POLICING A NEGOTIATED WORLD: AN EMPIRICAL ASSESSMENT OF THE ECOLOGICAL THEORY OF POLICING

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By
Travis A. Taniguchi
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Examining Committee Members:

Jerry H. Ratcliffe, PhD, Advisory Chair, Department of Criminal Justice
Elizabeth R. Groff, PhD, Department of Criminal Justice
Ralph B. Taylor, PhD, Department of Criminal Justice
David A. Klinger, PhD, Police Foundation & University of Missouri-St. Louis

ABSTRACT

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Doctoral Advisory Committee Chair: Jerry H. Ratcliffe, PhD

Klinger's (1997) ecological theory of policing addresses the intersection of environment and police organizational structure on police patrol practices. It argues that officer actions can be characterized along a continuum of formal authority ranging from vigorous to lenient, where arrest represents more vigor than non-arrest, filing a report more vigor than not filing a report, and so forth. The theory has the potential to explain the spatial patterning of police behavior by incorporating both formal and informal organizational practices and community characteristics. Although the theory has been cited extensively, evaluations have been limited. The single existing direct assessment of Klinger's theory was qualitative, on a small scale, and resulted in findings both consistent with, and in disagreement with, key theoretical postulates (Hassell, 2006).

This dissertation is an extensive quantitative examination of this key policing theory, which addresses the following research question; "Is police response to calls for service and self-initiated activity influenced by the level of serious violent crime?" Police responsiveness was measured by the final disposition given to a case and the number of arrests made for low seriousness events; self-initiated activity was measured by the level of traffic enforcement. Additional questions are also addressed such as: Does the relationship between police workload and responsiveness and police workload and self-initiated activity vary over time? If there is a cross-sectional relationship found between these factors, is it contingent upon socio-

demographic or land use characteristics of where the events occur? If Klinger's ecological theory of policing is correct it is expected that police will expend less vigor towards low seriousness events and self-initiated activity if there is a great deal of serious crime demanding their attention. The current work also extends the ecological theory in two ways: by expanding and clarifying the impact of environmental factors and by examining the proposed relationship between crime level and vigor within a longitudinal framework.

These questions were addressed using data supplied by the Philadelphia Police Department, demographic data from the U.S. Census, and environmental data drawn from a number of sources. Three dependent variables quantified police vigor at different stages of case processing; (1) the number of incidents that resulted in a final disposition of unfounded; (2) the number of low seriousness incidents that ended in an arrest; and (3) the number of traffic stops. These count outcomes were measured at both the census block group level and at the police district level of aggregation. Low seriousness offenses present the greatest opportunities for officer discretion and, therefore, provide officers the most latitude in selecting the vigor of their response. These data were analyzed using both cross-sectional multilevel model (MLM) design and a repeated measure MLM design. Additionally, exploratory spatial data analyses (ESDA) investigated the spatial distributions of these dependent variables.

Findings generally support key propositions of Klinger's ecological theory of variations in policing behavior. Vigor varied as a result of officer workload (the number of serious crime incidents) and resource constraint (the number of officer hours assigned to patrol duties). Yet other findings suggested that further conceptual development is still required. The relationship between vigor and key theoretical variables was frequently sensitive to the way vigor was operationalized. More problematically, variations in vigor were expected to be greatest in events of low seriousness. Yet, crime types fall along a continuum of seriousness and imposing arbitrary cut points between low seriousness events and high seriousness events was a difficult task that required either arbitrary distinctions between crime types or value judgments about the seriousness of a crime. Furthermore, these findings suggested that the spatial and temporal resolution through which vigor is investigated will have potentially dramatic impacts upon whether the findings support, or are in contradiction to, key theoretical relationships. These findings, taken a whole, suggest that the ecological theory of policing has strength and utility in explaining patterns of police activity but also that a number of issues could benefit from further conceptual development.

ACKNOWLEDGMENTS

There are a number of people that deserve credit not only for helping to create this dissertation but also helping me develop my understanding of criminal justice, academia, and the world at large. I am grateful for having worked with, and taken classes from, numerous professors in the Department. Jerry Ratcliffe once told me that looking smart requires surrounding yourself with smart people. To this end I'd like to take a few moments and acknowledge a few of the people that I have worked with that were necessary for the completion of this document.

I think the most appropriate person to begin with would be Jerry Ratcliffe. When I started graduate school I decided that I wanted to do research in policing. At the time I thought policing was a sufficiently defined area that I would be able to get a handle on things quickly. I quickly realized that that was not the case. Luckily I had an advisor that was able to quickly steer me into one aspect of policing that has proven to be not only intellectually rewarding but also professionally marketable. Because, realistically, graduating with a Ph.D. and moving back home because I couldn't find a job would not have been a crowning moment. Jerry's work reminds me that academic research doesn't have to be boring, stagnant, and filled with language that makes reading more of a chore than a pleasure. He taught me how to maneuver in a demanding academic discipline; challenged my academic and research abilities; kept people off my back when I needed space and pushed me out of slumps when I needed it more; and never doubted that I could be successful at this endeavor and for all these things I am thankful for having him as my advisor and guide through the graduate school experience.

This dissertation, in its entire analytic splendor, would not have been possible without the help of Ralph Taylor. Working with Dr. Taylor ensures two things. First you are going to be doing way more work than you ever expected and, second, the product you end up with will be absolutely top quality. I can hardly recall the numbers of times I left his office with a stack full of books and a list of journal articles to read (and on more than one occasion wondering how he remembered a 65 year old article in some obscure journal). Dr. Taylor's enthusiasm for research is second only to his desire to teach others about research. As such he frequently pushed me to learn about issues that were difficult, confusing, and occasionally esoteric and I am grateful for having the opportunity to learn so much about so many issues. Research is, of course, fraught with difficulties. At the end of particularly challenging meetings Dr. Taylor would say "hang in there". I take this small bit of advice with me as I head out into the new unexplored professional world.

I first met Liz Groff when she interviewed for the faculty position in the Department. I remember thinking that I hope she got the job because, quite selfishly, I wanted the opportunity to work with her. My expectations were completely founded because working with Liz has been a tremendous learning experience. I must thank Liz for being there whenever I needed to discuss some obscure technical detail about managing and analyzing spatial data. I have no doubt that her desire to keep her office door open has cost her precious work time but I am grateful for having the opportunity to drop in and chat. Her energy and interest in conducting research of the highest quality is remarkable and if I can achieve even a tenth of that energy I would consider myself successful.

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Anyone who has been through graduate school would attest to the fact that being successful is not just about academics and research. To this end I must thank my officemates and friends Jaime Henderson and Chris Salvatore for providing much need support and companionship along the way. I think the true test of a friend is that they will tell you when you are acting stupid, or childish, or are about to make a bad decision. To this end I could not have asked for better friends. Graduate school has been infinitely more bearable because of their friendship. If one thing saddens me about the end of graduate school it is the fact that we must all necessarily go our separate ways.

Numerous other graduate students (current and former) deserve special mention for making class discussions livelier, for commiserating over the difficulties of graduate school, and for just making life more interesting. To this end I must thank Marie Garcia, Brian Lockwood, Eric McCord, Caitlin McGuire-Taylor, Ke Wang, and Brian Wyant. These people all provided endless hours of entertainment both at work and outside the confines of the University.

This research would not exist were it not for the men and women that undertake the responsibility of policing this country. Policing is no doubt a challenging job, perhaps doubly so in a city like Philadelphia. Nevertheless the members of the Philadelphia Police Department that I know have been the utmost professionals and I continue to be impressed with their level of dedication to reducing crime and making Philadelphia a better place to live. A few people require special mention: Commissioner Charles Ramsey, Deputy Commissioner Patricia (Pat) Giorgio-Fox, Deputy Commissioner Jack Gaittens, Director of Strategic Communications Karima

Zedan, and Michael Urciuoli of the Crime Analysis & Mapping Unit. These individuals granted access to an unbelievable wealth of information and answered an untold number of questions and for that I am extremely grateful.

Finally I must thank my family for supporting me throughout my academic endeavors. I have no doubt my Mom, Terri, sacrificed greatly to provide me with a high quality education and I am forever thankful she made it a top priority in my life. I am thankful that my Dad, Brian, is the hardest working police officer I know because it has provided me with a never ending fascination with all things law enforcement and a work ethic that has served me well all these years. I must thank my Grandma Betty for being a guiding hand during my early education and for ensuring that I always had the best class projects. I must thank my Grandma Millie for opening her home to me so that I could finish my undergraduate degree while enjoying warm weather and year-around beaches. Finally I must acknowledge my Aunt, Uncle, and Cousin (Traci, Tom, and Tyler) for showing me that life isn't just about work and that if you are going to work this hard you better play hard too.

Douglas Adams once wrote "I may not have gone where I intended to go, but I think I have ended up where I needed to be." A truer statement about my life thus far cannot be said.

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CHAPTER 1:

INTRODUCTION

Klinger's (1997) ecological theory[1] of policing addresses the intersection of environment and organizational structure on police patrol practices. At its most basic level Klinger explores the impact of community characteristics and organizational structure upon police patrol practices and relates the macro-level organizational and demographic factors to the micro-level actions of police-citizen encounters. The current study sets out to empirically investigate the relationships posed by this theory. The overarching research question would be: Is the police response to calls for service and self-initiated activity influenced by the level of serious violent crime? Police responsiveness was measured by the final disposition given to a case and the number of arrests made for low seriousness events and self-initiated activity was measured by the level of traffic enforcement. Additional questions are also addressed such as: Does the relationship between police workload and responsiveness and police workload and self-initiated activity vary over time? If there is a cross-sectional relationship found between these factors, is it contingent upon socio-demographic or land use characteristics of where the events occur?

All of these questions hang on the fact that police operate with a great deal of autonomy, both as an organization (Brogden, 1982; Marenin, 1985) and as individual officers (Bittner, 1967; De Lint, 2000; Ericson, 1982; Lundman, 1979). Klinger argued that, although this is true, officers do not act without constraints. These constraints can come from either formal bureaucratic regulation or they can develop as part of the norms within a work group; it is these

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[1] Klinger's ecological theory of policing is, of course, not the only theory that attempts to explain the spatial variation found in police activity. A detailed review of these various theories can be found in the following chapter beginning on page 33. In the interest of clarity within this document, however, the term ecological theory is used solely to refer to Klinger's (1997) ecological theory of policing.

informal work group constraints that Klinger's ecological theory focuses upon. Klinger further argued that police officer actions can be characterized along a continuum of formal authority. This formal authority continuum ranges from vigorous to lenient. On this scale arrest represents more vigorous enforcement than non-arrest, filing a report more vigorous than not filing a report, and so forth.

Saying that officers operate with autonomy however does not necessarily imply that officers will exercise their discretion in the same way in all locations. Stated differently, officers may alter their discretionary behavior based on factors related to the individual incident, and more importantly for the current study, officers may alter their discretionary behavior based on the environmental characteristics of where the crime occurred. This suggests that there may be spatial variations in how and where officers exercise discretion. The idea that officers pattern their discretionary powers spatially is a key concept in Klinger's ecological theory of policing and is discussed more fully in the following section.

According to Klinger's ecological theory, the impact of organizational and community characteristics on the vigor of police patrol operates at the district level – an organizational but also spatial division within the police department. The district, therefore, represents the most appropriate unit of analysis when conducting research on the relationship between police organizational factors, community factors, and the vigor of police action. Klinger (1997: 130) states:

> As levels of deviance increase, officers become more cynical, view victims as less deserving of police protection, come to see more crime as normal…, and have fewer resources to deal with any specific incident… As a consequence, officers working in patrol areas characterized by higher levels of deviance will adopt a

> more lenient approach to their jobs, being less likely to vigorously enforce the criminal law, and thus let pass more minor sorts of criminal conduct.

The core idea of the ecological theory, namely that police vigor will vary (at the district level) based on work load, environmental characteristics, workgroup norms, and organizational factors has been cited extensively in existing research (for just a few examples see, Alpert, MacDonald, & Dunham, 2005; Jacobs, Topalli, & Wright, 2000; Lawton, 2007; Litwin, 2004; Stolzenberg, D'Alessio, & Eitle, 2004; Weitzer & Tuch, 1999). However, research aimed at directly evaluating these main propositions has been limited perhaps largely due to the difficulty in operationalizing key concepts, the difficulty in findings appropriate statistical tests, and the requirement for a high volume of crime in order to have adequate statistical power. The single study investigating Klinger's main propositions found results both consistent with and opposite to theoretical predictions (Hassell, 2006). A full discussion of Hassell's (2006) study can be found in the following chapter. Briefly, Hassell's (2006) study was conducted on one police department and found the following to be consistent with Klinger's theoretical predictions. First, the district was important as both an organizational unit and as a unit of analysis in empirical research. Second, Hassell found support for Klinger's argument that officers in high crime districts perceive more crime as normal than their peers in low crime districts. Third, officers were aware of the level of deviance within their district relative to other districts. Hassell (2006) also found a number of features inconsistent with theoretical predictions. First, officers in all districts shared similar perceptions of victim deservedness and cynicism towards the criminal justice system. Second, officers in high crime districts used more formal legal authority (e.g. wrote more reports, filled out more information cards, or conducted more traffic stops- suggestive of greater officer vigor) than officers in low crime districts.

Although this study was well constructed and provided insight into key theoretical constructs many questions remain unanswered. Hassell (2006) primarily utilized qualitative data to assess the various research questions. To this author's knowledge no study has directly assessed the ecological theory of policing using quantitative methods and administrative data. There are, however, a number of studies with implications for the theory that will be discussed in the following chapter. Furthermore because only a single study exists it was unknown how these results generalize to other organizations. As the theory purports to apply to the patrol units in all law enforcement agencies, this limitation of knowledge is particularly lamentable. Greater confidence in Klinger's conceptual model would be achieved by measuring the proposed relationships in conditions considerably different from the previous study. Finally, it remained an open question as to how facilities and land use impact upon work group norms related to vigor. This study sought to address these issues.

The Current Research Study

The next chapter will identify substantial gaps in the literature surrounding the ecological theory of policing. The current research addresses several of these limitations by evaluating the core premise upon which the ecological theory rests. Stated more succinctly the broad research question is: "Is the police response to less serious crimes conditioned on the level of serious crime after controlling for relevant organizational, socio-demographic, and land use factors?"

The ecological theory of policing would predict that there would be variation at the district level in the relationship between police response to less serious crimes and the prevalence of more serious crimes. For this reason, the dependent variables investigated police activity at various stages of processing and focused on low severity offenses. The focus on low severity offenses was driven by the understandings that police officers have the greatest discretionary powers in these types of events (Black, 1980; Gottfredson & Gottfredson, 1988). Less serious crimes are, therefore, most likely to show variation in the vigor of officer actions.

Klinger's ecological theory of policing specifies that communities with a higher population of minorities, lower socio-economic status, and/or higher levels of more serious crime will have officers that expect more widespread local deviance. This results in officers seeing more crime as normal, viewing fewer victims as deserving of police response, and increasing officer's cynicism towards crime and its victims. These factors reduce police work group norms towards vigor and ultimately reduce the vigor of patrol officers' actions. These can be summarized in the following hypotheses which are discussed as net effects after controlling for community demographics, the level of more serious crime, and officer staffing.

Hypothesis one suggests that areas containing higher minority populations will be perceived as having less worthy victims and are, therefore, less worthy of police vigor.

Hypothesis 1: Officers in areas with high minority population will display less vigor by (a) unfounding a greater number of events, (b) arresting in a smaller number of less serious events, and (c) conducting fewer traffic stops.

The ecological theory of policing argues that those officers working in low socio-economic districts view residents as less worthy and therefore deserving of less vigorous police actions.

Hypothesis 2: Officers in low socio-economic areas will display less vigor by (a) unfounding a greater number of events, (b) arresting in a smaller number of less serious events, and (c) conducting fewer traffic stops.

Hypothesis three suggests that officers in districts with more high seriousness crime (officer workload) perceive a greater severity of crime as normal and acceptable. The process of defining deviance downward results in less vigor towards a wider range of severity; an event worthy of vigor in a low crime district may not be worthy of the same level of vigor in a high crime district.

Hypothesis 3: High levels of serious crime will result in reduced vigor towards less serious events. Officers in these districts will display less vigor by (a) unfounding a greater number of events, (b) arresting in a smaller number of less serious events, and (c) conducting fewer traffic stops.

The analysis conducted here extends the ecological theory in three ways: (1) by expanding and better defining the impact of environmental factors and characteristics of the built environment, (2) by longitudinalizing the relationship between crime levels and vigor, and (3) by using multiple administrative datasets to operationalize key concepts of vigor, workload, and officer staffing.

First, this analysis includes demographic characteristics that have, in other circumstances, been shown to be related to criminal activity. Klinger argues that community demographic factors and other social problems, such as the prevalence of the mentally ill, alcoholics, or drug abusers, are related to the vigor of police actions. At the current level of development the ecological theory of policing does not explain how certain potentially criminogenic land uses link with the vigor hypothesis. The current research extends the reach of Klinger's ecological theory of policing by specifying community environmental factors, such as land use and the presence of criminogenic facilities, which impact upon officer vigor after controlling for community demographic factors, the level of more serious crimes, and organization staffing.

Hypothesis 4: Areas high in criminogenic land use will receive less vigorous police response than areas with lower levels of criminogenic land use, variation that will occur at a sub-district level of analysis. Officers will display less vigor by (a) unfounding a greater number of events, (b) arresting in a smaller number of less serious events, and (c) conducting fewer traffic stops.

Land use may have an effect upon police vigor because of its ability to concentrate both motivated offenders and suitable victims in space and because of its capacity to attract large numbers of people unknown to local patrol officers. Furthermore, the public nature of these locations means that disorder and crime occurring there will be visible to both the public and the police (Klinger, 1997). Insofar as these facilities have the ability to increase crime, make it more difficult for officers to distinguish between residents and non-residents, or increase the visibility of crime and disorder they may reduce patrol officer vigor.

