimes—a drug market—conditions travel distance.

Drug markets, crime pattern theory, and journeys to crime

In turn, also absent from the literature is an effort to theoretically explain drug offender travel distance. A dealer deciding where to sell his/her drugs must balance numerous factors (Eck, 1995). These include, among others, the likelihood that customers can locate his/her product, the likely flow of pedestrian and/or vehicular traffic in a location, the extent to which surrounding land uses provide plausible deniability for his/her presence there, and the degree of scrutiny he/she is likely to receive either from nearby residents or regular users of the space and surround (St. Jean, 2007). Furthermore, drug dealers cluster in space to (un)intentionally gain benefits from agglomerated economies (Taniguchi, Rengert, & McCord, 2009, p. 674). This may happen "due to search behavior of customers with imperfect knowledge … the larger the cluster [of illegal drug dealers] the more profitable it becomes as it is better known and will draw customers from a wider area" (op cit; see also Rengert et al. (2005) and Reuter and MacCoun (1992)).

The processes by which the above takes place may be explained using crime pattern and routine activity theories. Offender search patterns for suitable targets are far from random, but likely to include targets along major routes between central places of routine activity including the home, school, work, and places of recreation (Brantingham & Brantingham, 1993).

Some have taken journey to crime research a step further by theorizing that the journey to crime may be an intervening variable in the drug market/violence relationship. For example, Pattillo (1998) argued that although drug dealers in a middle-class African American neighborhood traveled to other neighborhoods to sell drugs, drug market conflicts would at times occur in the areas of the dealers. Reuter and MacCoun (1992) argued that the economic nature of drugs markets, dictated by their geographic influences has implications for the conflicts they facilitate. Although their typology is not tested here, it does provide a specific rationale for a) separating distances with drug market destinations from other destinations, and b) expecting that distances will vary across specific drug markets.

Current focus

In sum previous work on distance has focused on property and violent crime. The studies that have expanded the scope by venturing into drug offending suffer from a series of drawbacks. In addressing these limitations, the current study considers a number of empirical and theoretical questions. First, work on distance to crime suggests three reliable demographic correlates of longer distances: being male, white, and older. Is this also true for distances to illegal drug purchases? Limitations of previous relevant studies leave this question open. Second, can drug markets be differentiated by travel distance? Theoretical arguments suggest that drug markets vary by how far buyers are willing to travel to reach them. Third, does the evidence align with a crime pattern theory explanation of the search patterns of drug-buying arrestees?

Data and methodology

Site

Camden, New Jersey is a city of about nine square miles and 80,000 residents situated on the Delaware River, just east of Philadelphia (U.S. Census Bureau, 2000). According to the 2000 Census, 35% of Camden's residents live below the poverty level. Additionally, media reports suggest that Camden has developed a reputation among suburban drug users as a prime location to purchase heroin (Hinton, 2012). The problem has become so pervasive that the Camden Police Department recently decided to use its CCTV system to identify the registration information of vehicles used to travel into Camden to buy drugs. Vehicle owners were sent warning letters from the Camden Prosecutor's Office, in lieu of prosecution. As of February 10, 2012, 624 vehicles were identified, and 90% of those were registered to owners living outside the city of Camden (Mulvihill, 2012).

Drug purchase arrests

Drug purchase arrest data were sourced from the Camden Police Department's records management system in January of 2008, covering the previous three years (2005-2007). Data for 4,433 incidents included UCR codes describing the offense and type of drug involved, arrestee age, date of arrest, arrestee gender, offense location, and arrestee home address.

Approximately 94% of addresses were successfully geocoded, or 4,155 matched arrest cases. This measure of geocoding accuracy, known as a hit rate, exceeded an empirically-derived acceptable minimum of 85 percent (Ratcliffe, 2004). Home and arrest locations served as proxies for, respectively, origins and destinations to determine drug buying distance. For these arrests, distance to crime was computed as the Manhattan (right angle) difference in miles from the x,y coordinate of the home to that of the arrest location. Seventy-three cases reflecting arrests of individuals residing outside of the Philadelphia-Camden metropolitan area were then excluded from further analysis to focus on within-region offending patterns. The final remaining sample was composed of 4,082 drug buying arrests.

Delineating large drug markets

Sizable, individual drug markets were located by identifying statistically significant concentrations of drug arrests using Nearest Neighbor Hierarchical Clustering (Nnh).[2] With Camden drug arrest data, a polygon spatial file of first and second order clusters was created and exported to a commercial geographic information system (GIS), ArcGIS. Six second order clusters were generated by the Nnh analysis; and a Monte Carlo simulation using 1,000 iterations indicated that the likelihood of identifying any of the clusters by chance was less than .001%. These six clusters were overlaid on the locations of drug purchase arrests.[3] Arrests that fell within one of the six second order clusters were classified as occurring within a location of spatially concentrated market activity, i.e., within a sizable, agglomerated drug market (Taniguchi et al., 2009). These six markets covered two percent of the city's surface area. Arrests outside these clusters were considered part of market activity that was not spatially concentrated; that is, they took place in smaller markets or non-market locations throughout the remainder of the city. In total, 1,647 arrests (40%) occurred within the six spatially-significant drug markets, and 2,435 arrests (60%) fell outside of major markets. The locations of the six main drug market areas are shown in Fig. 1. One dummy variable was entered for each of the six major drug market areas, with the reference category being arrests that occurred outside of those major markets.