Land use was quantified as the percentage of land zoned as commercial within the block group or police district. Measuring the impact of specific facilities was more difficult. Facilities are often recorded as point locations, for example, their physical location is often represented by a single set of x-y coordinates. This is unfortunate because the hypothesized impact of such facilities extend beyond a single point location; these facilities may have an impact for several hundred feet. In order to quantify this impact a buffer was created around each facility. The impact of facilities was then measured by the percent of land "covered" by this buffer for census block groups and police districts. Details on how these land use variables were created can be found in Chapter 3.

Second, Klinger's ecological theory describes the relationship between vigor and other factors as cross-sectional. It argues that officer vigor varies by district characteristics and workload but does not specify how these factors relate over time. The current research extends Klinger's theory by longitudinalizing and testing this relationship. Investigating the relationship between vigor, workload, and officer staffing within a longitudinal framework provides a number of benefits. First, by longitudinalizing the relationship and utilizing both contemporary and time-lagged crime variables stronger causal arguments[2] can be made. Second, longitudinalizing these relationships may provide information that is more directly relevant to policy makers. A dynamic relationship, for example, between officer staffing and officer output would be much more informative than a simple temporally static relationship demonstrated by a cross-sectional model. Finally, demonstrating key relationships both cross-sectionally and longitudinally would suggest that Klinger's ecological theory is more powerful and useful than if the relationship could only be shown with one type of analytic technique.

Hypothesis 5a: The vigor expended towards less serious offenses and proactive work will vary, over time, with the level of more serious offenses. As the level of more serious offenses increases officers will expend less vigor on less serious offenses and

[2] Causality here refers to Granger (1969) causality. A discussion of this type of causality can be found in footnote 26 (page 104).This definition of causality speaks more to the temporal ordering of the relationship between variables and has less to do with cause and effect.

proactive police work. As the level of more serious offenses decreases officers will expend more vigor towards less serious offenses and proactive police work. Less vigor will be displayed by: (a) unfounding a greater number of events, (b) arresting in fewer less serious events, and (c) conducting fewer traffic stops.

A similar hypothesis was constructed for the relationship between officer resources and vigor:

Hypothesis 5b: The vigor expended towards less serious offenses and proactive work will vary, over time, with the level of officer resources. As the level of officer resources decreases officers will expend less vigor on low seriousness offenses and proactive police work. As the level of officer resources decreases officers will expend less vigor towards less serious offenses and proactive police work. Less vigor will be displayed by: (a) unfounding a greater number of events, (b) arresting in fewer less serious events, and (c) conducting fewer traffic stops.

Klinger's discussion of these issues is limited to saying that both organizational norms and responses to workload should be stable over periods of times. The length and the strength of this stability are not specified. A number of explanations can be postulated to explain why vigor may not be stable over time (change to police management, changes to the economy, etc.). Two possible explanations were addressed in the current study. First, organizational norms may shift in response to changes in factors such as community demographics or organizational structure. A competing explanation would be that vigor varies over time because of changes in the level of resource constraint. Although this analysis could not disentangle these opposing theories it was able to fully investigate the temporally dependent relationship between vigor, workload, and officer staffing. Distinguishing between the effects of changes in organizational norms and the effects of resource constraint must be left to future research.

Third, the existing study of Klinger's ecological theory was conducted largely with qualitative and observational data. The current study contributes to the understanding of Klinger's model by using multiple datasets that allow for exploring the utility and viability in operationalizing vigor with administrative records. The use of administrative records over observational data may have implications for the ability to externally validate these findings in other police departments in other settings.

These questions were addressed by combining data supplied by the Philadelphia Police Department, demographic data from the 2000 U.S. census, and environmental data collected from a number of sources. Three dependent variables were used to represent different aspects of police discretion. The first dependent variable was the number of incidents that result in a final disposition of unfounded. The second dependent variable was the number of less serious incidents that end in an arrest. The third dependent variable was the number of traffic stops. A higher count of unfounded events was indicative of less officer vigor while a higher count of low seriousness arrests and traffic citations represented increased vigor of patrol officer actions. These outcomes were explored at both the census block group level and the police district level of aggregation.

These data were analyzed using both cross-sectional two-level multilevel modeling (MLM) and two-level repeated measures MLM designs. MLM is particularly well suited to address the above mentioned research questions. Standard regression models assume that the error terms of observations are independent, an assumption that is often violated (Snijders &

Bosker, 1999). Because the policing that occurs within a block group falls within the broader policing mandate occurring at the district level it is prudent to assume that the error terms of block groups (level-1 within the cross-sectional models) within a district (level-2 cross-sectional models) are correlated with each other. For the longitudinal models it would be reasonable to assume that the error terms of the time varying level-1 units will be correlated within each district. The correlation of error terms violates one of the basic assumptions underlying multiple regression (Luke, 2004) and argues in favor of using multilevel modeling.

Furthermore, within the current study it would have been unrealistic to assume that census block groups are independent of other nearby census block groups (a phenomenon often referred to as spatial dependency). This is based on Tobler's first law of geography which argues that "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970: 236). More importantly, the use of MLM allows for modeling this spatial dependency as an interesting phenomenon in its own right (Snijders & Bosker, 1999). By nesting census block groups (level-1) within police districts (level-2) it was possible to investigate the impact of police districts while accounting for variations in socio-demographic characteristics without having to aggregate the block groups into police districts. Additionally, the ability to include time lagged independent variables in the longitudinal models allows for the exploration of temporal ordering between cause and effect.

The dependent variables in the longitudinal models were the (1) number of events that were unfounded, the (2) number of less serious events that end in arrest, and the (3) number of traffic stops. For the cross-sectional model the level-1 unit of analysis was census block groups (n = 1,816). The level-2 unit was the police district (n = 23). The dependent variables were measured at the block group level on a yearly, or a multi-year average, basis. Six sets of analyses were conducted. Each year, 2004 through 2008, was investigated separately. These years were then averaged and analyzed providing a composite of the five years. The use of individual years provided a form of test-retest reliability of results and further bolstered confidence in any findings while the five year average reduced the impact of temporary police initiatives that may increase or reduce the vigor of officer activity.

The dependent variables in the longitudinal models were the (1) number of events that were unfounded, the (2) number of less serious events that end in arrest, and the (3) number of traffic stops occurring per month, per district (crime data over 5 years, 2004 – 2008; n = 60). The level-1 model consisted of time varying covariates: the number of more serious crimes occurring within the district, the level of officer staffing, and estimated postcensal demographic data (estimate methodology can be found in Appendix B). The level-2 unit of analysis was the police district (n = 23). Time-lagged variables were employed to investigate the temporal relationship between serious crimes and its impact on vigor towards minor crimes.

Summary

This dissertation makes contributions to both criminological and police management theory. The ecological theory of policing represents an important step in integrating police organizational, community demographic, and environmental factors into a single cohesive framework. This framework can be thought of as nested within the broader area of organizational sociology; a research area that investigates the interface between organizations and the environments where they operate. The ecological theory of policing locates itself within this framework by postulating that law enforcement organizations affect vital societal process and are themselves influenced by those same processes (Lammers, 1981a, 1981b; Scott, 2004). The fact that Klinger's theory existed for over a decade with limited empirical assessment represents a serious gap in understanding how these institutions interact. The findings of this dissertation can be used to further refine the ecological theory of policing and ultimately clarify how vigor responds over time to changing workload demands and resource constraints. Furthermore the results here suggest several avenues for future research that could be undertaken to further clarify how vigor relates to demographic and land use characteristics.

From a police management perspective, the Philadelphia Police Department is a large modern metropolitan police agency responsible for policing a city that varies greatly along the dimensions of socio-demographic, economic, and environmental characteristics. Understanding the effects of these characteristics on officer work patterns may have the ability to influence and improve police responsiveness to local crime patterns. The cross-sectional models and the longitudinal models have related, but distinct, real world policy implications.

The cross-sectional models identify sub-district level demographic and environmental characteristics that link to the vigor of officer actions. Knowledge of these factors could be helpful in assessing the impact of planned changes to land use patterns on police vigor. The longitudinal models demonstrated that a police workgroup's ability to respond to disorder related offenses or quality of life issues varies over time – an especially salient factor in assessing the validity of cross-sectional analyses evaluating Broken Windows policing (cf. Taylor, 2001, for the application of longitudinal models to the assessment of Broken Windows style policing).

Overall, the differences between districts have implications for the allocation of police resources and leadership styles. Certain citywide policing mandates may have different impacts upon different districts. For example, the effect of a citywide policing initiative that focuses on increasing traffic stops and citations is likely to vary by district. Some districts may be more capable of dealing with these new orders while other districts may lack the resources necessary to do the same. Knowledge of these differences would allow police commanders to more carefully tailor both the mandates and the allocation of resources given to each district. At the least, these findings suggest that judging the success or failure of a district in meeting organizational wide mandates may need to be approached carefully and with the understanding that both organizational variables and organizational environmental variables (such as crime levels) may impact findings. Failing to account for the "starting point" of a district may undermine the effectiveness of citywide crime prevention mandates.

Looking Ahead

On the whole, the ecological theory of policing attempts to explain the relationship between district characteristics and the vigor with which patrol officers approach their work. Greater vigor of action can be manifested through founding a call instead of unfounding a call, arresting instead of not arresting, or conducting a traffic stop instead of not conducting a traffic stop (traffic stops were perhaps a unique measure of vigor as these activities are, with rare exception, dictated by officer discretion). Klinger (1997) predicted that incidents occurring in districts with high crime levels will receive less police vigor than similar incidents occurring in low crime districts. The literature evaluating the ecological theory (detailed in the following chapter) has provided a great deal of insight into mechanisms underlying the theory. Indeed, several critical features of Klinger's theory have found support. Klinger's main assertion, however, that vigor is lower in high crime districts, had not been evaluated using rigorous methodology. This study set out to correct this deficit while also positing several theoretical enhancements.

The following analysis advances understanding of the relationship between police activity and district level characteristics by testing the core assertions of Klinger's ecological theory of policing. The next chapter begins with a broad description of police and how police manage space. This quickly narrows to a more focused discussion of how Klinger's model relates police organization and community socio-structural factors into a single cohesive theoretical framework. This framework is then evaluated in light of existing empirical research. Chapter three then discusses the relevant data that were collected and the statistical methodology employed to test key theoretical propositions. Chapter four presents univariate and bivariate statistics along with the spatial statistics and the results from the cross-sectional and longitudinal analyses. Chapter five places the results within the framework of the ecological theory of policing and explores findings that are both consistent with and inconsistent with key theoretical predictions. Chapter six concludes with limitations of the current study as well as a research agenda that would be able to address these limitations.

CHAPTER 2:

RELEVANT LITERATURE

The relationships that Klinger discusses (between formal and informal organizations, legal regulations and work group norms, resources and enforcement, individual rights versus collective rights) have been discussed, and continue to be discussed, by many scholars. Klinger's theory integrates and formalizes the relationship between many well known characteristics of policing that have traditionally been discussed as separate entities. For example, Marenin (1985: 107) describes police work as:

> Work done publicly (frequently in uniform) in the streets and in constant interactions with publics; it is work constrained by legal mandates, public expectations, and cultural values and is guided by formal organizational and informally developed work group rules. Specifically, policing as organized work means that policing is difficult, sometimes dangerous, often frustrating, and always dirty work; that formal and informal work dynamics influence how directives are carried out; that police organizations may be beset by internal struggles (typical manager-worker tensions and compromises) which distort the execution of law and the application of force; that police officers and police organizations develop styles of reconciling conflicting demands on their time, attention, and services; that the police are interested in their work - they wish to control their work lives and give them meaning, and they struggle to produce policing which suits themselves as well as meets the demands imposed on them; and that the police think of themselves as a distinct, sometimes beleaguered, frequently mistrusted, and always unappreciated minority which must stick together, protect its own, and reject external criticisms.

Klinger's contribution was to utilize negotiated order theory, organizational management theories, and other community ecological theories to structure these diverse threads. This chapter is devoted to fully describing the ecological theory of policing and explicating the literature on which it is based.

Theoretical Foundations

Klinger's negotiated order theory is grounded in two theoretical perspectives: stability of punishment and the overload hypothesis. The stability of punishment theory argues that there is a general equilibration in the levels of deviance in a given population over time. Social control mechanisms also reach an equilibrium regarding the amount, or quantity, of punishment dispensed. Therefore, in high crime areas only highly deviant acts are punished (Durkheim, 1938). Acts that are seen as deviant in low crime areas are seen as acceptable in high crime areas (Moynihan, 1993). This position is well summarized by Blumstein and Cohen (1973: 200):

> If the population were to become more deviant… then the society can choose to retain the same punishment thresholds… and accept the consequently higher values of punishment. Alternatively, the society could accommodate to the shift by revising its standards toward greater leniency. It does so by creating new thresholds… or by creating revised punishment procedures and adjusting these such that the punishment… remains constant.

The second theoretical perspective is the overload hypothesis. The overload hypothesis explains the relationship between deviance and quantity of punishment through limitations in the capacity of social control institutions (Geerken & Gove, 1975, 1977). Increased crime rates strain the capacity of social control institutions resulting in less energy being devoted to each case thereby reducing the certainty of punishment. Geerken and Gove (1977: 429) state that: "this hypothesis predicts that police and judicial resources cannot easily expand to take account of rising crime rates, and thus the enforcement system is overloaded or strained beyond its capacity. The ability to capture, convict, and imprison offenders is thus diminished by a rising crime rate…" Both theories predict an inverse relationship between punishment and crime rates: as crime levels increase the amount of punishment meted out is not able to keep pace. Compensation for changing levels of deviance can come from any number of locations throughout the criminal justice system. Klinger (1997) suggests that police patrol officers function as early screeners within this system and that the intensity with which they pursue law enforcement is at least partially contingent upon the prevailing level of crime in an area.

The Ecology of Police Patrol

Research has demonstrated that police officers have broad understandings of the geographic areas to which they are assigned. These understandings often shape, and are shaped by, interactions between the officer and the community. Numerous researchers have noted the importance of how police conceptualize the space in which they work (Brown, 1981; Herbert, 1997). Knowledge of dangerous places, situations, or people is shared among officers so that common themes develop among patrol workgroups. Officers also develop common conceptions of "symbolic assailants"; these are people with individual or community characteristics that are believed to be precursors to violence and disorder (Skolnick, 1994: 44-47).

Klinger proposes a mediated model that links two factors driving the development of workgroup norms regarding the vigor utilized to enforce laws: the workload of the district and the prevalence of other social (non-criminal) problems in a district. These factors are discussed in more depth in the following sections. Briefly, the district workload sharply impacts on the amount of vigor officers are willing to expend on less serious offenses. Officers in districts with higher workloads will expend less vigor towards less serious events than officers in districts with lower workloads. Districts that are high in crime are also likely to be high in other non-criminal social problems such as mental illness, homelessness, and alcoholism (Faris, 1948). In Klinger's model workload and the prevalence of these other social problems drives the development of workgroup norms. These workgroup norms develop at the district level of the organizational structure. It is the variation in workload, community demographic, and environmental factors, that are the focus of the current study.

Police patrol is often organized around a specific spatial extent in order to facilitate rapid response to calls for service and emergency situations (Brown, 1981). The organization of police patrols can be divided into districts and further into beats. Officers often cross beat boundaries to assist officers in other beats that fall within their district. District boundaries, however, are not nearly as permeable as beat boundaries. Although officers frequently cross beat boundaries they rarely cross district boundaries. Furthermore, there exists a level of responsibility for crime within a district that does not exist across districts. Thus Klinger (1997: 286-287) argues that the district becomes the unit at which organizational negotiations are made:

> Because officers are cloistered in their respective patrol districts, separate negotiations take place in each district. Thus, the high degree of autonomy that officers possess and the nature of the division of police labor structure matters so that officers in each patrol district devise work rules largely unencumbered by direct outside influence… Variation in levels of deviance across patrol districts means that across districts officers will have different approaches to the police mandate to regulate deviance and different work to do and that ultimately work group negotiations will occur in different structural contexts.

Districts bound organizational culture. Officers within districts share the responsibilities and mandates necessary to control crime and maintain order. In Philadelphia the importance of the district in determining how patrol officers operate is consistent with historical policing practices. This makes the district the most appropriate unit of analysis when investigating patrol officer workgroup norms.

The Organizational Factors of Police Patrol

The ecological theory argues that patrol activities center around district boundaries, where the district boundary represents true ecological and organizational units. It distinguishes between work groups in policing and the work rules these groups develop. The ecological theory first argues that several unique characteristics of patrol activity precipitate the development of work groups distinct from other areas of the police organization.

Klinger identified several police organizational factors that lead to the development of stable police patrol work groups. Klinger asserts that these factors, which are consistent across jurisdictions, have to do with how police patrols are organized and how the command structure deals with the activities of the patrol officer. First, police patrol is usually a clearly identifiable group separate from other branches of the organization. Second, officers generally patrol a district on a semi-permanent basis. Officers tend to patrol the same areas with the same co-workers over extended periods of time. Finally, two or more officers usually respond to any incident that may pose a risk to officer safety. This means that officers must work in groups in order to resolve many situations. The stability of patrol officer workgroups and the group interaction is important because it builds a district-wide shared understanding of the community in which they police. Within the context of the current study, extensive contact with the Philadelphia Police Department and numerous observations of routine patrols conducted by these officers, it is possible to say that these generalities, if not necessarily their underlying implications, are consistent with actions of Philadelphia police officers.

Turning to work rules, Klinger argues that regardless of the type, structure, or nature of the organizational structure, administrators can only provide limited supervision of patrol officers. Formal rules cannot cope with the complexity of interactions that police are required to handle. Administrators must defer to broad formal mandates regarding the appropriate actions in any particular situation. This leaves patrol officers with a high degree of autonomy regarding the enforcement (or non-enforcement) of laws. Administrators in law enforcement organizations are further hampered by the spatial and temporal distribution of police patrol work. As supervisors get more distant, either organizationally, spatially, or temporally, they have less direct influence over how patrol officers handle any particular situation.

This does not, however, indicate that individual officers are able to exercise their discretion in isolation from other members of the organization. Although some authors argue that each officer constructs individual styles of policing (Brown, 1981; White, 1972), Klinger (1997) instead argues that it is a combination of both individual and organizational factors that determine how patrol work is conducted: “the idea that each officer creates and follows his or her own rules of conduct… runs counter to a large body of organizational literature… while patrol officers enjoy an exceptional degree of autonomy from administrative control, they are by no means free to individually devise and act upon whatever rules they see fit” (Klinger, 1997: 295). Instead groups of officers conduct negotiations to effectively set rules that allows them to handle situations within the organizational framework.

The ecological theory of policing suggests, then, that rule negotiations occur within individual districts. These negotiations are based on, at least in part, the understanding of district level deviance shared among officer work groups. First, districts vary on both the quantity and type of work that an officer may encounter. Officers in high crime districts tend to be busier than officers in low crime districts, even after accounting for variations in officer staffing. Because of triage procedures designed to reduce the number of low-deviant and non-deviant calls, officers in high crime districts will, on average, encounter more serious crimes than officers in low crime districts. Second, officers within a district share a common communications system. This shared communication system informs officers how busy their peers are and the types of activities that are being conducted. Officers also discuss, both formally and informally, the nature and details of the calls that they handle. Third, how officers perceive district-level deviance is shaped by the public life of residents and visitors to their patrol area. In high crime districts officers are more likely to see criminals in public and are more likely to see crimes committed in public (Klinger, 1997). High crime areas also have a greater proportion of highly visible activities such as prostitution and open-air drug distribution (Rengert, Ratcliffe, & Chakravorty, 2005; Weisburd et al., 2006). High visibility criminal activity means that the police will be aware of the criminal activity occurring in their patrol areas.

To summarize, the ecological theory argues that officer understanding of district deviance is shaped by the district workload, a shared understanding of district deviance, and officers observing deviance occurring in public spaces. These understandings are shared among officers within a district because these factors are stable over time and because patrol work tends to be group work. These understandings ultimately form the basis of workgroup norms.

One area where Klinger (1997) leaves room for further development is in detailing how facilities and land use concentrate crime and deviance and, therefore, structure the spatial patterning of police vigor. Broadly speaking, crime prone locations can be classified into two categories: crime generators and crime attractors (Brantingham & Brantingham, 1995). Crime generators are locations where large numbers of people are drawn for reasons unrelated to crime. Crime generators produce crime simply by the volume of people (both offenders and targets) brought together in space and time. Although offenders are not drawn to the location specifically to commit crime, they are frequently willing to exploit an opportunity. Crime attractors, on the other hand, draw offenders into a location for the specific purpose of committing crimes. Common examples of crime attractors are drug markets and prostitution areas (Brantingham & Brantingham, 1995).

There are two concerns regarding crime generators and crime attractors related to the ecological theory. First, these land uses have the potential to bring more potential offenders and suitable victims into an area than other types of land uses. Second, these land uses have the capacity to attract people from outside the immediate area that may be unknown to local patrol officers. Both factors may have an impact on the vigor of police action. These facilities may increase crime levels thereby increasing the district workload and the level of district deviance. This may, in turn, increase an officer's expectation of more widespread local deviance resulting in crime being seen as more normal, victims being seen as less deserving, and officers feeling higher levels of cynicism. Decreasing an officer's ability to distinguish between residents and non-residents may make it more difficult for officers to accurately judge the nature of the community in which they work. Furthermore, the public nature of the locations makes the activities taking place there more visible to both residents and patrol officers. Taken together these factors culminate in a reduction of group norms favoring vigor and ultimately reduced vigor of patrol officer activity.

It should be made clear that these explanations propose an indirect relationship between land use and vigor. Insofar as land use has the capacity to spatially and behaviorally structure both residents and non-residents, it may link with changes to an officer's understanding of an areas level of deviance. Changes to an officer's understanding of district deviance may impact an officer's perceptions towards the normality of crime, the deservedness of victims, or their cynicism level.

Previous research has established that non-residential land use links to greater physical deterioration and incivilities (Taylor, Koons, Kurtz, Greene, & Perkins, 1995). Land use also appears to link with police calls for service. In areas with mixed land use more non-residential land use has been tied to a higher volume of police calls for service (Kurtz, Koons, & Taylor, 1998) and a greater perception of physical incivilities (e.g. the presence of litter or garbage in the street, abandoned houses or buildings, and poor street lighting) (Wilcox, Quisenberry, Cabrera, & Jones, 2004). What remains unknown then is how, or even if, the perception of district level deviance is affected by land use and criminogenic facilities. If patrol officers consider these factors it may manifest itself as reduced vigor in districts with higher level of commercial land use and criminogenic facilities. This dissertation seeks to disentangle this relationship by investigating the link between land uses and police vigor. The following section discusses negotiated order theory and its application to police patrol work.

Negotiated Order in Police Work

The most complete early theoretical framework of negotiated order developed from the study of work groups in two psychiatric hospitals (Strauss, Schatzman, Bucher, & Sabshin, 1963). These researchers were concerned with how order could be maintained within the complex organizational framework of the hospital which is comprised of numerous work groups (such as doctors, nurses, and administrators) that must interact daily. The variation in training, experience, and occupational norms means that "they represent a multitude of theories and/or perspectives regarding how the general tasks of patient care will be conceived, who will perform them, how they will be performed or, in general, how the total division of labor will be carried out" (Day & Day, 1977: 129). According to traditional rational-bureaucratic theory (Weber, 1947: see also Udy, 1959) actors should turn to administratively defined rules and regulations when dealing with these complex situations.

Strauss et al. (1963) identified two limitations with this perspective. First, many actors within the system were not fully aware of all the rules. Second, hospital rules and regulations were neither extensive nor explicit enough to deal with the many situations that hospital personnel encountered. Taken together this suggests that an organization may have too many rules and at the same time these rules lack the depth necessary to encompass all potential situations an employee may encounter. This applies, with very little modification, to police patrol work. It is especially true that laws and regulations regarding officer conduct provide only the most general instruction on the appropriate course of action. Given the limitations of formal rules and regulations, an informal structure must develop. This informal structure permits the day to day operations of the organization, whether hospital or police department, to continue.

The previous discussion, however, omits an important factor in the negotiation of order, one that becomes especially important in the application of negotiated order to police patrol work. Order is negotiated with respect to both internal and external forces. Outside forces, whether they be other organizations or the public at large, have an influence upon how individuals in an organization interact (Rahaman & Lawrence, 2001). The effect of external influences upon negotiations have been historically understudied in organizational research (Day & Day, 1977).

Negotiated order theory can be summarized in four main points (Fine, 1984). First, all social order is negotiated. Organizations do not exist without negotiations. Second, negotiations are contingent upon the structure of the organization. Negotiations follow channels of communications giving rise to patterns of negotiations. Third, negotiations change over time. Fourth, changes to organizational structure result in the re-negotiation of order (Fine, 1984). Any order that is negotiated is necessarily temporary and subject to change (Callaghan, 2008). The remainder of this chapter details the ecological and organizational dimensions of police patrol work. These dimensions are then more fully developed in order to explain exactly how order is negotiated in patrol work.

Klinger's (1997) contribution was to utilize the negotiated order perspective in order to explain how differences across patrol districts lead to differences in negotiated work group rules. Klinger (1997) argues that negotiations of work group rules are based on four factors: the normality of the criminal event, the deservedness of the victim, officer cynicism, and district workload. Negotiations are determined by environments, mandates, and the work that must be done. The environment is of particular importance because patrol officers become totally immersed in the social and ecological context of their district (Reiss & Bordura, 1967). Both the mandates and workload depend upon the level of crime within the district. Klinger (1997) articulates these ideas through the following four points: normal crime, deservedness of victims, police cynicism, and workload.

First, officers in high crime districts will tend to define deviance downward. These officers bear witness to serious crimes more frequently than officers in lower crime districts. Officers in high crime districts, therefore, view disorder related offenses as normal and not warranting of a vigorous police response. As district level deviance increases officer will view more high seriousness crime as more normal or acceptable than will their peers in low crime districts.

Second, officers in both high crime and low crime districts believe that many victims bring crime upon themselves. Furthermore, officers are aware of the fact that many victims of crime are themselves criminals. The criminal in one situation can quickly become the victim in another (Lauritsen, Sampson, & Laub, 1991). Officers believe that when offenders are victimized, they are less worthy of a vigorous police response. In high crime districts, officers are more likely to come into contact with victims that are also criminals. Officers in high crime districts are more likely to encounter situations where the distinction between an individual's status as an offender or a victim is ambiguous. Therefore, as district level deviance increases, officers will believe that fewer victims of crime are worthy of vigorous police response.

Third, officers in high crime districts are more cynical compared to officers in low crime districts. High crime areas are indicative of a failed criminal justice system. Officers in high crime districts arrest the same people time and again. Repeated contacts with the same criminals leave officers with the feeling that, regardless of their actions, criminals will be returned to the street and crime will remain high in their district. This cycle of processing people through the criminal justice system increases officer cynicism. Officers in high crime districts deal with this cyclical process to a greater degree than officers in low crime districts. This increases cynicism and reduces officer vigor.

Finally, districts with a greater workload will be less vigorous in the enforcement of laws. Officers are aware of the workload in their assigned district; they know that a backlog of calls requiring their attention is likely to occur if they do not deal with events efficiently. Stated another way, officers must make decisions regarding the disposition of cases that come to their attention. The ultimate decision for the officer rests upon how much time, effort, or resources should be devoted to any particular case. Assuming that an officer's time and resources are finites, officers must allocate their efforts in such a way that maximizes benefits. These decisions are made even more important by the organizational structure of management. In earlier discussion it was argued that patrol officers have a great deal of autonomy from supervision. Klinger (1997: 292) argues that "while they [supervisors] cannot monitor what officers do in every encounter, administrators can – by simply reading reports of patrol activity – know how well patrol officers are handling their workload." In other words, officers have greater autonomy around incident disposition than they do around work quantity assigned. In these situations, officers have incentives to focus on more serious crimes and reduce the amount of time spent on minor crimes. This process of triage allows resources to be allocated, for better or for worse, to where officers believe they are most needed (Lipsky, 1980).

Reduced vigor will be most pronounced for events that are of a low priority. It is self evident that low priority calls are less important than high priority calls. These low priority calls, however, still require an officer's time and effort. This makes the officer unavailable if a higher priority call occurs. As Brown (1981: 147) points out "The decision to arrest a drunk may mean a lost opportunity to catch an armed robber, and the latter is conceded to have more importance than the former”. Officers must consider both their current and future workload before determining how much vigor to expend.

It is worth reiterating here that these factors affecting the negotiation of police actions occur at the district level making the key ecological unit for police patrol operations the patrol district. According to Klinger, administratively defined boundaries are the key ecological unit for police patrol officers. Klinger’s (1997) causal model can be found in Figure 1.

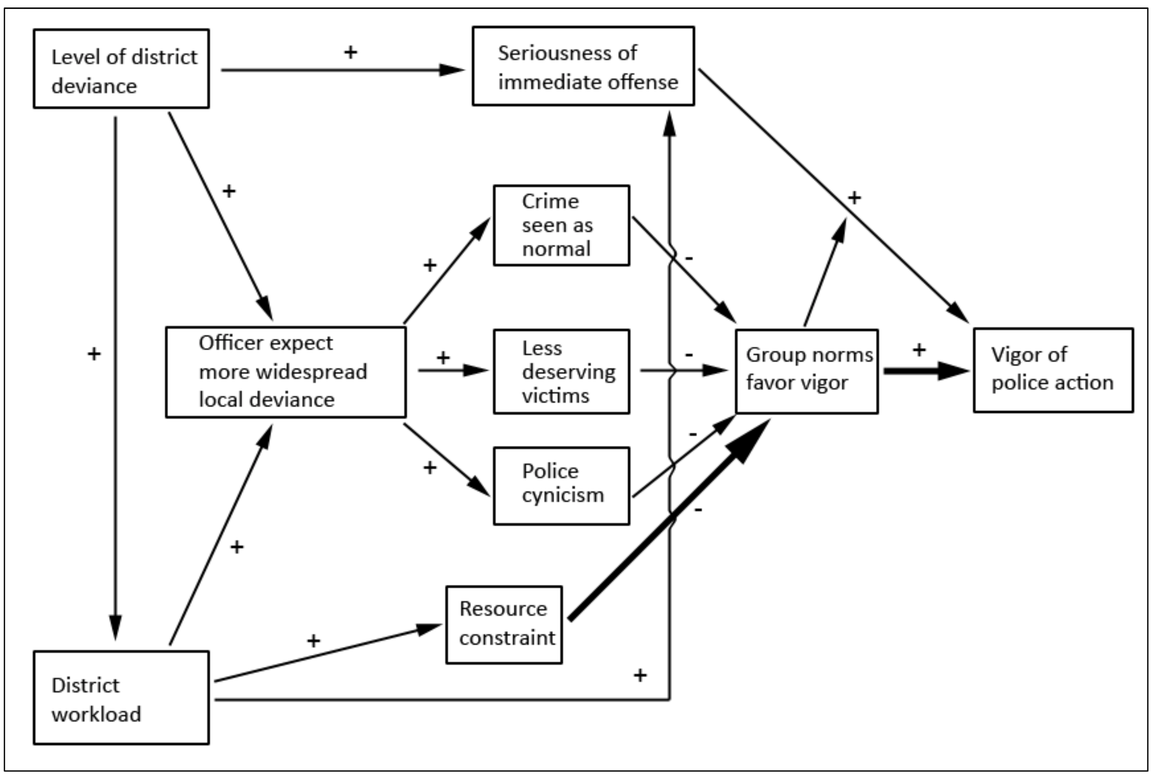

Figure 1: Klinger's (1997) causal model
Note: Bold arrows represent stronger causal pathways.

Two important limitations to negotiations are worth mentioning. First, homicide always results in vigorous police actions regardless of other situational or organizational factors, Klinger writes “no matter how busy the district, no matter how cynical the officers, no matter how routine the homicide, and no matter how undeserving the victim, the rule regarding murder in each and every district will be the same – all murders should receive highly vigorous police actions by patrol officers” (1997: 296). Second, events threatening officer safety will always receive vigorous police actions. These events are never considered normal; they always result in the most vigorous law enforcement efforts. Klinger (1997) summarizes by stating: **“**Except for murder and crimes that jeopardize officer safety, as district-level rates of crime and other forms of social deviance increase, work group rules will hold that deviant acts of a given level of seriousness should receive less vigorous police attention”.

Specifying the Relationship between Serious Crime and Minor Crime

Klinger’s theory predicts that officers in high crime districts will expend less vigor on less serious events. At the aggregate level this relationship should manifest itself with an inverse relationship between the prevalence of serious crimes and the vigor expended on minor crimes. As the number of serious crimes increases the vigor spent on minor crimes should decrease. This would represent officers in high crime areas expending less vigor on minor crimes. Figure 2 illustrates the relationship between serious crimes and minor crimes under Klinger’s ecological theory of policing perspective.

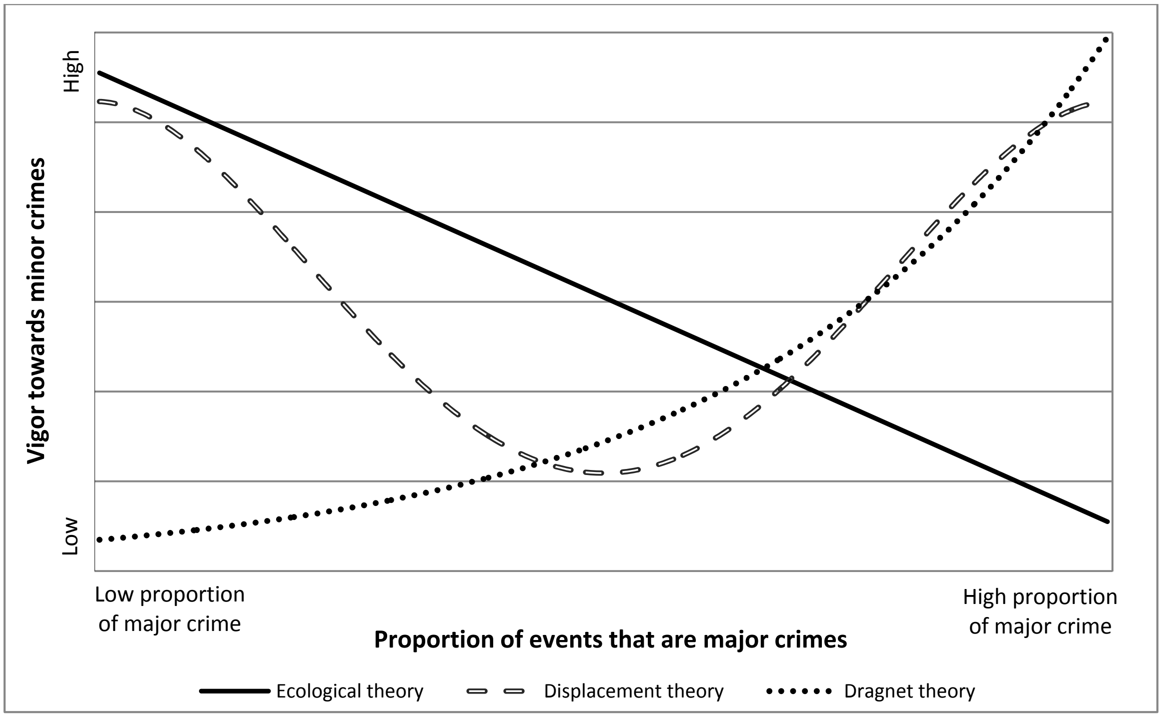

Figure 2: Relationship between rate of major/minor crimes and vigor towards minor crime
Note: Neither Britt and Tittle (1975) nor Klinger (1997) specify the exact relationship (i.e. linear, exponential, etc) between arrest rates for serious crimes and arrest rates for minor crimes. This figure should be treated as an illustrative example consistent with theoretical predictions but not necessarily the only functional form of this relationship.