Outcome distribution and model selection

A series of negative binomial regression models were used to account for the strong positive skewness of the outcome variables which were travel distance to marijuana, cocaine, and heroin arrests. Histograms of the dependent variables resembled an over-dispersed Poisson distribution, assuming that certain events, in this case extreme travel distances, are rare. As such, travel distance to a given arrest can be represented as:

$$f(y_i|x_i) = \frac{e^{-\mu_i}\mu_i^{y_i}}{y_i!}$$

assuming:

$$\mu_i = e^{(X'_i\beta)}$$

such that the second equation, known as the exponential mean function, represents the exponentiation of model parameters (Cameron &

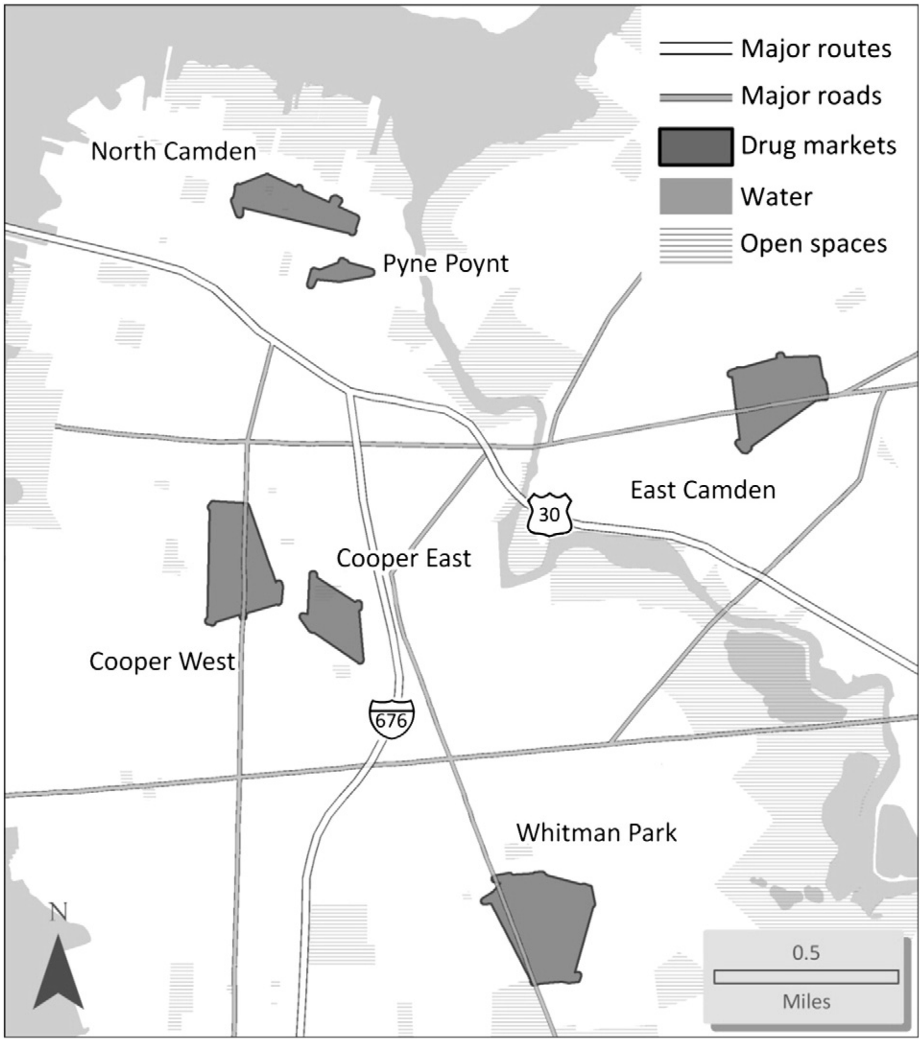

Fig. 1. Six Major Drug Markets, Camden, NJ.

Trivedi, 1998, p. 61). Error terms are assumed to be uncorrelated. Distributions of equal mean and variance are relatively rare and are more likely to resemble under-dispersion where the variance is less than the mean, or over-dispersion in instances where the variance exceeds the mean (Cameron & Trivedi, 1998). Such distributions can be addressed by fitting an error term to the Poisson function, also known as negative binomial (NB) modeling. The NB1 model is appropriate for addressing under-dispersed distributions, while the NB2 is relevant to over-dispersed distributions (Cameron & Trivedi, 1998). Negative binomial models add an error term to the Poisson function:

$$\mu_i = e^{(\beta_0+\beta_1 x_{i1}+\beta_2 x_{i2}\ldots)\delta_i}$$

where δ is equal to the exponentiated form of ε (Long & Freese, 2006, p. 372). Both NB1 and NB2 models are defined by variance function:

$$\omega_i = \mu_i + \alpha\mu_i^p$$

where α is the dispersion parameter, and $p=1$ for underdispersion, and 2 for overdispersion (Cameron & Trivedi, 1998, p. 63).