The ecological theory of policing is, of course, not the only theory postulating a relationship between serious crimes and minor crimes. Two other possible relationships have been hypothesized: the displacement hypothesis and the dragnet hypothesis (Britt & Tittle, 1975). The displacement hypothesis argues that there is an inverse relationship between the level of serious crimes and the amount of attention police focus on minor crimes. This is consistent with the argument put forth by Klinger. The displacement hypothesis differs, however, in the predicted relationship during times of very high violent crime. According to Klinger's model extremely high violent crime will simply depress vigor directed towards minor crimes. In contrast, the displacement hypothesis predicts that police will actually focus *more attention* on minor crimes during periods of extremely high serious crime levels. Because police cannot effectively manage the serious crime problem they must justify their continuing existence by increasing focus on a criminal problem they can manage – minor crimes. Figure 2 (dashed line) demonstrates the relationship between the prevalence of major crimes and its effects on minor crimes under the displacement hypothesis.

The dragnet hypothesis predicts an alternative relationship between major crimes and minor crimes. Under the dragnet hypothesis there is a positive relationship between major and minor crimes. That is, as the level of major crimes increases so too does the focus on minor crimes. This hypothesis is grounded in the knowledge that it is easier to establish probable cause for minor crimes. Therefore police will increase the number of arrests for minor crimes in the hope of turning up evidence of more serious crimes. Figure 2 (dotted line) demonstrates the relationship between the prevalence of major crimes and its effects on minor crimes under the dragnet hypothesis.

Britt and Tittle's (1975) investigated the relationship between serious crimes and minor crimes with city level data from the Florida Uniform Crime Reports (1971-1972; n = 261). Arrest rates for major crimes were constructed by summing eight offense categories (murder, manslaughter, forcible rape, robbery, larceny, aggravated assault, breaking and entering, and auto theft) and standardizing by the population. Arrest rates for minor crimes were constructed by summing the number of liquor law and drunkenness violations, disorderly conduct, vagrancy, curfew, and loitering violations and then standardizing by population. Using various time-lagged regression models they found results more closely supportive of the dragnet hypothesis over the displacement hypothesis. These results, and this relationship, do not appear to have been subjected to further empirical testing since the original study. In light of philosophical and organizational changes made by police departments in the last 30 years it remains an open question if these relationships persist in the same manner as found by Britt and Tittle (1975). The current study was able to assess this relationship indirectly using reported serious crimes (as opposed to arrests for serious crimes) and arrests for less serious events.

Distinguishing Klinger's Ecological Theory of Policing

Astute readers would note that Klinger's conception of vigor sounds a great deal like Black's (1976) conception of the quantity of law. Klinger argues that vigor is "similar to, but not isomorphic with, Black's idea of variation in the quantity of law embodied in police behavior" (Klinger, 1997: 280). Black (1976) argues that use of force and the amount of time allocated to a call are related to the quantity of law. Klinger argues, however, that the quantity of law, such as force and time allocated to a call, can vary independently of formal authority. Officers can use coercive physical tactics (greater quantity of law) in situations where no one is arrested (less formal authority). Increased use of time may also result in situations where less formal control is applied (for example, mediation sessions can take longer than simply arresting one of the parties). In other words, it is simple to create scenarios in which an officer exercises a greater quantity of law while simultaneously being less vigorous in the application of formal authority. Klinger does not preclude the possibility that these ideas are compatible; instead he argues that factors such as time and force may vary systematically across space. If this is true, the factors that affect the vigor with which formal authority is utilized may also explain the amount of time or force used. These constructs should then be thought of as distinct variables.

Researchers have already begun to apply Klinger's conceptual model to outcomes other than police vigor. Notably, Lawton (2007) attempted to address this issue by investigating the relationship between officer use of force and ecological characteristics of the district in which force was applied. Lawton (2007) found district level violent crime to be only marginally related to the amount of force utilized by the officer. Higher district level violent crime rates were weakly associated with the application of less force, net of officer and situational characteristics. Other studies have found neighborhood characteristics to be important in understanding police officer use of force (Garner, Maxwell, & Heraux, 2002; Terrill & Reisig, 2003; Werthman & Piliavin, 1967).

Given the lack of research surrounding Klinger's original formulation of the theory, it would be inappropriate to speculate on its applicability to other dependent variables. This dissertation must make the assumption that police vigor on the application of formal authority represents a distinct construct similar to, but distinguishable from, Black's (1976) quantity of law hypothesis.

One other perspective, the territoriality thesis (Herbert, 1997), is worth mentioning at this point. Herbert (1997) articulates a different perspective on how police interact with their environment. Although the focus of this study is on the ecological theory of policing as defined by Klinger (1997) it is nevertheless instructive to review how these theories relate. For Herbert (1997) police work is fundamentally about controlling space. For example, police have the ability to resolve conflict by separating involved parties, they force people such as gang members and prostitutes from view of the public, and in severe cases use the power of arrest to formally remove someone from a location. Police have the power to create and enforce boundaries that restrict people's movement. Herbert (1997: 13) summarizes this position by stating:

> The police remove people from one location and place them in another… The process of internal pacification so central to the authority of modern state readily depends on the capacity of the police to mark and enact meaningful boundaries, to restrict people's capacity to act by regulating their movements in space.

Several parallels between Klinger's ecological theory of policing and Herbert's territoriality thesis exist. First, both recognize that the written law is insufficient to explain how and why police function as they do. As such, each seeks to define and explain other factors that contribute to how police operate. Second, both theories recognize the importance of both formal and informal organizational structure. Third, both theories make implicit assumptions about the importance of space to police patrol practices.

Underlying these similarities are substantial differences between the two theories. Although both theories focus on the importance of space they differ on their level of resolution. Herbert's (1997) theory focuses on the micro-geographies of where individual events occur. This is more specific than Klinger's theory which focuses on police districts. These theories also differ on the proposed informal organizational structure believed to affect how police work. Klinger argues that the normality of crime, the deservedness of victims, and police cynicism impacts the level of officer vigor. Herbert (1997: 3), in contrast, refers to six "normative orders" as the cause of police territorial behavior: law (preserving legal regulations), bureaucratic control (maintaining internal organization), adventure/machismo (demonstrating courage), safety (preserving life), competence (capability), and morality (good triumphing over evil). Herbert (1997) does not specify which normative order, or combination of orders, is most important.

The weight of each order varies by the department and within the individual officer. Furthermore, while both Herbert and Klinger agree that space and underlying demographics have an effect on how police officers operate they diverge on the importance of organizationally bound space. For Herbert, the relationship between space and officer action is much more direct; officers pattern their actions based on the characteristics of where they work– a direct affect that would not be mediated by group norms or organizational factors. Klinger would argue that the relationship between space and officer action is a district level construct. Officers pattern their activity based on a shared understanding of district level deviance.

Although it is beyond the scope of this dissertation to test these competing theories, distinguishing their differences provides further insight into Klinger's theoretical model. It is perhaps not so much that these theories are incompatible as they are representative of different perspectives on policing and different scales of conceptualization. Klinger's theory only purports to explain patrol officer behavior while Herbert's theory casts itself as being able to explain the actions of officers at all levels of the organization. Through further development it may be possible to integrate these theories. For example, integrating how police manage space at the micro-level may help explain the differences manifested in vigor at the macro-level. The remainder of this section is devoted to empirical literature testing Klinger's model and other key features of the ecological theory of policing.

Evaluations of Negotiated Order in Patrol Work

The following section will detail several areas of research that are relevant to Klinger's (1997) ecological theory. This section begins by discussing the literature that has set out to directly test Klinger's causal model. Following that is a discussion of other related literature that helps to shed light on how police interact with the community.

An extensive literature search reveals a single study aimed directly at assessing the key points of Klinger's (1997) theory (Hassell, 2005)[3]. This study was methodologically sound and shed a great deal of light on many of Klinger's (1997) key postulates. The study was conducted in an undisclosed Midwestern City police department with 760 sworn police officers. Midwestern City (population 400,000) was predominantly white (78.4%) with African Americans (13.3%) and Hispanics (6.1%) comprising the largest minority groups. Midwestern Municipal Police Department (MMPD as it is referred to) contained four precincts which were further divided to nine individual districts[4]. Hassell (2005) used observational field work (434 hours), structured (n = 72) and unstructured (n = 76) interviews, and official data (precinct level documentation on type/nature/quantity of crimes; command structures; policies) provided by the MMPD. Hassell (2005) finds limited support for a number of Klinger's (1997) key theoretical components.

When asked about the normality of crime, officers responded in a manner consistent with theoretical predictions. Officers in high crime districts perceived higher serious crime as more normal than officers in low crime districts. This finding, however, was muddled somewhat by the lack of consistency in the responses. Officers in high crime districts provided more consistent responses to this line of questioning than officers in low crime districts.

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[3] This single study resulted in a number of publications. See also Hassell (2006; 2007a; 2007b).

[4] Hassell (2005) refers to precincts as the organizational unit relevant to Klinger's theory. Careful reading of the study suggests that what Hassell refers to as precincts is synonymous with Klinger's conception of districts. What Hassell refers to as districts (an organizational subdivision of the precinct) would be labeled by Klinger as a beat and by the Philadelphia Police Department as a sector. For consistency the term district will be used throughout.

Officers in all districts shared similar perceptions of victim deservedness. Most officers also viewed the people calling 911 as worthy of police attention. This was inconsistent with theoretical predictions. Theory would have predicted that officers in high crime districts would view citizens as less deserving of vigorous police activity.

The ecological theory would predict that officers in high crime districts should be more cynical of the criminal justice system than officers in low crime districts. Officers in high crime districts should perceive the criminal justice system as less effective in preventing crime and punishing criminals than officers in low crime districts. This prediction was unsupported by Hassell's (2005) research. Officers in all districts showed similar levels of cynicism. Consistent with theoretical predictions, however, was the fact that officers believed that the criminal justice system is largely ineffective in its efforts to reduce crime.

Klinger's theory argues that officers should be aware of the level of crime within their district. Officers should know where their district ranks in overall crime level compared to other nearby districts. Additionally, officers in high crime districts should perceive themselves as busier than officers in low crime districts. Hassell (2005) found that officers did have similar understandings about the level of deviance in their district. Officers in high crime districts were more consistent, however, than officers in low crime districts. The bigger issue was that officers in both high and low crime districts perceived similar workloads. Officers in high crime areas did not perceive a greater level of work than officers in low crime areas.

The area that Hassell (2005) found most support for was in the importance of the district as an organizational unit. Officers perceived that situations were handled differently based on the district where that the event occurred. These precinct variations were attributed to differences in individual officers, experience, the culture and expectations of residents, and the nature of the calls for service. Officers also perceived that supervisory styled varied across districts. These were attributed to differences between individual supervisors. Finally, district boundaries were found to be relatively impermeable. Officers rarely handled situations occurring outside of the district in which they were assigned.

Klinger's theory makes a number of predictions about the activity of officers in different districts. Hassell (2005) asked officers about their use of formal authority through writing reports, filing information cards, and conducting traffic stops. Most officers from all districts perceived that officers in high crime districts use the most formal authority; officers in low crime districts use less formal authority. Officers were also asked about the percentage of traffic stops ending in a citation versus a verbal warning. Officers in the lowest crime district reported issuing the fewest citations per officer. These findings disagree with Klinger's predictions but should be interpreted with some caution. They resulted from survey questions asking officers to rank districts that utilize the most formal authority (i.e. wrote more reports, filled out more information cards, or conducted more traffic stops). It remains unknown if these relationships would persist when using official administrative data. Additionally, it is possible that officers were mixing the volume of their actions with the vigor of their actions. Officers may not have been acting more vigorously once the workload and officer staffing levels were considered.

Overall Hassell (2005) found that although Klinger's theory has some merit, its overall utility in explaining variations in patrol practices was limited. Numerous key predictions were not supported by the findings. Hassell (2005) concluded that the general causal model demonstrated utility in analyzing police activity. Perhaps most importantly police patrol practices did demonstrate substantial variation at the district level. As such the district level was a valid aggregate unit for study. The more specific and nuanced predictions made by the model, however, were unsupported by the findings. Findings were inconsistent with theoretical predictions regarding victim deservedness (officers in all districts regarded people as deserving of police services), police cynicism (officers in all districts reported similar levels of cynicism), and perceived workload levels (officers in both high and low crime districts perceived similar workloads).

Other qualitative studies have asked police officers about aggressiveness of enforcement. One such study (Brown, 1981), found that officers generally responded they were more aggressive in high crime areas. Brown (1981: 166) also noted that “however aggressive a patrolmen may be, their aggressiveness is tempered to what they believe are the crime problems of an area. Over 80 percent of the patrolmen believe that rigorous enforcement and stop and question tactics are justified in ‘some neighborhoods’”. Officers identified “some neighborhoods” as those with high crime levels, low socioeconomic status, and / or those with a high minority population. This finding was contradictory to the model put forth by Klinger (1997). The ecological theory would suggest that areas with high crime, low socioeconomic status, or areas with high minority populations should receive less police vigor than areas with low crime, higher socioeconomic status, or a lower minority population.

This finding should be interpreted with caution for two reasons. First, much like Hassell (2005), Brown (1981) used qualitative interviews to establish these relationships. It is unknown how these relationships manifest themselves with administrative data. Second, there was no indication of why officers stop people more frequently in some areas over other areas. It may be that officers were stopping people in bad neighborhoods more frequently in order to look for evidence of serious crimes. In doing so, they may in actuality have been ignoring many minor crimes. With these caveats in mind Brown (1981) did find that officers prioritized the importance of certain activities. Officers in high crime districts were more likely to consider minor violations such as drinking or possession of small amount of marijuana as less important than officer in low crime districts. This finding is consistent with Klinger's (1997) theoretical predictions.

Other studies have looked more generally at the application of negotiated order to police activity. Schafer (2004), for example, investigated the negotiated order between policing and youth drinking in an unnamed mid-west community with less than 100,000 residents. The study was conducted using field observations and interviews with both general patrol officers and officers specifically deployed to combat alcohol-related incidents. A number of important findings relevant to Klinger's theory appeared.

First, officer activity was sensitive to both internal and external forces. Within the organization officers were given a broad mandate by the chief of police: officers were expected to regulate the consumption of alcohol and its attendant problem but were not required to take formal enforcement actions. External to the department, officers had to deal with citizens calls regarding parties and loud noise and businesses engaged in the distribution of alcohol. Second, officers were keenly aware of organizational resource constraints. They recognized that in many situations the effort required to properly enforce liquor control laws greatly outstripped organizational capacity. Both officers and administrators argued that the limited resources of the department would be better spent on patrol rather than attempting to process dozens of intoxicated individuals. In these situations officers selectively enforced the law against only the most serious offenders. Third, events that threatened officer safety were taken very seriously. Fights in and around bars could easily become out of control dangerous situations involving numerous people and weapons. For this reason officers demonstrated less leniency towards people engaged in fighting. These findings would be consistent with theoretical predictions made by the ecological theory of policing.

The Effects of Neighborhoods on Policing

Broadening the scope of relevant research produces numerous studies that have looked at the relationship between community socio-structural factors and the police. With few exceptions researchers have found that neighborhood characteristics have a substantial impact upon police activity[5]. The effects of neighborhoods and underlying socio-demographic characteristics cannot be overestimated. “Policeman, with remarkable agreement, expect to be used in rather different ways in different parts of the city. By and large they expect to be presented with clearest enforcement cases, unambiguous criminal events, in the middle- and upper-class area… the most discretionary situations, however, occur in the poor and minority residential areas” (Bayley & Mendelsohn, 1969: 89). This finding has important implications for Klinger’s theory. The true nature of police vigor will be most manifest in situations that have the

[5] One of the few exceptions to this finding was the research conducted by Slovak (1986). Slovak (1986) analyzed police activity along three dimensions (police initiated activity, percent of cases formalized, and police response time) at the neighborhood level in three cities. Although neighborhoods did vary significantly on all three measures these variations were often very small. Slovak (1986: 103) states: “Area-action relationships are statistically significant but substantively weak… for all the social, economic, and demographic differences that separate each from the other, this consistency seems rather remarkable”.

most situational ambiguity. Therefore, an analysis of patrol officer vigor is most likely to result in variation in regards to acts that are considered less serious.

Smith (1986) found that officers were less likely to stop a suspicious person in high crime areas. If officers did stop a person in high crime areas they were three times more likely to make an arrest. Officers were also less likely to file an official report in high crime neighborhoods. These findings are partially consistent with Klinger’s (1997) theory. Officers stopping fewer suspicious people and filing fewer reports is consistent with Klinger’s theory. Unlike the findings from Smith (1986) however, the ecological theory would have predicted fewer arrests. Smith (1986) argued that his findings more closely conformed to Black’s (1976) theory of law. Arrests act as an indicator about the degree of law imposed (a greater quantity of law imposed on lower status individuals) and reports act as an indicator about the extension of law (less law being available to lower status individuals).

Reiss and Bordura (1967) argue that informal practices in police departments allows officers to vary their use of formal authority depending upon the position of the social group involved. Critical to this analysis, Reiss and Bordura (1967) argue that police may accept higher levels of crimes among disadvantaged minority communities. If this were true the relationship may manifest itself in a manner consistent with predictions under the ecological theory of policing.

With rare exceptions such as Slovak (1986) the literature has consistently shown that community factors impact upon where and how police services are delivered (Terrill & Reisig, 2003). Underlying the discussion of how police services are rendered is the idea that police operate with a great deal of discretion. Discretion structure is unique within a law enforcement organization. The following section discusses how discretion plays a central role in police patrol work.

Discretion in Police Patrol Work

Klinger's conception of vigor can be related back to a larger body of discourse on discretion in the criminal justice system. Studies on discretion in the enforcement, or non-enforcement, of law have a rich history. Roscoe Pound wrote in 1908 that "we must observe that complaints of non-enforcement of law are perennial… the cause of this complaint are inherent in the administration of justice, and appear in all systems at all times" (Pound, 1908: 401). Klinger's conception of vigor versus leniency mirrors this larger discussion of discretion within the criminal justice system.

One of the unique features of policing is that the greatest discretionary power is vested in the lowest ranks of the organization (Wilson, 1977). Discretion has long been recognized as a necessary, but often misunderstood and mischaracterized, component of police work (Goldstein, 1963; Goldstein, 1960). Herbert (1997: 55) describes how both law and discretion work together to define how patrol officers decide to take action: "The law shapes how police officers conceptualize the areas they patrol by defining the crimes they are likely to encounter in those areas… legal evidence of a crime does not always impel police action, nor does the lack of such evidence prevent it".

Goldstein (1963) argues that police discretion results from a number of characteristics that are inherent to the legal and social system. First, laws are generally written in broad, often ambiguous, terms. This ambiguity may be intentional, a failure to consider how the law would be operationalized, or a reflection of limitations of language. Second, laws often reflect the temporary moral sentiments of the community. As such these laws may become irrelevant and outdated. For fear of being seen as soft on crime, politicians are often unwilling to call for the repeal of laws. Instead they convey an unwritten understanding to officers that these laws no longer need to be enforced. Third, police departments do not have the capacity to enforce all laws. New laws are often passed without consideration for the increase demand on police resources. This means that police officers must decide which laws to enforce and how vigorously to enforce them (Goldstein, 1963).

All of these factors lead to the development of a system whereby police officers must make discretionary decisions regarding their activity. Goldstein (1963) argues that discretion is exercised more frequently in minor cases; more serious offenses are subject to less discretionary power. This sentiment has been echoed by others: "Even though a patrolman may take the point of view that all of the laws are important, and that a policeman should pay as much attention to minor violations as to serious ones, no patrolman entirely escapes the necessity of choosing priorities" (Brown, 1981: 147). This prioritization develops into unwritten policies regarding the appropriate disposition of cases. In Klinger's terms these understandings would develop as work group norms at the district level.

Patrol officers have a variety of formal and informal options available for dealing with the variety of situations that are encountered daily. Research has demonstrated that an officer decides between formal and informal avenues of resolving situations through a complicated framework encompassing many different variables. Officers frequently consider both situational (the demeanor of the victim or suspect or the availability of alternative avenues of conflict resolution), ecological (neighborhood context), and organizational variables (time and resource constraints) in determining the appropriate course of action (Ericson, 1982; Goldstein, 1963; Herbert, 1997; Schulenberg, 2003). The ecological theory of policing argues that differences in formal and informal decision-making drives work group norms that vary by police districts. It is the manifestation of these differences that is the focus of the current study.

Value of the Current Research

An ISI reference search resulted in 81 articles and books citing the ecological theory of policing. A more in-depth search of these references revealed only one empirical assessment directly testing the main proposition put forth by Klinger. This single piece of research (Hassell, detailed above) was well conducted but opened several avenues for further research and development.

The current study contributes to the literature by: (1) expanding the scope of relevant environmental variables to include land use and facilities; (2) longitudinalizing the relationship between officer workload and vigor of activity; (3) expanding the severely limited number of evaluations designed to test Klinger's hypothesis; and (4) being the first study to evaluate Klinger's model using administrative data to operationalize Klinger's key concepts and quantitative methodologies

First, the inclusion of environmental variables represented a first attempt at elaborating the environmental side of Klinger's theory. A great deal is known about the relationship between place and crime (Brantingham & Brantingham, 1993; Rengert, Chakravorty, Bole, & Henderson, 2000; Sherman, Gartin, & Buerger, 1989). This relationship between place and police vigor, however, has not been explored. It was hypothesized that both commercial land use and the presence of certain facilities may be tied to a reduction in the vigor of police actions.

A measure of commercial land use, as it relates to resident's perceptions of territorial control (Kurtz et al., 1998; Taylor et al., 1995) and because of its ability to concentrate crime attractors and crime generators (Kinney, Brantingham, Wuschke, Kirk, & Brantingham, 2008), was included. Given the fact that facility locations are likely to reside on land that is zoned as commercial, these variables were checked for issues of multicollinearity before being entered into regression models. No issues relating to multicollinearity were identified[6].

For facilities a number of variables were selected as they relate both theoretically and empirically to higher levels of crime. These variables include alcohol establishments, check cashing and pawn shops, social service facilities, and facilities relating to mass transit. Areas with more facilities that distribute alcohol have been linked with higher violence (Murray & Roncek, 2008; Roncek & Bell, 1981; Roncek & Maier, 1991) and other anti-social behaviors (Freisthler, Gruenewald, Remer, Lery, & Needell, 2007). Both check cashing facilities and pawn shops were included in this analysis. These facilities have strong links to both property crimes and drug crimes; Anderson (1999: 26) has referred to them as "banks for thieves" because "they are places where stolen goods can be traded for cash, few questions asked".

[6] This is perhaps a bit surprising given the fact that facilities must be located on land that is zoned commercial. The lack of a high correlation between facilities and commercial land use may stem from two related factors. First, while a number of facilities are considered in this analysis they are only a small portion of the total number of businesses that reside on commercially zoned land. Second, the buffer method used to quantify facilities is very likely to encompass land that is not zoned as commercial; buffers may capture all, some, or very little commercially zoned land. These two factors may lead to a situation where commercially zoned land use and facilities are correlated but not to the point where they impede regression analyses.

Social service facilities such as halfway houses, homeless shelters, and outpatient drug treatment centers have the potential, at least in theory, to congregate crime prone individuals. In reality the empirical evidence surrounding the criminogenic impact of these facilities is sparse. The siting of these facilities often causes a "not in my backyard" (NIMBY) reaction from local residents (Substance Abuse and Mental Health Services Administration, 1995). Given the lack of empirical research on the criminogenic impact, and given their at least theoretical orientation to attracting crime prone individuals, these facilities were included in this analysis.

Transit systems configure how and where people are able to travel and therefore have the potential to structure the spatial distribution of crime. Though somewhat limited, evidence suggests that crime may be higher around nodes of public transportation (La Vigne, 1996; Loukaitou-Sideris, Liggett, & Iseki, 2002). This relationship seems to be at least partially conditioned on the socio-demographic and crime levels of the areas in which they are located. These facilities were included because they have the ability to bring large numbers of offenders and victims into close proximity (Block & Block, 2000). Transit systems extend an offenders cognitive map and familiarity with areas surrounding transit nodes. Offenders are more likely to commit crimes in, and around, locations that they feel the most comfortable (Rengert & Wasilchick, 2000; van Koppen & de Keijser, 1997). The effects of trains, subways, and bus routes were explored. This study sought to extend knowledge on the relationship between facilities and land use and their impact upon police vigor. The presence, and spatial distribution, of these facilities and land uses leads to the second contribution of the current study.

Second, Klinger argues that the processes driving the vigor of activity operate at the police district level. Demographic characteristics factor into the formulation of group norms which, in turn, drive the quantity of vigor that will be expended. This process occurs within organizational workgroups leading to the expectation that districts, and not sub-districts, will show variation in vigor. However, there exist several reasons to believe that police vigor will vary at the sub-district level. The fact that crime is not evenly distributed throughout the urban landscape is one of the most often reported and consistent research findings; crimes cluster in a relatively few locations and these locations are responsible for a disproportionately large number of crimes (Griffiths & Chavez, 2004; Sherman et al., 1989; Tita & Greenbaum, 2009; Weisburd, Bushway, Lum, & Yang, 2004). Demographic characteristics and land uses are also non-uniformly distributed throughout an area (Glasmeier & Farrigan, 2007; Reardon et al., 2006). To the extent that police are responsive to these features, independent of organizationally driven dynamics, there is the possibility that vigor will vary in response to the diverse characteristics of locations at the sub-district level of analysis. By using hierarchical linear modeling and separating level-1 demographic characteristics from level-2 police districts it was possible to test these alternative perspectives.

Third, this study investigates how crime levels at $time_1$ impact police vigor at $time_2$. Klinger's original presentation of this theory does not fully develop the impact of time on the dependent variable. Klinger's discussion of temporal effects is limited to the following observations. First, an officer's understanding of district level deviance, victim deservedness, and level of cynicism are stable over long periods of time. Second, officers are unlikely to increase vigor simply because of short term periods of calm. This is consistent with Lipsky (1980) who found that police (and many other public service institutions) often need to keep some capacity in reserve because of the unpredictable nature of demand for their services. Klinger's vigor-stability discussion is limited to short temporal periods (seemingly over the course of a single shift or work period) and does not address longer term temporal patterns.

Yet there exists at least a theoretical basis to believe that crime and vigor will move together over time. Stark (1987) made 30 propositions about the relationship between place and crime. Propositions 25 through 30 have a direct relation to the research questions being proposed here[7]. These propositions described how stigmatized neighborhoods suffer from more lenient law enforcement. More permissive law enforcement increases moral cynicism among residents and, in turn, increases both crime and deviance. Areas with more permissive law enforcement become known to people outside of the neighborhood as a place to commit crime. The people who are drawn to a neighborhood for the sole purpose of committing crimes increase the visibility and opportunity of crime and disorder. Higher visibility of crime and disorder makes it appear that these actions are acceptable and unlikely to be interfered with by law enforcement. Based on Klinger's theory, an additional proposition might be: *Higher crime neighborhoods will suffer further stigmatization by police officers resulting in even less vigorous enforcement of law*. If and as crime increases in a locale vigor may subsequently decline. By

[7] Propositions 25 through 30 (Stark, 1987: 902-904):
Proposition 25: Stigmatized neighborhoods will suffer from more lenient law enforcement.
Proposition 26: More lenient law enforcement increases moral cynicism.
Proposition 27: More lenient law enforcement increases the incidence of crime and deviance.
Proposition 28: More lenient law enforcement draws people to a neighborhood on the basis of their involvement in crime and deviance.
Proposition 29: When people are drawn to a neighborhood on the basis of their participation in crime and deviance, the visibility of such activities and the opportunity to engage in them increase.
Proposition 30: The higher the visibility of crime and deviance, the more it will appear to others that these activities are safe and rewarding.

using a repeated measures design it was possible to investigate this temporal relationship, albeit indirectly through proxy measures.

Fourth, this study expanded the limited number of studies aimed at evaluating Klinger's key policing theory. The lack of high quality empirical research is lamentable given that the theory purports to explain the patterning of patrol activity for all police departments. Finally, this study will be the first to attempt to evaluate numerous linkages developed in Klinger's model through the use of quantitative analyses and administrative data. One criticism of negotiated order theory, and studies of symbolic interactionism generally, is their overreliance upon qualitative participant observation methodology: "In recent years it has been argued that symbolic interactionist studies frequently have deteriorated into little more than noncritically oriented descriptive accounts…" (Day & Day, 1977: 134). The limited studies evaluating Klinger's theory of negotiated order have relied primarily on such methodologies. This study extended the literature by attempting to verify the findings of other qualitative researchers through the use of quantitative methodologies and sophisticated statistical modeling techniques.

At this point it is worth addressing an important question that is likely to arise: why is there no cross-sectional, district level test of Klinger's conceptual model? Stated more critically one could ask why bother extending Klinger's conceptual model when the basic underlying arguments have not been tested using rigorous quantitative methodologies. The reason for failing to provide a basic, district level test of Klinger's conceptual model was twofold. First, testing the entire model was impossible given the complexity of the underlying processes. Klinger proposes relationships that require understanding of both individual and group level dynamics, information that at least in this setting, was not captured in any official record. Given the complexity of this model it is unlikely that any department anywhere would capture the relevant data in existing data systems. This, of course, is not to say that the necessary data are immeasurable. Given sufficient time and resources these data could have been collected which leads to the second, related issue.

The ecological theory of policing is at its core about group level dynamics. Klinger argues that these group level dynamics occur at the police district level. Therefore, comprehensive tests of this model would investigate vigor at this aggregate spatial unit and utilize the district as the main unit of analysis. This creates a rather substantial problem regarding a lack of statistical power. Philadelphia, the sixth largest police department in the nation, has 23 normal operation police districts. This low number of police districts presents substantial difficulty to statistically analyzing the dynamics at play in Klinger's model. Even New York City Police Department, by far the largest police department in the nation (based on the number of sworn officers), with 76 police districts operating across five boroughs would face substantial challenges imposed by the low number of districts. Given the difficulty in operationalizing the key concepts in Klinger's model, the substantial hurdle of collecting those data, and the general lack of statistical power created by a low count of districts, a direct test of the Klinger's main dynamics is probably not directly testable. What this dissertation sets out to do then is to test some of the key ideas behind Klinger's model while extending the theory in a direction necessary for empirical assessment.

Summary

Klinger's theory proposes a relationship between environmental and organizational factors on the vigor of police patrol activity. Individual events occurring within districts with high crime levels will receive less vigorous police actions than crime events occurring in districts with less crime. Vigor, according to Klinger, can be measured in a number of ways. Greater vigor is demonstrated by an arrest versus a non-arrest, filing a report versus not filing a report, and so on. Although Klinger's theory has been cited numerous times there has been a limited effort to quantitatively evaluate the main tenets of this perspective. The results from existing literature present a mixed picture. Support has been found for several key hypotheses the most important of which was the importance of the police district as an organizational unit of analysis. The specific and nuanced predictions generated by Klinger's model, however, have found less support. Officers in high and low crime districts did not differ on measures of victim deservedness, policy cynicism, and perceived workloads.

The current study extends and contributes to understanding the spatial patterning of vigor in the following ways. First, this analysis clarifies and expands the scope of relevant environmental variables to include both commercial land use and facilities commonly linked to increased criminal activity. Second, the relationship between vigor and workload is presented as primarily cross-sectional. Klinger discusses the effects of differences across districts but does not specify how changing crime levels over time will impact vigor. Analyses presented in the following section investigate this potentially temporally dependent relationship. Third, this study substantially expands the limited empirical assessment of this key policing theory. Finally, this is the first study to evaluate Klinger's model using administrative data and quantitative methodologies. The chapter to follow describes the data and methods that were used to empirically test the relationship between crime levels, organization, and vigor.

CHAPTER 3:

METHODS

These analyses use data provided by the Philadelphia Police Department (PPD). The PPD follows a para-military structure, employs over 6,000 uniformed police officers (the fourth largest department in the country), and has an operations budget in excess of $500 million per year (City of Philadelphia, 2008; Philadelphia Police Department, 2008a). The patrol bureau is commanded by a single chief inspector. This is further divided into 6 divisions and 25 districts[8]. Each division is headed by an inspector and each district is headed by a captain. Districts can further be divided into sectors and then beats. These boundaries are hierarchical so that beats nest within sectors, sectors nest within districts, and districts nest within divisions (Philadelphia Police Department, 2008b). For reasons articulated by Klinger (discussed in chapters 1 and 2), and the organizational structure of the Philadelphia Police Department, the district is the organizational unit appropriate for this analysis. As discussed previously the census block group will be used to represent the underlying demographic characteristics of the police district.

These data were retrieved directly from the Records Management System (RMS) of the PPD[9]. Records were acquired from several different stages of administrative processing. The main focus of this analysis will be upon incident level data. A description of how these data originate is useful to place them in context.

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[8] There are 23 districts excluding special function districts such as those operating in Fairmount Park or around the Philadelphia International Airport. For the remainder of this study reference to the districts is made in regards to the 23 normal operations districts.

[9] All police data used in these analyses were subject to IRB protocol review (protocol number 12781) and were found to be exempt under "Exemption 4: Collection or study of existing data."

Records available at the incident level originate from several sources. The most relevant to this analysis are those that began as calls placed to 911 and officer-initiated activity. The Philadelphia Police Department utilizes a computer-aided dispatch (CAD) system. With this system calls from 911 are routed to dispatchers who collect relevant data. Calls are prioritized according to the importance of the situation. Events that result in officers being dispatched then proceed to the incident level dataset.

The second originating source for events in the incident dataset come from officer initiated work. For recordkeeping and officer safety reasons, officers radio dispatch when performing activities such as traffic or pedestrian stops. These events end up as records in the incident level dataset. One limitation to utilizing CAD data is that a single event may have multiple records. This occurs, for example, when several people call 911 about the same incident. Because this poses problems for statistical analyses that assume independence of observations (Zimmerman, 2004) these data were not used until multiple records have been collapsed into a single event; an action that occurs when moving from the CAD record to the incident level data. Figure 3 presents the processing of events through the PPD records management system.

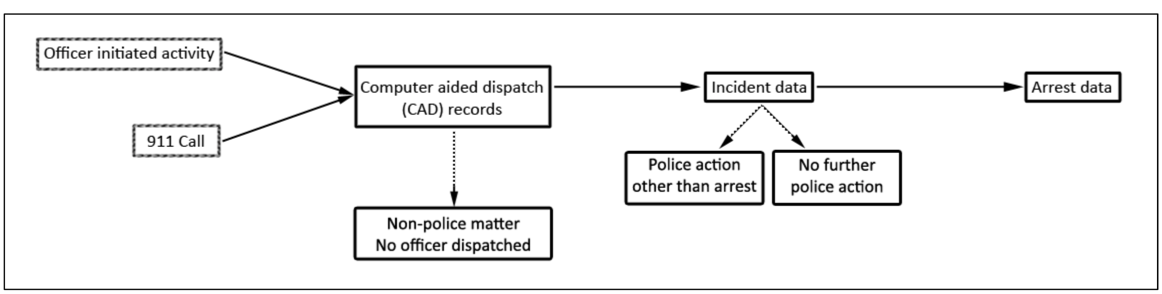

Figure 3: Processing of events through PPD records system

The incident level dataset contained information on both criminal and non-criminal matters involving communication between police officers and central dispatch. These events can either be dispatched or self-directed. These data are available from January 2004 through December 2008. The incident level dataset contained standard police record keeping information such as time of dispatch, location of event, and the responding unit. Contained within these records is also information about the final disposition of the incident. These disposition codes provide important information about how police officers processed incidents.