Independent variables

Demographics included race/ethnicity, gender, and age. For race, a dummy variable for white (=1, all else 0) was included, and for ethnicity a dummy variable for Hispanic (=1, all else 0) was entered. Gender was also measured using a dummy variable (1=female, 0=male). Age reflected each individual's age in years at the time of arrest. In accordance with recent research by Levine and Lee (2013), an interaction variable (age*gender) was included to measure the effect of being young and male on travel distance to arrest. Ideally, the age portion of the interaction variable would be reflective of an under 18 years versus adult dichotomy. The distribution of the age variable, however, rendered the above approach inadequate as only 13 individuals were under the age of 18 at the time of arrest. Instead, the young male indicator reflects those under 26 years of age—the median for the sample. Therefore, the age*gender variable was coded as 1=male and 25 or younger, 0=all else.

To control for the effect of an offender being arrested multiple times, a variable was included that reflects the count of each person's arrests within the study period (Levine & Lee, 2013). Statistically, this approach addressed the concern of repeat offenders having undue influence on model estimates. Furthermore, it considers the extent to which having earlier contact with the criminal justice system may lead to an arrestee altering their drug searching behaviors to avoid subsequent arrests. A total of 2,606 individuals were arrested once, while the remaining 661 were arrested multiple times for drug purchases during the study period.

An additional control variable captured the distance from each arrestee's home address to downtown Camden (Levine & Lee, 2013).

This variable permits modeling travel distance to arrest independent of the confounding effect of residential proximity to the inner city, since all markets and arrest locations are in the city of Camden. Lastly, a series of dummy variables captured whether an arrest occurred within one of six drug market areas described earlier in the manuscript.

Results

Descriptives

Table 1 displays descriptive statistics of variables used in the negative binomial models. Marijuana buying arrestees had the shortest median distance to arrest (0.70 miles) while heroin arrestees had the longest (1.21 miles). Cocaine arrestees fell in the middle (median 0.78 miles). Histograms of all three distance distributions (results not shown) indicated that as distance from the home increased, arrest for purchasing illicit drugs became less likely. Each distance distribution was slightly buffered out from zero, a property also seen in burglary distance distributions (Brantingham & Brantingham, 1991) and probably reflecting arrestees' desire to avoid being recognized by nearby neighbors and acquaintances.

Considering demographics and criminal justice system contact, whites were the least represented among marijuana and cocaine arrests (4% and 9%, respectively), but formed 18% of heroin buying arrests. Hispanics composed about one-fourth of marijuana and cocaine arrests, but 38% of heroin arrests. Across all three drug purchase offense types, arrests were disproportionately of males, with some variation in age. On average, marijuana arrestees were about 3 years younger than cocaine arrestees, and 5 years younger than heroin arrestees. Whereas 62% of marijuana arrestees were young males, this group made up 47% of cocaine arrestees, and 38% of heroin arrestees. Most commonly, arrests were of individuals with 1 prior arrest. The median distance from arrestees' residence to downtown Camden ranged from 1.8 miles for heroin to 2.2 miles for marijuana.

The lower section Table 1 also displays the proportion of arrests for each crime type occurring within each of the drug markets. Generally less than 10% of marijuana and cocaine arrests occurred within one specific market area. There are exceptions, however. Whitman Park contained about 17% of the city's marijuana arrests, and 10% of its cocaine arrests. In regards to heroin, multiple markets contained substantial proportions of arrests. Twenty-two percent of the city's heroin arrests took place in North Camden. Furthermore, 11% of Camden's heroin arrests took place in Cooper West, and another 20% in East Camden. These findings suggest that although all markets provided multiple options, there did appear to be some specialization by location.

Multivariate results

A series of negative binomial regression models were run to predict marijuana, cocaine, and heroin trip distances to arrest. Across all outcomes (marijuana, cocaine, and heroin distances to arrests), two sets of models were employed. Model A assessed the roles of offender characteristics such as demographics, prior contact with the criminal justice system, and the distance from each arrestee's home to downtown. Model B, the full model, also included indicators of arrest location. Reduced models (not shown) indicated a non-significant relationship between age at arrest and trip distance across all outcomes. Models described below include the age*gender interaction (young male), while controlling for the main effects of age and gender. Tolerance (all above .728) and variance inflation factor statistics (all below 1.3) indicated that multicollinearity was not a problem among the independent variables in any of the models.

Predicting travel distance to marijuana arrest

Table 2 displays results modeling distance to arrest for marijuana purchases. Model A predictors are contrasted against African American males 26 years and older, with zero prior arrests, living downtown. Model A reveals that lengthier trips were correlated with white arrestees, residences farther from the downtown area, and male arrestees. Shorter trips were correlated with females and young males, which is line with prior research by Levine and Lee (2013) on drug dealing. Specifically, controlling for other predictors in the model, white arrestees are expected to travel 33% farther than African American males for the purchase of marijuana ($\exp(b) = 1.332$). Modeling indicates that the average expected travel distance (AED) for a white arrestee in the sample is about 1.8 miles. Female travel distances were about 30% shorter ($\exp(b) = 0.703$) than the intercept group. Young males' trip distances were 12% shorter than males in the intercept category. Each unit increase in residential distance from the city center correlated with a 20% increase in travel distance to arrest for marijuana purchases ($\exp(b) = 1.195$).

Model B of Table 1 controls for the location of the arrest by including six dummy variables which indicate whether or not an arrest took place in one of six drug market areas, or the remainder of the city. Now the intercept group is similar to Model A, but includes those arrested outside of market areas. The effects of Model A offender characteristics on travel distance remain after controlling for arrest location effects. In addition, Model B reveals that offenders with multiple drug arrests made slightly lengthier trips than those arrested only once within the 2005-2007 study period ($\exp(b) = 1.037$), $p = .053$).

Market variables yielded significant effects on trip distance. Arrests in Cooper West ($\exp(b) = 1.258$), East Camden ($\exp(b) = 1.086$), and Pyne Poynt ($\exp(b) = 1.539$) tend to be associated with lengthier travel distances than drug arrests in non-market areas. Conversely,

Table 1
Descriptive statistics of arrestees

	Marijuana				Cocaine				Heroin			
	n	Mean	SD	Mdn	*n*	Mean	SD	Mdn	*n*	Mean	SD	Mdn
Distance	636	2.21	4.25	0.70	2,740	2.77	5.43	0.78	706	4.04	7.26	1.21
White	636	0.04	0.19	–	2,740	0.09	0.28	–	706	0.18	0.39	–
Hispanic	636	0.27	0.45	–	2,740	0.26	0.44	–	706	0.38	0.49	–
Female	636	0.07	0.25	–	2,740	0.09	0.28	–	706	0.09	0.29	–
Age at arrest	636	25.72	7.50	24.00	2,740	29.30	10.29	26.00	706	30.90	10.46	29.00
Young male	636	0.62	0.49	–	2,740	0.47	0.50	–	706	0.38	0.49	–
Number of arrests	636	1.50	0.85	1.00	2,740	1.50	0.75	1.00	706	1.50	0.78	1.00
Distance from residence to downtown	636	3.30	4.20	2.19	2,740	3.54	5.38	2.01	706	4.47	7.17	1.79
Cooper East	636	0.03	0.18	–	2,740	0.04	0.20	–	706	0.03	0.17	–
Cooper West	636	0.02	0.13	–	2,740	0.06	0.24	–	706	0.11	0.31	–
East Camden	636	0.03	0.17	–	2,740	0.07	0.25	–	706	0.20	0.40	–
North Camden	636	0.02	0.15	–	2,740	0.08	0.28	–	706	0.22	0.42	–
Pyne Poynt	636	0.02	0.12	–	2,740	0.02	0.15	–	706	0.03	0.17	–
Whitman Park	636	0.17	0.37	–	2,740	0.10	0.30	–	706	0.03	0.17	–

Table 2
Predicting travel distance to arrest for purchasing marijuana

	Model A: Offender characteristics				Model B: Full model			
	b	RSE	exp(b)	AED	b	RSE	exp(b)	AED
Intercept	−0.164	0.224	0.848	0.720	−0.118	0.181	0.889	0.789
Offender characteristics								
White	0.287**	0.093	1.332	1.775	0.285**	0.094	1.330	1.769
Hispanic	0.041	0.117	1.042	1.086	−0.013	0.068	0.987	0.975
Female	−0.352***	0.089	0.703	0.495	−0.342***	0.101	0.710	0.505
Age at arrest	−0.003	0.005	0.997	0.995	−0.004	0.005	0.996	0.993
Young male	−0.110**	0.040	0.896	0.803	−0.127**	0.046	0.880	0.775
Number of arrests	0.012	0.010	1.012	1.025	0.036†	0.019	1.037	1.075
Distance from residence to downtown	0.178***	0.008	1.195	1.428	0.176***	0.007	1.192	1.422
Drug markets								
Cooper East					-0.327***	0.026	0.721	0.520
Cooper West					0.230***	0.011	1.258	1.583
East Camden					0.082***	0.008	1.086	1.178
North Camden					−0.100***	0.015	0.905	0.818
Pyne Poynt					0.431***	0.030	1.539	2.369
Whitman Park					−0.179***	0.012	0.836	0.698
Dispersion parameter	0.267	0.027			0.257	0.026		
Log pseudo-likelihood	−981.478				−977.913			
AIC	1,974.956				1,967.826			
BIC	2,001.687				1,994.557			

Note: Results from a negative binomial model predicting distance. Models employ robust standard errors (RSE), adjusting for arrests within six drug markets and the remainder of the city. AED = Average expected distance to an arrest characterized by a predictor. † $p = .053$, * $p < .05$, ** $p < .01$, *** $p < .001$. $n = 636$ marijuana arrests.

arrests in Cooper East (exp(b) = 0.721), North Camden (exp(b) = 0.905), and Whitman Park (exp(b) = 0.836) correlated with shorter trip distances than drug arrests in non-market areas. Significant b-weights across all arrest location predictors, controlling for offender characteristics, indicated that the attraction of marijuana buyers varies by place. Decreases in the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values from Model A to Model B indicated that Model B, which accounts for place, is a better model fit in explaining trip distance to marijuana arrest. A BIC difference of 7 corresponds to a "strong" improvement in fit (Long, 1997, p. 112; Raftery, 1995, p. 139).