The use of data from 2004 through 2008 presents limitations that are discussed more fully in the following section. Briefly, however, the use of data from 2004 through 2008 means that the dependent variable will be temporally dissociated from the time when several of the independent variables were measured. The decision to use crime data from 2004 through 2008 was made in an effort to keep the results of this analysis current and applicable to how the police operate. The use of current crime data makes the findings from the study more relevant to contemporary police policies. Table 1 provides a description of disposition codes utilized by the Philadelphia Police Department.

Table 1: Disposition codes by year

Disposition: Description	Status	2004 n	2004 %	2005 n	2005 %	2006 n	2006 %	2007 n	2007 %	2008 n	2008 %
Arrest (ARR): An apprehension has been made on the assignment.	ARR	48,157	(2.6)	50,556	(2.7)	56,855	(3.0)	58,593	(3.2)	66,863	(3.4)
Cancelled (CAN): Incident cancelled.	NFPA	12	(0.0)	15	(0.0)	19	(0.0)	15	(0.0)	1	(0.0)
Called back complainant(CBC): Complainant called	PA	0	(0.0)	0	(0.0)	0	(0.0)	0	(0.0)	195	(0.0)
Dispersed by police (DBP): A disorderly crowd dispersed by police without incident.	PA	53,884	(2.9)	62,983	(3.4)	73,323	(3.9)	60,595	(3.3)	62,075	(3.2)
Duplicate (DUP): Duplicate record.	NFPA	84	(0.0)	82	(0.0)	74	(0.0)	36	(0.0)	195	(0.0)
False alarm fire (FAF): Alarm activated to alert police of a fire, where no fire is present (used for defective or tripped alarms only).	NFPA	13,434	(0.7)	14,342	(0.8)	13,446	(0.7)	15,902	(0.9)	17,490	(0.9)
False alarm (FAL): Alarm activated in the absence of an emergency to which the police must respond.	NFPA	119,697	(6.4)	108,170	(5.8)	101,859	(5.4)	99,275	(5.4)	92,320	(4.7)
Gone on arrival (GOA): Complainant had gone before police arrived.	NFPA	25,682	(1.4)	27,733	(1.5)	32,900	(1.7)	14,214	(0.8)	5,199	(0.3)
Hospital case, No action (HCN): The complainant was transported to the hospital by someone other than the police.	NFPA	18,564	(1.0)	21,708	(1.2)	22,022	(1.2)	19,403	(1.0)	17,560	(0.9)
Investigation of unoccupied vehicle (IVU): The investigation of a vehicle which appears suspicious and is unoccupied by any person(s).	PA	28,458	(1.5)	31,052	(1.7)	35,615	(1.9)	28,549	(1.5)	23,042	(1.2)
Necessary action taken (NAT): To be utilized only when a disorderly crowd is dispersed without incident.	PA	9,340	(0.5)	11,310	(0.6)	12,517	(0.7)	4,918	(0.3)	48	(0.0)
Not false alarm (NFA): Alarm activated to alert police to actual burglary/robbery or due to weather conditions, power outage, or extraordinary circumstances.	PA	3,877	(0.2)	3,932	(0.2)	3,972	(0.2)	3,868	(0.2)	3,712	(0.2)
Pennsylvania State Police(PSP): Incident handled by the Pennsylvania State Police[1]	NFPA	0	(0.0)	0	(0.0)	0	(0.0)	266	(0.0)	626	(0.0)
Referral (REF): Complainant was referred to another agency.	NFPA	329	(0.0)	333	(0.0)	245	(0.0)	87	(0.0)	0	(0.0)

Table 1: Disposition codes by year (cont.)

Disposition: Description	Status	2004 n	%	2005 n	%	2006 n	%	2007 n	%	2008 n	%
Report to follow (RTF): An assignment requiring a 75-48 that does not fall into any other disposition category.	PA	1,136,261	(60.7)	1,168,528	(62.5)	1,202,852	(63.3)	1,221,663	(66.0)	1,340,689	(68.6)
Traffic violation (TVR): Traffic ticket was issued. No other action taken.	PA	24,962	(1.3)	20,425	(1.1)	17,031	(0.9)	11,341	(0.6)	8,050	(0.4)
Unfounded (UNF): Where an assignment proves to be totally groundless in that no offense, complaint or incident was committed or attempted. Never use when officer takes any action at the location.	NFPA	389,123	(20.8)	347,693	(18.6)	327,322	(17.2)	310,565	(16.8)	315,058	(16.1)
Warrant advised (WAR): Complainant advised to secure private criminal complaint	NFPA	50	(0.0)	61	(0.0)	43	(0.0)	6	(0.0)	2	(0.0)
Missing: Disposition code omitted	UNK	1,261	(0.1)	1,188	(0.1)	1,179	(0.1)	621	(0.0)	22	(0.0)
Total		1,873,175	(100)	1,870,111	(100)	1,901,274	(100)	1,849,917	(100)	1,952,952	(100)

[1] During 2007 the Pennsylvania State Police took control of policing interstates that travel through the City of Philadelphia. These incidents receive the PSP disposition.
ARR- Arrest
NFPA- No further police action by the Philadelphia Police Department
PA- Police action (other than arrest) taken
UNK- Unknown final disposition

The last processing phase for which data were available is at the arrest stage. By utilizing a unique identifier it was possible to link an event contained in the incident level dataset with an arrest in the arrest dataset. The arrest dataset contained information about the arrest location, arrest time, and demographic characteristics (age, gender, and race) about the individual arrested. These data were available from 2004 through 2008.

As shown in Figure 3, events can be filtered from the records system at several stages. Dispatchers may remove calls that are not police matters and do not require dispatching an officer. Dispatchers also collapse events that result from multiple calls into a single record. For example, a single shooting may result in eight 911 calls. These 911 calls are collapsed into a single incident in the incident level dataset. Relevant to this analysis were those events that were filtered out by police officers after an event has made it to the incident data. Officers have several official methods of handling incidents. For clarity of display these dispositions have been condensed to (1) arrest, (2) police action other than arrest, and (3) no further police action.

Dependent Variables

The ecological theory proposes a relationship between environmental and organizational variables and general police actions. These actions range on a scale of formal authority ranging from high vigor to leniency. The dependent variable, therefore, must quantify an officer's actions along this continuum. The ideal dependent variable would measure vigor in situations where officers have the greatest possible level of discretion.

For this reason there was a need to distinguish between serious and less serious incidents. Less serious incidents are regarded as providing the officer with more ambiguity and therefore greater discretion. The more serious versus less serious distinction was made on the basis of Federal Bureau of Investigations (FBI) Uniform Crime Reports (UCR) part one (high seriousness offenses) and part two (disorder related offenses) classification system. Furthermore, only crimes that patrol officers were likely to encounter were selected[10]. The crimes used in this analysis can be found in Table 2.

[10] Crimes excluded from this analysis can be found in Appendix A.

Table 2: Description of UCR codes utilized in analysis

UCR Code	Crime Description	Category
100 Series	Homicide	Serious
200 Series	Rape	Serious
300 Series	Robbery	Serious
400 Series	Aggravated assault	Serious
500 Series	Burglary-residential & non-residential (including attempts)	Serious
600 Series	Theft	Serious
700 Series	Vehicle theft (including attempts and recoveries)	Serious
900 Series	Arson	Serious
800 Series	Other assaults	Disorder
1400 Series	Vandalism & criminal mischief	Disorder
1500 Series	Violation of the Uniform Firearm Act (VUFA)	Disorder
1600 Series	Prostitution and commercial vice	Disorder
1701-1707, 1708, 1710, 1711, 1713, 1716	Other sexual offenses- public indecency, open lewdness, Incest, indecent assault, corrupting the morals of a minor, involuntary deviate sexual intercourse, statutory sexual assault, aggravated indecent assault	Disorder
1800 Series	Narcotics offenses	Disorder
1900 Series	Gambling violations	Disorder
2100 Series	Driving under the influence of alcohol / controlled substance (DUI)	Disorder
2200 Series	Liquor law violations	Disorder
2300 Series	Public drunkenness	Disorder
2602, 2614, 2616, 2629, 2640, 2649, 2654, 2671-2674, 2680-2685, 2684-2685, 2688, 2676, 2686	Cruelty to animals, trespass, obscenity, possession of burglary tools, ticket scalping, and curfew violations, Illegal or short dumping, inciting to riot, failure to pay transportation fare, violation of protection order	Disorder
2701	Investigation of person	Disorder
3107, 3129, 3140	Damages to private property, truancy, suspected child neglect	Disorder
3300 Series	Minor disturbances	Disorder

UCR codes utilized in the construction of the district level crime measure. Crimes that patrol officers were most likely to encounter were selected for analysis.

Officer vigor can manifest itself at several stages in the handling of an event. This makes it necessary to measure vigor at different levels and in different types of police-citizen interaction. Using information available from the incident level dataset and arrest dataset a number of dependent variables were created. These dependent variables were constructed using only the disorder related offenses defined above.

First, a variable was constructed representing the number of unfounded events. Events are only unfounded if an officer investigates a call and no offense or incident was completed or attempted. This disposition code is intended for use only when officers take no action on the call. Events that are founded represent more officer vigor than cases that are unfounded. Unfounding events occurs as one of the earliest stages of processing. The ecological theory predicts that there will be systematic variation in the number of unfounded calls. The highest crime districts should have the highest number of unfounded calls.

Unfounded events have been used in previous studies of police activity. For example, Maxfield, Lewis, and Szoc (1980) used the rate of founded to unfounded events to investigate police performance. They had three key findings. First, there were dramatic differences between what callers reported to dispatchers and what police officers officially reported. Second, and consistent with the theory being tested here, the ratio of founded to unfounded events was dependent upon the level of demand for police services. Higher demand for police services was related to a greater percentage of unfounded events. Finally, the relation between founded and unfounded was not dependent upon racial or socio-economic characteristics of where the event occurred.

Relatidly, Donald Black (1970: 734) argued that reported events, unfounded events, and the relationship between reported events and unfounded events represent “an empirical phenomenon with its own existential integrity.” He further argued that the study of unfounded events can be used to inform about official police understanding of deviance (in contrast to a citizens understanding of deviance). The current study uses unfounded events to better understand how police officers shed workload in the face of varying levels of serious crimes.

The second measure of officer vigor was the number of less serious incidents that end in an arrest. Making an arrest represents greater vigor than not making an arrest. It was expected that the number of events ending in an arrests would vary systematically by district. Districts with the highest crime levels should have the lowest number of events ending in arrest. Table 3 presents the distribution of frequency of low seriousness arrest type by year.

Table 3: Frequency of low seriousness arrest type by year

		2004		2005		2006		2007		2008	
Crime Description	**UCR Code**	n	(%)	n	%	n	%	n	%	n	%
Other assaults	800 Series	5446	(11.6)	5067	(11.3)	4849	(10.5)	5155	(10.2)	5836	(11.9)
Vandalism	1400 Series	811	(1.7)	784	(1.7)	948	(2.1)	974	(1.9)	910	(1.9)
VUFA	1500 Series	2551	(5.5)	2476	(5.5)	2577	(5.6)	2295	(4.5)	2232	(4.6)
Prostitution	1600 Series	1720	(3.7)	1471	(3.3)	1390	(3.0)	1319	(2.6)	1359	(2.8)
Other sexual offenses	1701-1707, 1708, 1710, 1711, 1713, 1716	894	(1.9)	787	(1.8)	724	(1.6)	770	(1.5)	727	(1.5)
Narcotics	1800 Series	2757	(59.0)	26571	(59.3)	26593	(57.5)	29974	(59.1)	26007	(53.2)
Gambling	1900 Series	252	(0.5)	298	(0.7)	314	(0.7)	255	(0.5)	265	(0.5)
DUI	2100 Series	4602	(9.8)	4670	(10.4)	5340	(11.6)	6186	(12.2)	7141	(14.6)
Liquor law violation	2200 Series	491	(1.1)	434	(1.0)	671	(1.5)	924	(1.8)	1069	(2.2)
Public drunkenness	2300 Series	194	(0.4)	231	(0.5)	266	(0.6)	285	(0.6)	462	(0.9)
Other offenses	2602, 2614, 2616, 2629, 2640, 2649, 2654, 2671-2674, 2680-2685, 2684, 2685, 2688, 2676, 2686	2219	(4.7)	2026	(4.5)	2478	(5.4)	2421	(4.8)	2832	(5.8)
Investigate person	2701	2	(0.0)	2	(0.0)	78	(0.2)	107	(0.2)	32	(0.1)
Damage property	3107, 3129, 3140	0	(0.0)	0	(0.0)	0	(0.0)	2	(0.0)	5	(0.0)
Minor disturbance	3300 Series	1	(0.0)	3	(0.0)	5	(0.0)	15	(0.0)	11	(0.0)

More complete descriptions of the UCR codes used can be found in Table 2.

The third measure of officer vigor was the number of traffic stops. Previous researchers have used traffic enforcement patterns to study both formal and informal police organizational management practices (Brown, 1981; Campbell, 1999) and police officer discretionary practices (Lichtenberg, 2002; Schafer & Mastrofski, 2005). Traffic stops are generally a discretionary decision made by the officer and therefore present an excellent opportunity to measure police action that is contingent upon other influences. It was expected that districts with higher crime levels will have lower counts of traffic stops. Table 4 presents the nature codes that were utilized to identify officer activity referred to as traffic law enforcement.

Table 4: Nature codes used to identify officer activity related to traffic stops

Description	2004		2005		2006		2007		2008		Combined	
	N	%	N	%	N	%	N	%	N	%	N	%
Investigate occupied auto	10,881	3.4	9,908	3.1	10,274	3.3	12,155	3.9	13,146	3.6	56,364	3.5
Car stop	229,220	72.1	226,639	71.5	220,535	71.5	229,143	73.0	273,597	75.9	1,179,134	72.9
Investigate auto	49,835	15.7	49,760	15.7	51,253	16.6	46,423	14.8	40,994	11.4	238,265	14.7
Live Stop[1]	27,867	8.8	30,652	9.7	26,370	8.5	26,293	8.4	32,675	9.1	143,857	8.9
	317,803		316,959		308,432		314,014		360,412		1,617,620	

[1]The Live Stop program was implemented by the PPD in order to reduce the number of vehicles operating illegally within the City of Philadelphia. Under the Live Stop program a vehicle is impounded if any of the following conditions are met: (1) the vehicle is unregistered; (2) the vehicle is operating under a suspended registration; (3) the driver is unlicensed; and/or (4) the driver has had their operating privileges suspended or revoked.

A fourth dependent variable, the number of traffic citations issued, was originally proposed for this dissertation. These events were going to be identified through the disposition code (TVR) associated with the incident. Investigation of this disposition code by year showed substantial decline between the beginning of the study period and the end of the study period. In 2004 there were 24,962 events that ended in a traffic citation. This value had declined to 8,050 by the year 2008. Discussion with various personnel within the Philadelphia Police Department suggested several potential explanations for this decline. First, changes to the computer aided dispatch system altered the types of events that could receive a final disposition of TVR. For instance, under the new dispatch system citations for illegal parking could no longer be given a disposition of TVR. Second, changes to PPD policy now require a follow-up report for some traffic offenses, a change that results in a final disposition of “report to follow” (RTF). Because incidents that end in a traffic citation were not consistently identifiable, their utility as a dependent variable was diminished and their use was not further pursued.

Correlations between dependent variables were checked to ensure that differences between variables existed. Expectedly, the correlation within each variable over time (cross-sectional model; year 2004-2008) is generally very high. Pearson's r values for the yearly unfounded event counts ranged from 0.79 to 0.94. For low seriousness events these values ranged from 0.76 to 0.90. Correlation between years for the traffic stop outcome ranged from 0.70 to 0.94. The correlations between outcome measures (unfounded events, low seriousness arrests, and traffic stops) were not as high. These correlations along with the spatial distribution of the outcome measure assure that modeling of related, but different, phenomena was taking place. Table 5 displays the correlation between the three dependent variables in the longitudinal model.

Table 5: Correlation between dependent variables

	Unfounded events	Low seriousness arrests	Traffic stops
Unfounded events	--	0.680*** / 0.634***	0.449*** / 0.603***
Low seriousness arrests		--	0.597*** / 0.411***
Traffic stops			--

Longitudinal model outcomes (N = 1,380) / cross-sectional model outcomes (N = 1,810)
Pearson's r values reported
*** $p < .001$

It is worth spending a bit of time detailing some conceptual differences between the outcome variables. Traffic stops have the clearest link with officer initiated activity. These events are, with rare exception, entirely driven by an officer's decision to engage, or not engage, in the event. On the other hand traffic stops (and perhaps to a greater extent, traffic citations) may be clear indicators of officer activity that can be easily reviewed by commanding officers. Therefore officers may use traffic stops as a method of demonstrating vigorous activity to supervisors. Just as Klinger argues that a backlog of calls is anathema to organizational efficiency and easily reviewed by supervisors, traffic stops may be a clear indicator of officer vigor that is also easily reviewed by supervisors. How this visibility impacts officer vigor is not directly quantifiable in the current study. What it does, however, is suggest that some types of formal authority may be subject to greater supervisory oversight than other manifestations of vigor.

Unfounding an event is, by and large, a disposition that would be used in response to a citizen's call for service. The officer must make a key decision on whether they will file a report or unfound the event. The length and complexity of a report will vary and filing a report does not necessarily mean a substantial imposition on the officer's time. This is especially true if officers can submit reports electronically from computers located in their vehicles. Furthermore, a report does not necessarily need to be filed immediately and can be delayed until an officer is not occupied with other activity.

By comparison the decision to make an arrest – or not – presents a great deal more complexity than the previous two outcome measures. Black (1971), for example, argued that the decision to arrest is associated with a number of individual and situational characteristics such as the suspects race, the legal seriousness of the crime, the evidence supporting the allegation, the complainant's advocacy for action, the suspects deference to police authority, and the manner by which the event came to be known to the police. The decision to arrest also has rather substantial implications for an officer's future workload as processing an arrest can take an officer (perhaps several officers) off the street for several hours. This time requirement is also an immediate commitment unlike filing a report which can often be deferred till the end of the officer's shift. Taken together this suggests that studying vigor at different stages of processing and at different levels of officer discretion may provide valuable insight into the theoretical model set forth in the ecological theory.

A critical choice must be made between using crime rate or the count of crimes as the dependent variable (Harries, 1991). Many analyses use a rate variable as an outcome in the following form:

$$Rate\ of\ event = \frac{Number\ of\ events\ observed}{Population\ at\ risk}$$

where the numerator is the phenomena of interest and the denominator provides an adjustment for the environmental risk or opportunity (Harries, 1991). Several limitations to the use of rates as dependent variables have been identified. Most importantly, including a denominator in the dependent variable changes the relationship between the outcome of interest and the independent variables. The relationship between the independent variables and the denominator may be different than the relationship between the independent variables and the numerator. This, combined with the fact that the numerator and the denominator may interact with unmeasured variance in different ways, indicates that the use of rates can be problematic (Gibbs & Firebaugh, 1990).

The use of rates also presents specific problems when dealing with rare events. As Osgood (2000: 22) points out: “when populations are small relative to offense rates… the discrete nature of the crime counts cannot be ignored. Indeed, for a population of a few thousand, even a single arrest for rape or homicide might correspond to a high crime rate”. This creates two related problems for ordinary least squares (OLS) regression. First, the precision of the estimated crime rate varies by population size. Predictions of crime rates would be expected to produce larger errors in areas of low population and smaller errors in areas of high population. This violates the assumption of homogeneity of error variance (Knoke, Bohrnstedt, & Mee, 2002). Second, the error terms will not be normally distributed when the number of events is small. Error terms become increasingly skewed as crime rates approach zero (Osgood, 2000). Under these circumstances count regression models are appropriate (Long & Freese, 2006) and were therefore adopted in these analyses.

Strengths and Limitations of the Dependent Variables

These variables were constructed using administrative data from the Philadelphia Police Department. Although the use of administrative data has real advantages it also brings with it several limitations that are worth discussing. Most importantly, it was not possible to verify the accuracy of the administrative data on which these analyses are based. A number of studies have questioned both the level of reporting and the accuracy of the information contained in official reports (Meehan, 1986, 1998). Slovak (1986) raises three concerns regarding the use of police dispatch logs[11]. First, police dispatch logs generally lack the sensitivity necessary to analyze events at the individual event level. A great deal of contextual information about a particular event is not recorded. Thus, dispatch logs are more suited to aggregate level studies. Second, organizational records such as dispatch logs are subject to institutional filtering. Organizational rules or individual officers have the capability to manipulate records. Third, the quality of record keeping may not be consistent across jurisdictions.

In response to the first criticisms it is argued that much improvement has been made to police administrative data since Slovak (1986) voiced these concerns. Improvements in geographic information systems, database management, and the availability of large digital storage media has resulted in crime data that can be spatially located with high precision.

[11] It is clear from the description in Slovak (1986) that the use of the term “dispatch logs” is synonymous with what the Philadelphia Police Department and this analysis refer to as incident level data.

Although administrative data certainly do not capture all information relevant to every incident, it does collect the information necessary for this analysis. This concern, therefore, does not present substantial roadblocks to the analysis carried out here.

In response to Slovak's (1986) second point, it is true that this analysis may be open to criticisms that any results found are a product of biased police reporting and not real differences in police activity level. The accuracy and utility of police administrative data has long been debated. Researchers have argued that these data do not accurately reflect the true level of crime (Beattie, 1960; Cressy, 1957). Instead this information represents a measure of police behavior – especially when dealing with highly discretionary police activities such as enforcing drug and prostitution laws (Kitsuse & Cicourel, 1963). Given the focus of Klinger's theory this criticism actually serves as justification for the use of administrative data. The use of administrative crime records serves as the appropriate data for analyzing police organizational practices.

Slovak's (1986) third point, that records vary across jurisdictions, does not apply to this analysis because only data from the Philadelphia Police Department will be used. Comparing the findings of this analysis with data from other jurisdictions will represent an important avenue for future research.

More generally, the use of administrative data inevitably means that the dependent variable will not capture informal police activity or activity not recorded in official logs. For example, officers may engage in pedestrian stops that they do not report to dispatchers. The vigor of this action would not be recorded in the official datasets used here. While the use of administrative data is consistent with Klinger's conception of vigor, it cannot measure other potentially relevant indicators of officer activity and officer vigor. This is a limitation of the current analysis and represents an issue worth investigating through different measures in future research.

The use of administrative records also means that the events used in this analysis have already gone through an organizational filtering process. The events we see are the outcome of this filtering process, not the inputs into the system. In other words, what we see recorded in the dataset are events that have already been subject to review by officers and their supervisors. This filtering process may have the capacity to bias results in an unknown direction. Determining how this organizational filtering process effects the measurement of officer vigor must be left to future studies.

Finally, the current study measures vigor at an aggregate level of analysis- either census block groups or police districts. This departs from Klinger's original conception of the theoretical processes which were largely confined to individual events. In other words the current study tests the theory at an aggregate level of analysis while the original theory discusses dynamics largely at the individual event level. Taking this approach is not without its limitations. An aggregate level approach means that it is not possible to apply these results directly to individual interactions; attempting to do so would run afoul of an issue similar to the ecological fallacy (Chainey & Ratcliffe, 2005). Notwithstanding this important limitation, the aggregate level approach was adopted for a number of reasons. Most importantly, collecting data on individual interactions was far outside the resources of the current study. Such a study would require an army of researchers to observe the behavior of officers. The benefit of this aggregate level approach is that it can be done using administrative data which allows for data analysis within a longitudinal framework.

Exposure Variables and the Use of Counts as Dependent Variables

Count models frequently employ an exposure variable to control for the population at risk. The exposure variable is calculated as the natural log of the population at risk with a fixed coefficient of one (Long & Freese, 2006; Osgood, 2000; Osgood & Chambers, 2000). Selection of the most appropriate exposure variable is difficult for a number of reasons. Concerns over theoretical (e.g. simply defining the population of interest), methodological (e.g. combining spatially incompatible datasets), and practical (e.g. cost feasibility) issues have been identified as substantial roadblocks to adopting appropriate exposure variables (Andresen, 2006; Andresen & Jenion, 2008; Boggs, 1965; Harries, 1991; Qin, Ivan, & Racishanker, 2004).

The most difficult task in creating an exposure variable for crime related measures is defining and measuring the population at risk. Using the residential population, as measured in the census, for example does not fully capture the population at risk for most crimes; where people live is not necessarily the same place where they would be the victim of a crime. This problem is especially pronounced in high density commercial areas (such as Center City) where the residential population has little relation to the average daily commuter population. This issue is even more dramatic when considering crime related, but not actual crime, outcomes such as unfounded events. It is difficult conceptually, not to mention practically, to identify the population at risk for unfounded events.

Other more methodological concerns over using exposure variables exist. Certain assumptions are made regarding the exposure variable and the dependent variable of interest.

Entering population, for example, as an exposure variable makes the assumption that the relationship between crime and population is linear. There is an assumption that the relative likelihood of crime does not change with increasing population. Given that there may be a non-linear relationship between population and crime (consider the larger discussions about the relationship between population density and crime undertaken below) this assumption is not necessarily advantageous. For these reasons exposure variables were not included in these analyses. Instead variables that were relevant to the likelihood of crime, such as population (Nolan, 2004), were entered into the statistical models as independent variables. This allows the coefficients to be estimated from the data instead of a priori fixing the relationship.

Independent Variables

A number of independent variables relating to demographic characteristics, environmental characteristics, organizational characteristics, and spatial effects were included in this analysis. The remainder of this section discusses independent variables relevant to Klinger's model: socio-demographics, features of the built environment, violent crime level, officer cynicism, officer staffing levels, and the spatial distribution of crime. These are discussed in turn beginning with socio-demographic characteristics.

Demographics

Independent variables representing underlying social structure of the community were drawn from the 2000 U.S. census and postcensal estimates generated for each year 2004 through 2008. These variables were selected on their well established relationship with crime. The work in factorial ecology has, over several decades and a wide range of community settings, found three broad community structural dimensions consistently related to crime: status, race/ethnicity, and stability/familism (Hunter, 1971, 1972; Janson, 1980; Taylor & Covington, 1988). Other researchers have looked at characteristics common to locations with persistent crime and deviance problems. Stark (1987) distilled community characteristics related to crime into five factors: (1) population density, (2) poverty, (3) mixed commercial / residential land use, (4) population mobility, and (5) the physical condition of the built environment.

A recent meta-analysis by Pratt and Cullen (2005) found socioeconomics and race to be the most consistent predictors of community crime rates. Indicators of both factors were included in this analysis (Blau & Blau, 1982; Blau, Blum, & Schwartz, 1982). Measures of residential stability, as a precursor to the formation of local supervisory controls, were also included (Bursik, 1988). Finally, on the basis of Hassell (2005) one other demographic variable, a measure of linguistic isolation, was also included.

The longitudinal component of this analysis required the use of temporally varying demographic data. Unfortunately, because the U.S. Census is only conducted once every 10 years there are no readily available sources of demographic data at the spatial and temporal resolution required by this analysis. Instead this analysis employed demographic estimates created by GeoLytics; a well established provider of demographic data frequently used in social science research and business optimization strategies (GeoLytics, 2009). These postcensal estimates are not without their limitations. In general they are less accurate for smaller geographies and less accurate the further away in time you get from the original data source (Raymondo, 1992). Nevertheless, these data provided the best possible solution to the otherwise intractable problem of conducting longitudinal analyses on variables that are contingent upon the changing socio-demographic fabric of the community. Details of GeoLytics' estimation methodology can be found in Appendix B.

The relationship between population density and crime continues to be a debated issue. The specific effect, whether high population density links to higher, lower, or has no effect on crime, remains an open question with empirical support for all three positions. For example, Stark (1987: 894) argued that high population density is one of the "essential factors" in predicting areas of high deviance. This position finds support in a number of empirical evaluations (Sampson, 1983; Shaw & McKay, 1942; Skogan, 1977). Other researchers have argued that population density is not related, negatively related, or only spuriously related to crime (Kvalseth, 1977; Shichor, Decker, & O'Brien, 1979, 1980; Spector, 1975). Research in this area also suggests that population density is sensitive to how one operationalizes the concept of density; options include population per area, housing units per area, number of rooms per housing unit, or number of persons per room (Sampson, 1983). Of greater concern is the difficulty in disentangling the effects of population density from other socio-demographic characteristics with which it is frequently correlated (Galle, Gove, & Miller, 1972). In light of these competing theoretical expectations, population, and not population density, was used in these analyses.

Demographic variables were needed at the census block group level and at the police district level. This was complicated by the fact that block groups do not nest neatly within police districts. The areal units of the census geography frequently overlapped and crossed the boundaries of the police district (Saporito, Chavers, Nixon, & McQuiddy, 2007). To minimize the impact of this spatial incompatibility a method of areal weighting was employed (Downey, 2006;

Flowerdew & Green, 2001). Data from the census block groups were disaggregated into small areal units. These units were then recombined on the basis of district boundaries in order to provide census data at the police district level. Appendix C contains a detailed description of the process by which census data are areally weighted to police districts.

Environmental Characteristics

As articulated previously, the ecological theory places the environment as one of the central factors of how police conceptualize the space they patrol. Yet the exact specification of these effects was not clearly defined in the original conception of the theory. What is not specified is how environmental variables such as facilities and land use (such as business or residential areas) affect police vigor. A great deal of research has shown environmental factors to be related to crime levels. Research has also shown that facilities have an impact upon perceptions of crime (McCord, Ratcliffe, Garcia, & Taylor, 2007). The current study further develops these issues through the inclusion of measures related to land use and the prevalence of crime prone facilities (Clarke & Eck, 2007; Felson, 1987).

Commercial land use was included in the analysis because of its impact on territorial control and because of its ability to concentrate crime attractors and crime generators (Kinney et al., 2008; Kurtz et al., 1998; Taylor et al., 1995). This variable was measured as the percentage of land zoned as commercial within the block group or police district[12]. Zoning data for the City

[12] One difficulty in constructing this variable is that zoning parcels may overlap census block group or police district boundaries. Therefore it was not possible to simply summarize the quantity of area within each census block group or police district. The following procedure was used. Commercial land uses were selected and exported from the full land use dataset. Commercial land use polygons were then clipped to the census block group polygons through the “intersect” operation found within the GIS. The intersect operation produces new polygons wherever polygons from the first layer overlap polygons from the

of Philadelphia were obtained from the Pennsylvania Spatial Data Access website (Pennsylvania State University, 2009). This dataset provided zoning information for every parcel of land within the city. Parcels that were zoned as mixed-use commercial areas (C1, C2, and C3), commercial areas (C4 and C5), commercial centers (C7), commercial entertainment district (CED), neighborhood shopping centers (NSC), area shopping center (ASC), and office commercial (OC) were selected for inclusion in this analysis (Philadelphia City Planning Commission Department, 2009).

Measuring the effects of specific facilities tends to be more problematic because their physical locations are generally represented within the geographic information system (GIS) as point data. This was undesirable from both a methodological and conceptual perspective. Although facilities are represented as points, their hypothesized criminogenic effects extend an unknown distance into the surrounding area. Use of simple quantification methodologies such as containment or point-in-polygon tests (Gombosi & Zalik, 2005) are highly sensitive to zoning (a subset of the modifiable areal unit problem), where small changes in the boundaries of the areal unit produce substantially different results (Chainey & Ratcliffe, 2005; Dark & Bram, 2007; Openshaw, 1984a, 1984b; Openshaw & Taylor, 1979; Yule & Kendall, 1950).

To reduce the impact of zoning and issues related to the modifiable areal unit problem a modified buffer approach was utilized. This method begins by constructing 400 foot buffers

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second layer. The area for these newly created polygons was then calculated. Next, a spatial join was performed. The areas of the polygons falling within each census block group or police district, calculated in the previous step, are summed. This produces the amount of commercial land use in each census or police geography. The values were then divided by the total area of the census or police geography to produce the percentage of land use zoned as commercial.

around each facility[13]. This buffer represented the hypothesized criminogenic impact of that facility. Stated another way, the buffer represented the area where the facility was likely to impact crime. The proportion of each unit of analysis (block group or police district) "covered" by this buffer was then calculated. This was defined by the following equation:

$$Facility\ A\ = \frac{Area\ of\ Facility\ A_{1+2+\ldots n}}{Area\ of\ Geographic\ Unit}$$

This can range from 0% if no buffer is present in the areal unit to 100% if the entire areal unit is covered by a buffer from facility. A variable representing this value for each facility type is entered into the regression equation. Figure 4 illustrates how buffers are used to quantify the effects of point locations.

[13] The length of an average city block in Philadelphia was 365 feet but varies considerably throughout the city (σ = 341 feet). 400 feet was chosen as it extends slightly beyond one city block. This helped to account for any effects associated with parameter selection, such as side and end offsets, required by the geocoding process.

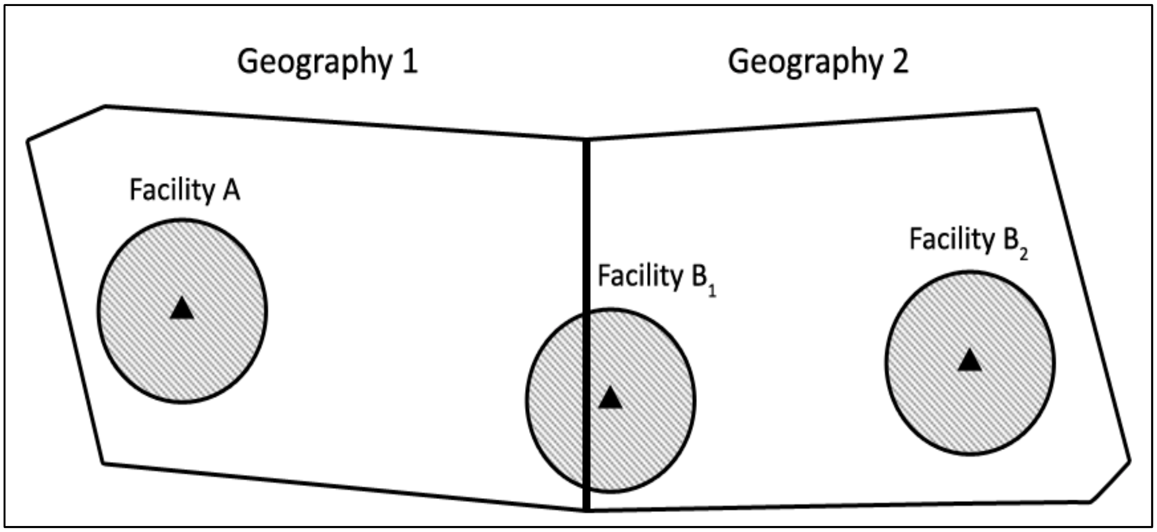

Figure 4: Utilizing buffers to quantify the effects of point locations
Note: Counting the number of points falling within each geography would indicate that Geography 1 contains one Facility A and zero Facility B locations. Geography 2 contains two Facility B locations. In this example Geography 1 has an area of 10,000 square feet. The circular buffers surrounding each facility are 2,000 square feet. Facility A falls completely within Geography 1 indicating that 20% of Geography 1 (2,000 sq ft/10,000 sq ft) contains Facility A buffer. Because only part of Facility B_1 buffer falls within Geography 1 a smaller portion, about 8%, is allocated. The remaining area of Facility B_1 buffer is allocated to Geography 2.

Figure 4 demonstrates the utility of using buffers to quantify the effects of point locations. The method of counting points in polygons is particularly sensitive to zoning effects (a subset of the modifiable areal unit problem) where small changes in the boundaries of the geographic unit produce large changes in the outcome of interest. To ameliorate this problem a buffer approach was adopted. This approach was sensitive both to the number of facilities within the geography as well as those facilities in nearby geographies.