Predicting travel distance to cocaine arrest

Offender characteristic b-weights predicting distance to cocaine arrest are relatively constant across Models A and B. Focusing on Model B of Table 2, arrests of whites, males, those with greater numbers of prior arrests, and those residing farther from downtown tend to be associated with lengthy trip distances.

Turning to the effect of being arrested in one of six drug markets, Model B reveals that all markets with the exception of North Camden have average expected trip distances significantly different from the rest of the city. Whitman Park appears to serve a comparatively local cocaine purchasing clientele (exp(b) = 0.802, AED = 0.643 miles). Cooper East, East Camden, and Pyne Poynt arrests also have shorter trip distances than non-market arrests. Arrests in Cooper West, on the other hand, describe longer trip distances with an average expected distance of 1.15 miles (exp(b) = 1.074). The BIC difference between the two models corresponds to a "very strong" improvement in fit after destination specifics are included (Long, 1997: 112).

Predicting travel distance to heroin arrest

Trip distance to heroin arrest is considered in Table 4. Focusing on Model B, lengthier distances to arrest tend to be executed by whites, individuals with multiple prior arrests, and those residing farther from downtown. Different from marijuana and cocaine arrests, however, is the significant effect of ethnicity, and the non-significant effect of gender. Hispanics arrested for heroin purchases traveled distances about 25% shorter than African American males arrested in non-market areas for the same purchase.

Drug market effects appeared for only 2 of 6 areas. Arrests in Cooper East, and Cooper West were associated with significantly shorter trip distances to arrest than non-market heroin arrests. Compared to the average expected distance of the intercept category arrestees (1.392 miles), Cooper East and Cooper West arrestees traveled about one half a mile and .86 miles to arrest locations, respectively. The BIC fit change of about 3 provides "positive" but not "strong" evidence that Model B provides better fit (Long, 1997: 112). Adding the drug market correlates improves fit, but not as markedly as it did when predicting distance to marijuana or cocaine arrests.[4]

Discussion

How distances to crime are distributed, and why, and the correlates of longer distance, continue to be debated. Work on distance to purchase illegal drugs, in comparison to the work on distance to property crimes like burglary, is relatively undeveloped with only three empirical studies. The current investigation sought to improve on those earlier works by controlling for specific destination, focusing solely on the individual level, separately modeling travel distance for multiple drug types, and using an entire, multi-year population of drug arrests for a high crime, high poverty, and urban municipality.

The separate models employed in the current study predicting distance by drug type found trips to heroin purchase arrest tend to be lengthier than trips to arrest for marijuana and cocaine. The influence of drug type sought on distance confirmed Forsyth et al.'s (1992) UK finding, and applied it to a more racially, ethnically and locationally diverse US sample. Such findings may lend support to anecdotal arguments that Camden is well known as a prime location for heroin (Hinton, 2012). And, they contribute to earlier work on drug type and distance by showing the link persisted even after controlling for type of destination. Specifically, model intercepts revealed that the average expected distances of marijuana and cocaine arrestees were about .7 and .8 miles, respectively, while heroin arrestees had an average expected distance of 1.4 miles. Confidence intervals of model intercepts reveal some overlap; however, the upper confidence limit (UCL) of the heroin model exceeded the next highest UCL (marijuana). This may suggest real differences among model intercept estimates.[5] Perhaps even more significant, however, is that trip distances to arrest

Table 3
Predicting travel distance to arrest for purchasing cocaine

	Model A: Offender characteristics				Model B: Full model			
	b	RSE	exp(*b*)	AED	*b*	RSE	exp(*b*)	AED
Intercept	−0.189**	0.063	0.828	0.686	−0.155*	0.071	0.856	0.733
Offender characteristics								
White	0.337***	0.066	1.401	1.963	0.324***	0.057	1.383	1.914
Hispanic	−0.001	0.062	0.999	0.997	−0.025	0.043	0.976	0.952
Female	−0.127***	0.027	0.881	0.776	−0.114***	0.028	0.892	0.796
Age at arrest	−0.002	0.002	0.998	0.997	−0.002	0.002	0.998	0.996
Young male	−0.075	0.050	0.928	0.861	−0.072	0.049	0.931	0.866
Number of arrests	0.088***	0.018	1.092	1.193	0.091***	0.018	1.095	1.199
Distance from residence to downtown	0.154***	0.007	1.167	1.362	0.154***	0.007	1.166	1.361
Drug markets								
Cooper East					−0.082***	0.008	0.921	0.849
Cooper West					0.072***	0.007	1.074	1.154
East Camden					−0.039*	0.017	0.962	0.925
North Camden					0.007	0.015	1.007	1.013
Pyne Poynt					−0.162***	0.018	0.851	0.724
Whitman Park					−0.221***	0.011	0.802	0.643
Dispersion parameter	0.276	0.036			0.275	0.036		
Log pseudo-likelihood	−4,430.627				−4,423.337			
AIC	8,873.253				8,858.674			
BIC	8,908.748				8,894.168			

Note: Results from a negative binomial model predicting distance. Models employ robust standard errors (RSE), adjusting for arrests within six drug markets and the remainder of the city. AED = Average expected distance to an arrest characterized by a predictor. * $p<.05$, ** $p<.01$, *** $p<.001$. $n=2{,}740$ cocaine arrests.

for marijuana, cocaine, and heroin were *differentially* conditioned by demographic, agency contact, and destination correlates.

Demographics and agency contact

The current research confirmed some earlier demographic links with distance to crime. Race mattered in the same way (Warren et al., 1998; Wiles & Costello, 2000). Regardless of drug type, whites traveled farther than blacks, even after controlling for prior contact with the criminal justice system and destination. Depending on drug type, whites traveled between 33% and 42% farther than African American men. The racial difference undoubtedly depends in complex ways on both broader urban and suburban segregation patterns, as well as the spatially segregated pattern of drug market availability.

This research also found that Hispanics' distances to drug buying arrests were significantly shorter than other racial groups, but only for the purchase of heroin. Following Charles' (2003, p. 176) discussion, perhaps Hispanics' shorter distances to drug crime arose from those Hispanics in the data set who were low on acculturation.

Table 4
Predicting travel distance to arrest for purchasing heroin

	Model A: Offender characteristics				Model B: Full model			
	b	RSE	exp(*b*)	AED	*b*	RSE	exp(*b*)	AED
Intercept	0.147	0.085	1.158	1.342	0.165*	0.078	1.180	1.392
Offender characteristics								
White	0.371***	0.081	1.450	2.102	0.345***	0.088	1.412	1.995
Hispanic	−0.261***	0.052	0.771	0.594	−0.289***	0.040	0.749	0.561
Female	−0.031	0.101	0.969	0.939	−0.019	0.097	0.982	0.964
Age at arrest	−0.003	0.002	0.997	0.994	−0.003	0.002	0.997	0.994
Young male	−0.120	0.082	0.887	0.787	−0.115	0.087	0.891	0.794
Number of arrests	0.106**	0.035	1.112	1.236	0.112***	0.032	1.119	1.252
Distance from residence to downtown	0.123***	0.008	1.131	1.280	0.123***	0.008	1.131	1.280
Drug markets								
Cooper East					−0.355***	0.023	0.701	0.492
Cooper West					−0.076***	0.015	0.927	0.860
East Camden					0.004	0.023	1.004	1.008
North Camden					0.026	0.015	1.027	1.054
Pyne Poynt					−0.016	0.035	0.984	0.968
Whitman Park					0.032	0.031	1.032	1.065
Dispersion parameter	0.209	0.043			0.208	0.043		
Log pseudo-likelihood	−1,251.847				−1,250.136			
AIC	2,515.694				2,512.271			
BIC	2,543.052				2,539.629			

Note: Results from a negative binomial model predicting distance. Models employ robust standard errors (RSE), adjusting for arrests within six drug markets and the remainder of the city. AED = Average expected distance to an arrest characterized by a predictor. * $p<.05$, ** $p<.01$, *** $p<.001$. $n=706$ heroin arrests.

Acculturation involves "the accumulation of time in the United States and English language fluency," and facilitates broader spatial assimilation. Linking Hispanic arrestees' home census block groups to the percentages for foreign born, and linguistically isolated, would be a first indirect way to approximate the relevance of acculturation. At the very least, findings suggest that Hispanics, compared to African Americans and whites, are likely to live closer to heroin-selling drug locations.

On the other hand, the Hispanic variable should be interpreted with some degree of caution. Face recognition research has shown that individuals perform best when identifying earlier sightings of someone of their own race, rather than someone of another race (Brigham & Barkowitz, 1978). In turn, during the initial booking stage, it is possible that police officers may incorrectly identify the race and/or ethnicity of an arrestee. This would be especially problematic in instances where an arrestee does not carry identification.

In contrast to journey to crime research generally, age at arrest proved irrelevant to journey to drug buying in Camden. An additional demographic measurement was of young males under 26 years of age, the median of the sample. In accordance with recent findings by Levine and Lee (2013) on trip distance to drug dealing, young males traveled shorter distances than the intercept group. Females made significantly shorter trips than males to marijuana and cocaine arrests. Conclusions on gender differentials in criminal offending patterns are far from settled. Yet, research on female participation in illicit drug markets suggests that criminal behavior is conditioned by personal economic interests but also, at times, by relationships with men (Brownstein, Spunt, Crimmins, & Langley, 1995).

Also of interest is the finding that individuals with more arrests demonstrated lengthier trips to arrest. This contradicts similar research examining trip distance to drug dealing arrests (Levine & Lee, 2013). It is possible that repeat arrestees altered subsequent travel patterns to evade arrest, albeit unsuccessfully. Also noteworthy are differences in the economic perspectives of buyers versus sellers. Buyers, knowledgeable of the spatial availability of drugs may be willing to expand their search patterns to avoid arrest. Sellers, on the other hand, may be more reluctant to identify new dealing locations due to potential conflicts with other drug dealers, and the loss of profitable locations (St. Jean, 2007).

Drug markets

Adding to prior research on journeys to drug arrests is the consideration of market influences. Recent criminological literature has underscored the significance of drug market place effects (Taniguchi, Ratcliffe, & Taylor, 2011; Taniguchi et al., 2009). The current work significantly expands our understanding of the relevance of drug market place effects (Taniguchi et al., 2011; Taniguchi et al., 2009); results here show that the impact of markets on distance, and the spatial reach of markets, depends on both the specific market in question and the type of drug sought by the arrested buyer. For example, modeling indicated that Pyne Poynt attracted marijuana buyers from over 2 miles away, although heroin buyers to the same market traveled no farther than those in the intercept group (about 1.4 miles). On the other hand, cocaine buyers were predicted to travel about 3/5ths of a mile to Whitman Park. We believe the findings here draw attention not only to the uniqueness of places as it pertains to drug markets but also on the type of illegal behavior, that is, the type of drug bought.

Theoretical implications

The current work focused on trip variation in distance, finding that arrest for illicit drug purchases is most likely to occur near the home of the arrestee. The similarity to distance distributions for property crimes like burglary probably reflect how daily routines, and the activity and awareness spaces they generate, centered at the residence, help shape where offenders go to burgle a house (Rengert & Wasilchick, 1985) or purchase illegal drugs. Aware of the friction of distance and seeking to minimize effort, nearby sites are most likely to be chosen. Of course, additional work learning more specifically how trips to buy drugs connect with daily activity spaces and broader awareness spaces is still needed.

Results reported here lend support to the idea that crime pattern theory also may be applicable to drug-buying journeys to arrest. Net of knowledge regarding individual routine activities, what is known is that the middle distance to arrest scores for buyers ranges from 0.70 to 1.21 miles from the home, depending on the drug type. Admittedly, the methodology here does not permit testing crime pattern theory; it lacks information about other nodes besides the home, pathways, and barriers. Nonetheless, findings here align with crime pattern theory, suggesting that the home structures the spatial behavior of drug buyers as well as the law-abiding.

The current research unfortunately, is unable to draw strong comparisons between the travel distances to purchase drugs, and other crime types. Theoretically, the search behaviors of drug purchasing arrestees would relate to those of burglary offenders, as both are searching for rewards. The distance findings of drug buyers, however, could just as easily align with violent offenders, as both find their targets in close proximity – at least in an urban core municipality like the city of Camden. Illicit drugs may be so readily available in Camden that there isn't a need to travel long distances to market locations. On the other hand, it is important to remember that the city encompasses an area of only 9 square miles, and arrestees were disproportionately city residents.

Looking ahead, as suggested by Townsley and Sidebottom (2010), it *is* important to separate intra- from inter-arrestee individual-level variation in distance to crime studies as researchers seek to establish the shape of that distance distribution. It is not clear, however, that the best way to gauge distributions of distances to crime is by focusing on intra-offender variation, i.e., the distribution of distances across the set of detected crimes for one individual. One major concern is that for many offenders the total number of detected distances in a distribution is rather small, making it difficult to separate normal-distributions-plus-one-outlier from distributions following a distance decay distribution (see online appendix). This research partially addressed Townsley and Sidebottom's (2010) point by conducting a supplementary analysis limited to each person's first trip to arrest in the study period. The results indicated that market destination and drug type matters regardless of whether all trips or the just the first trips are included; however, the specifics of distance links do shift (see endnote 3).

Also looking forward, a second concern is the difficulty of gauging the impacts of justice agency actions on later crime distances. This concern has two aspects. First, how do prior justice agency interactions involving the individual offender affect future spatial behavior? The current work sought to roughly take this into account by controlling for the number of previous drug arrests in the time frame. But it is not known what *happened* to individual offenders as a result of each previous arrest, i.e., the severity of sanctions that may have been administered. Second, how are justice agency actions patterned *ecologically*? This is considered below.

Policing implications

Potentially relevant are impacts of previous sanctions and differential policing by location (Klinger, 1997; Koper, 1995; Mazerolle, Soole, & Rombouts, 2007; Taniguchi, 2010; Wyant, Taylor, Ratcliffe, & Wood, 2012). Given these spatiotemporal variations, it is likely that some of the major markets identified here were more heavily policed than others at certain times. Police presence differentials or variations in types of enforcement probably deserve to be incorporated into drug buying crime distance research, especially in locations where markets in multiple municipalities are investigated.

Is it possible for these policing differentials to alter the spatial reach of major markets? One reason one of the major markets (Cooper East) where heroin was most likely to be bought did *not* have a relatively long median distance may have been because of these policing differentials. More intensive policing may have discouraged potential longer-distance buyers from this market. Those buyers may not have understood enough about the timing and location of police presence to figure out safe buying times and spots within this major market.

Turning to the issue of interdiction, results here suggest that it may be very difficult in some major markets. The extremely short buyer distance for some of the major markets—Whitman Park for cocaine and Cooper East for marijuana—may portend strong social ties among buyers and dealers. Such connections may generate local social capital (Hipp & Perrin, 2009). Social capital can be used as a resource to shield drug offenders from formal measures of social control, such as policing (Pattillo, 1998). Thus, drug buyers *and* sellers may benefit from social capital. Links among ties within markets, social capital, and distance, deserve scrutiny in future research.

Revisiting Reuter and MacCoun's (1992) typology of drug markets, findings here provide an impetus to investigate the extent to which drug buyers' journeys mediate the drug market/violent crime relationship. It is now known that some drug markets draw patrons from significantly shorter and longer distances than others. Future research should explore whether markets that have the shortest aggregate travel distances also have the lowest levels of violence. Such an investigation would provide the opportunity to affirm or suggest modifications to Reuter and MacCoun's (1992) typology, but also would have implications for policing. If, for example, a police department wishes to focus resources on violent drug markets, findings affirming the above hypothesis would suggest they should first identify markets in which arrestees are traveling the longest distances.

Conclusion

The work presented here addressed a number of concerns of prior empirical studies. First, *all* geocodable drug arrests for a multi-year period in a moderate size and high crime urban municipality were analyzed. This resulted in a sample that was broader than samples used in the two earliest works on this topic. This sample was multi-racial and multi-ethnic, and included suburban as well as urban buyers on trips to buy a variety of drugs. Second, this is the first study to control for whether the arrest destination was a major market, and if so, separate out which one. Given earlier work on agglomeration economies (Taniguchi et al., 2009), this seemed an important inclusion. Third, a transparent and replicable procedure was used for operationalizing major drug markets. Fourth, previous drug arrests were taken into account.

Although the present work addressed some weaknesses of prior research, there were some limitations. First, due to the quality of the data we are unable to determine to role of co-offending on travel patterns. Second, we are without knowledge of the land uses of the arrest locations. We do recognize, however, that prior research has demonstrated co-offending and land use type effects on travel distance to drug dealing (Levine & Lee, 2013). Third, the work relied on the operational simplification, found in other studies, of using the home as the origin. Within the context of quantitative research with large numbers of cases it is the best currently available solution for studying distance to crime. Fourth, using arrest data it is difficult to assess the robustness of arrestee home addresses. The Camden Police Department only collects data on each arrestee's most current address. Thus, conclusions cannot be formed about whether recent past residences influence the crime journey (as done in the Bernasco (2010) study), or the effect of an arrestee being homeless. Lastly, it was not possible to verify that the arrest location was the drug purchase location. Arresting officers may have witnessed the transaction at one location, yet allowed the arrestee to travel to a location safer for conducting the arrest. Discussions with Camden Police Department officers suggested that this created little slippage as the incident location was customarily recorded as the drug purchase location, irrespective of the place of arrest.

In spite of limitations, this paper presents a first step in understanding travel behaviors of drug buying arrestees. Additional research is necessary to refine operationalizations of travel distance. For example, qualitative methods would do well to capture arrestees' last known locations prior to arrest. Such an approach would do well to understand the travel patterns of homeless drug users who are unable to report home addresses, and the possibility that other buyers aren't traveling directly from their homes to market locations. Considering that drug buyers represent one half of the drug exchange, future work should also investigate if and the extent to which the travel patterns of drug selling arrestees differ from buyers. Finally, and in light of the drugs/violent crime nexus, journey to drug crime research stands to better our understanding of if- and the extent to which travel patterns explain market conflicts (Reuter & MacCoun, 1992).

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Notes

1. The intercept included whites, adult males, with no crimes committed prior to 2006, without co-offenders, who engaged in crime in commercial areas or on a street, outside of a city- or town center, and live in the city center.

2. Nearest Neighbor Hierarchical Clustering (Nnh) generates clusters from points and classifies them into ordinal groups. Hierarchical clustering techniques have existed for many decades (Johnson, 1967) in both parametric and non-parametric forms (D'Andrade, 1978). Nnh identifies geographic events demonstrating spatial proximity and groups them within a first order of clusters, assuming that those events are closer than a user-selected threshold distance at the $p<.05$ significance level. Second-order clusters are created by grouping the centroids of first order clusters that are below an algorithmic-generated threshold distance from one another. According to Levine (2004, p. 6.2), "the second-order clusters, in turn, are clustered into third-order clusters, and this re-clustering process is continued until either all clusters converge into a single cluster or, more likely, the clustering criteria fails."

3. Specifically, the first order clusters were spatially merged within a GIS with the convex hull polygon representing the second order clusters. In this way, arrests that contributed to the existence of the first order cluster were also included in the aggregation process for the second order cluster merge.

4. An alternative method of modeling travel distance to is to limit the analysis to each arrestee's first arrest. This approach controls for the possibility that some individuals may come in contact multiple times with the police, but alter their behavior over time to avoid subsequent arrests during the study period. Parallel models limited to each person's first arrest were run for comparison purposes to original models that include drug market correlates. A few differences are worth noting. In the case of marijuana, gender and number of arrests had no real effect on on travel distance to arrest ($n=527$).

Considering cocaine in terms of offender characteristics, the first-arrest-only model was generally consistent with Model 2 in Table 3. Ethnicity, contrary to the main model, achieved a significant effect ($p<.05$). Modeling predicted Hispanics to travel distances about 1% shorter than the intercept group. Turning to market effects, the exclusion of subsequent arrests led to the effect of being arrested in East Camden switching from negative to positive ($n=2{,}153$).

In the case of heroin, drug market correlates differ notably from the original models. Earlier models indicated that only Cooper East and Cooper West demonstrated significant (and negative) effects on travel distance. First-arrest-only models on the other hand, indicated that in addition to the above, North Camden and Whitman Park arrestees travel significantly lengthier distances than the intercept group ($n=577$).

5. Marijuana: $LCL=-0.473$, $UCL=0.237$, cocaine: $LCL=-0.295$, $UCL=-0.016$, heroin: $LCL=0.012$, $UCL=0.318$.

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