Counting the number of points falling within each geography would indicate that Geography 1 contains one Facility A and zero Facility B locations. Geography 2 contains two Facility B locations. In this example Geography 1 has an area of 10,000 square feet. The circular buffers surrounding each facility are 2,000 square feet. Facility A falls completely within

Geography 1 indicating that 20% of Geography 1 (2,000 sq ft/10,000 sq ft) contains Facility A buffer. Because only part of Facility B_1 buffer falls within Geography 1 a smaller portion, about 8%, is allocated. The remaining area of Facility B_1 buffer is allocated to Geography 2.

A number of facility types were selected because of their common association with crime and their ability to concentrate both suitable victims and motivated offenders. This includes: alcohol establishments[14], check cashing and pawn shops, social service facilities such as halfway houses, homeless shelters, and outpatient drug treatment centers, and facilities relating to mass transit such as train stations, subway stations, and bus routes.

Bus routes were quantified differently than other facility locations. Quantifying the effects of bus routes presents two problems. First, bus routes were not easily quantifiable as point locations. The frequency of bus stops makes the buffer approach discussed above unsuitable. Second, both census block group boundaries and bus routes were likely to run along the same major streets. This presents another example of the modifiable areal unit problem discussed previously. In order to resolve these difficulties bus routes were mapped in a geographic information system. A line segment, offset from the original by a small distance, was constructed on both sides of the route. Both sides were used because of the above mentioned zoning issue. If the bus route falls along the boundary to two geographies this method allows for it to be allocated to both geographies. The distance of all bus route lines occurring within the

[14] Pennsylvania has numerous liquor control licenses that impact both how, when, where, and under what circumstances alcohol may be sold. Typical categories such as those separating on-site drinking facilities from facilities that sell alcohol for off-site consumption are not possible based on these licenses. For this analysis three types of alcohol distribution licenses were selected for inclusion. These have been labeled clubs, liquor and beer eating establishments, and state controlled liquor distributors.

census geography was then summed and divided by the area of the census geography[15]. This value was entered into the regression equation and represented the distance of bus routes within the geography standardized by area.

The correlation between commercial zoning and facility variables were checked to ensure that inclusion of both land use measures in the analysis did not produce issues relating to multicollinearity. This analysis used facility variables at two units of aggregation: census block groups and police districts. Because the relationship between these variables can change at different levels of aggregation (an issue related to the modifiable areal unit problem) separate correlations were generated for census block groups and police districts. For census block groups Spearman's rho values are reported because of the high positive skew[16] found among the land use variables. At the census block group level, variance inflation factor (VIF) and tolerance values were within acceptable limits (VIF < 1.6; tolerance > 0.70). Table 6 displays the correlations between various land use variables at the census block group level of analysis.

[15] This method double counts the distance of the route when they are not on the boundary to a block group. This double counting should not be seen as problematic because the over counting is consistent across all the geographies. This does, however, suggest that interpretation of the coefficient generated by this variable must be handled with caution.

[16] Skewness values at the census block group ranged from 0.64 for the length of bus route to 7.84 for the percent of area covered by a pawn shop buffer

Table 6: Correlation between land use variables at the census block group level

Variable	% Comm.	% St. Liquor	% Alcohol	% Club	% Pawn	% Check	% Home.	% Drug	% H. house	% Rail	% Sub	Bus†
% Comm.	1.00	0.17**	0.48**	0.11**	0.18**	0.24**	0.21**	0.13**	0.16**	-0.02	0.27**	0.39**
% St. Liquor		1.00	0.10**	-0.03	0.02	0.08**	0.03	0.01	-0.05	0.03	0.07**	0.09**
% Alcohol			1.00	0.20**	0.14**	0.19**	0.13**	0.07**	0.08**	-0.10**	0.21**	0.40**
% Club				1.00	0.03	0.07**	0.10**	0.07**	0.10**	-0.01	0.10**	0.08**
% Pawn					1.00	0.18**	0.07**	0.12**	0.06**	0.00	0.23**	0.15**
% Check						1.00	0.19**	0.06**	0.12**	-0.01	0.22**	0.13**
% Homeless							1.00	0.16**	0.22**	-0.01	0.15**	0.13**
% Drug								1.00	0.07**	0.03	0.14**	0.06*
% H. house									1.00	-0.00	0.08**	0.07**
% Rail										1.00	-0.01	-0.13**
% Sub											1.00	0.20**
Bus†												1.00

N = 1,810
† Standardized by area of the census block group
* p < .05
** p < .01

Results at the police district level were substantially different. Variables at the police district level were far less skewed (skewness < 2.4 for all land use variables; Pearson's correlation values reported). Analysis indicated strong significant correlations between many land use variables. Table 7 presents the correlations between land use variables at the police district unit of analysis.

Table 7: Correlation between land use variables at the police district level

Variable	% Comm.	% St. Liquor	% Alcohol	% Club	% Pawn	% Check	% Home.	% Drug	% H. house	% Rail	% Sub.	Bus†
% Comm.	1.00	0.35	0.75**	0.68**	0.69**	0.68**	0.74**	0.66**	0.47*	-0.03	0.87**	0.73**
% St. Liquor		1.00	0.57**	0.35	0.00	0.34	0.42*	0.06	0.10	0.09	0.39	0.71**
% Alcohol			1.00	0.83**	0.70**	0.58**	0.55**	0.46*	0.43*	-0.11	0.76**	0.87**
% Club				1.00	0.59**	0.46*	0.56**	0.39	0.43*	-0.12	0.69**	0.67**
% Pawn					1.00	0.57**	0.51*	0.76**	0.55**	-0.07	0.70**	0.62**
% Check						1.00	0.82**	0.66**	0.82**	-0.05	0.80**	0.64**
% Homeless							1.00	0.72**	0.77**	0.17	0.81**	0.71**
% Drug								1.00	0.52*	0.08	0.80**	0.57**
% H. house									1.00	-0.11	0.57**	0.46*
% Rail										1.00	-0.03	-0.01
% Sub.											1.00	0.78**
Bus†												1.00

N = 23
† Standardized by area of the police district
* p < .05
** p < .01

The high correlation between various land uses at the district level created substantial impediments to analysis. This was further confirmed through unacceptable VIF and tolerance levels (VIF > 10; tolerance < 0.05). These values indicated that it would be problematic to include all of these land uses as independent variables in the regression models at the police district (level-2 in both the cross-sectional and longitudinal models) unit of analysis.

A number of possible solutions to this issue were considered. For example, data reduction through factor analysis was performed on land use variables at the census block group and the police district level. These results (not shown) suggested that theoretically relevant and reliable scales could not be constructed at both levels of aggregation. Another possibility considered was to include only a few land use variables at both the census block group and police district level. This option was rejected because even the inclusion of three land use variables at the police district level produced issues of multicollinearity. After extensive exploratory data analysis and careful consideration of various approaches it was decided that the optimal approach would be to include different land use measures at different units of analysis.

This created limitations for the analyses conducted here. First, it was not possible to fully explore the various dimensions of land use at the police district level. This limited the ability to speak to the unique influence of each facility on the dependent variable. Second, failing to include variables at both levels of analysis limits the ability to determine the influence of changing levels of aggregation upon the relationship between land use and outcome variables. Stated another way, by including the same land use variables at both the census block group as well as the police district it would have been possible to ascribe any differences between the parameter coefficients to changes in the dynamics brought about by different levels of aggregation. Unfortunately this was not possible given the high correlation between land uses at the police district level.

The benefits, however, of using different land use indicators at different levels of analysis are substantial. The critical benefit derived from this approach was the ability to investigate links between the independent variables and the dependent variables at the smallest unit of analysis. Previously it was argued that features of the environment, such as land use, would impact how police perceive their district and, therefore, how they approach policing their respective areas. Implicit in this perspective is the understanding that nearby micro-space characteristics are more important than broader contextual factors that may be happening on the other side of the district, possibly several miles away. The solution to this problem of multicollinear variables then was consistent with the theoretical framework while simultaneously being feasible within the statistical approach adopted here.

Organizational Characteristics

District workload is a critical component to the ecological theory of policing. Vigor towards less serious events is reduced when workload is high and resources are scarce. As mentioned previously, however, there are two situations in which negotiations towards vigor do not take place: homicide and issues of officer safety. The number of homicides was used as a measure of officer workload. Unlike other crimes, homicides cannot be ignored by the patrol officers making it an excellent proxy variable for workload. However, because the count value of homicides becomes unstable when broken down by months and by districts this measure was not adopted for the longitudinal model. Instead the longitudinal model employed violent crimes (as defined previously) as a control over workload. The number of officer assaults was also included as an independent variable. Klinger argues that officers react with the greatest vigor towards events that threaten officer safety[17].

One key dimension of the ecological theory is officer cynicism. As officers perceive greater levels of district deviance they should respond with increased levels of cynicism. Higher levels of cynicism result in lower levels of vigor. To capture this construct data from a larger study investigating police integrity in Philadelphia was utilized[18] (Green & Piquero, 1998). This study surveyed 499 police officers assigned to patrol (rank police officer, sergeant, or lieutenant)

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[17] Calls for service were also considered as a measure of officer workload. The use of this measure was not pursued for a number of reasons. First, numerous calls for service may exist for a single "event". For example, four people may call 911 to report a shooting. This would result in four records in the incident database. No reliable method of collapsing these records into a single event could be found. Second, calls for service in Philadelphia are not automatically geocoded by the Police Departments records management system. This means that millions of records would need to be geocoded manually- a process that would have taken an unreasonable amount of time.

[18] Special thanks to Dr. Matthew Hickman for providing these data.

as of January 2000 (population n = 3,810)[19]. Comparisons between demographic characteristics of the sample versus the population of officers showed no substantive differences between the two groups (Hickman, 2005; Hickman, Piquero, & Piquero, 2004). Individual values of officer cynicism were averaged based on the district in which they were assigned. The cynicism value of each district and the number of officers per district can be found in Table 8.

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[19] The following questions were used to assess officer cynicism. Responses to questions were coded as *strongly disagree* = 1, *disagree* = 2, *neutral* = 3, *agree* = 4, and *strongly agree* = 5.
(1) Police supervisors are very interested in their subordinates. (2) Disciplinary action is a result of pressure on supervisors from command staff to give out discipline. (3) Arrests are made because the police officer is dedicated to performing his/her duty. (4) The best arrests are made as a result of hard work and dedication to duty. (5) A college degree requirement for appointment to the police department would result in a much more efficient and effective police department. (6) When you get to know the department from the inside, you begin to think that it is a wonder that it does one-half as well as it does. (7) Police academy recruit training should be cut in half. (8) Professionalization of police work is already here for some groups of officers. (9) When a police officer appears before the Police Board of Inquiry, the officer will probably be found guilty even when he/she has a good defense. (10) Police officers are dedicated to the high ideals of police service and would not hesitate to perform police duty even though he/she may have to work overtime without extra pay. (11) The rules and regulations dealing with officer conduct off duty are fair and sensible. (12) The public is more likely to obstruct police work than cooperate. (13) Getting special assignments in the police department depends on who you know, not on merit. (14) When testifying in court, police officers are treated like criminals when they take the witness stand. (15) Police department citations for summary offenses are issued by police officers as part of a sensible pattern of law enforcement. (16) The public shows a lot of respect for the police. (17) Youth problems are best handled by officers who are trained as juvenile officers. (18) Police officers have a different view of human nature because of the misery and cruelty of life which they see everyday. (19) The newspapers generally try to help police departments by giving prominent coverage to items favorable to the police. (20) Detectives have special qualifications and are superior to patrol officers.

Table 8: Mean officer cynicism by district

District	Officers per district	Mean cynicism score	SD
1	18	62.22	7.53
2	26	54.58	7.57
3	32	60.72	7.58
4	20	60.00	7.83
5	20	59.50	7.11
6	38	62.74	6.44
7	17	57.00	5.81
8	20	57.85	6.56
9	21	60.43	6.26
12	24	61.38	9.24
14	25	57.60	7.64
15	19	58.42	6.87
16	16	59.75	8.05
17	19	57.42	7.73
18	31	58.71	6.69
19	30	55.87	9.55
22	23	59.35	7.48
23	17	59.35	6.86
24	15	60.20	6.94
25	16	60.88	9.36
26	15	59.33	6.28
35	18	54.00	6.02
39	19	60.63	6.56
Total	499	59.08	7.60

The use of survey data from a time outside of the main analysis time could create several limitations. This was necessary for the following two reasons. First, it was beyond the scope of this study to recreate the survey and data necessary to obtain these values. Second, the alternative to using this direct indictor of officer cynicism is to utilize a proxy variable. Having a direct indictor of one of Klinger's main theoretical constructs is better than utilizing a questionable proxy variable[20]. Although the use of data that was temporally dissociated from

[20] Klinger argues that, among other things, the relative presence of repeat offenders in an area can increase officer cynicism. He argues that repeat offenders represent failings of the criminal justice system and therefore lead to increased officer cynicism. Therefore using the number of parolees or probationers

the main variables in question was not ideal it still represented a substantial improvement over other more questionable proxy measures. For this reason, it is acknowledged that this variable represents a less than ideal, but arguably still acceptable, measure of officer cynicism. Figure 5 illustrates the spatial distribution of officer cynicism scores by district.

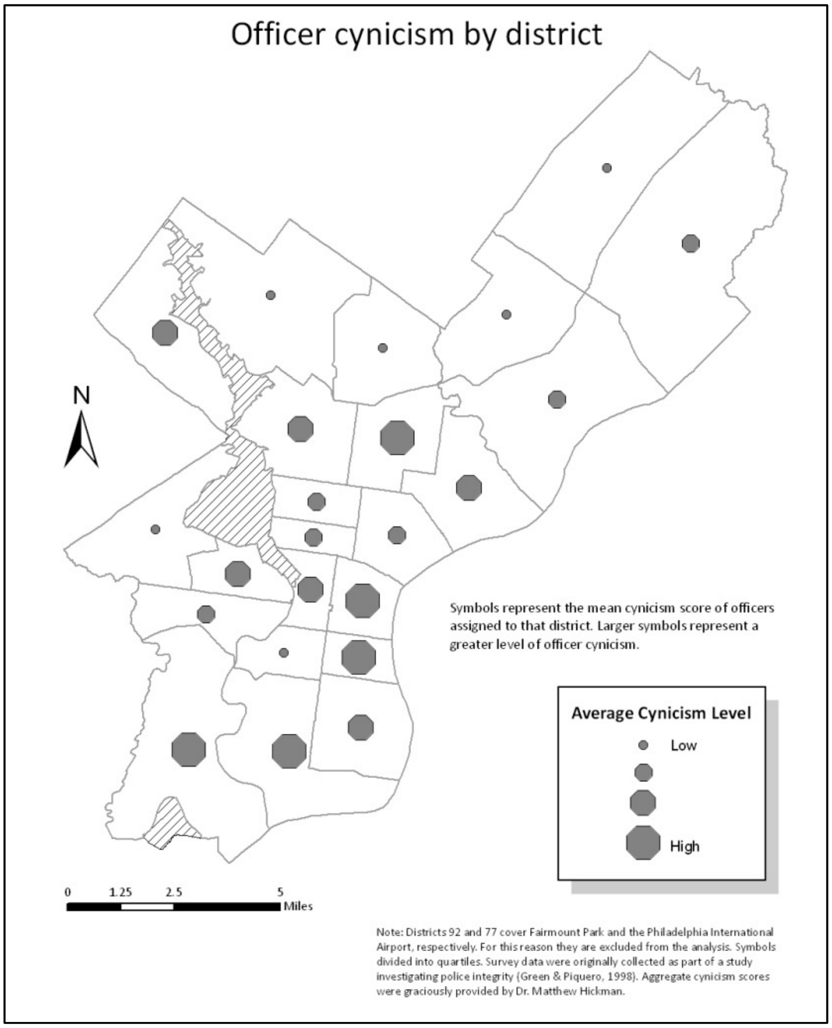

Figure 5: Spatial distribution of officer cynicism scores by district

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within an area may have been a functional proxy for cynicism. Nevertheless, there exists a rather large gap between the proxy and the outcome of interest which is why a true estimator of cynicism was used.

Officer staffing levels are critical to the relationship between vigor and crime for two reasons. First, the ecological theory argues that it is the relationship between crime and officer staffing levels, not the absolute values of either, that determines how vigorously officers respond to an incident. Second, because police strength has been linked theoretically and empirically to police effectiveness (Crank, 1990; Klick & Tararrok, 2005; Levitt, 1997, 2002; McCrary, 2002), higher levels of police presence may act as a deterrent to crime.

Officer staffing was measured with two variables: (1) the number of patrol officer-hours working within each district and (2) the number of officer overtime-hours working within each district. These measures were constructed from de-identified officer staffing records obtained directly from the Philadelphia Police Department. These data contained the work status (for example, if the officer was working, on vacation, or out sick) of every officer within the department. Data from the second Tuesday of every month during the study period was obtained. This day was selected because it represented an "average" day for the department that was free from overlapping shift schedules. The officer staffing on the second Tuesday of the month was used to represent the officer staffing level of each district for that specific month[21]. These measures of officer staffing were therefore time-variant and were included at level-1 of the longitudinal model. In the cross-sectional model, however, officer staffing must be measured at the district level (level-2) because the data lacked geographic identifiers necessary to allocate officer-hours to geographies smaller than the police district.

[21] Ideally data from every day in the month would have been obtained and averaged to make an average monthly officer staffing measure. Unfortunately the process to retrieve data from the personnel management system was extremely time intensive and doing so would have placed an unacceptable burden on the PPD employees responsible for querying the necessary data.

From this dataset it was possible to identify which officers were working on patrol and to which district they were assigned. The first step was to select only cases that were assigned to district specific units. Unfortunately, this variable was only able to provide information about the assigned district; no smaller geographic identifier that would have allowed imputation down to census block groups was available. Officers that were assigned to specific districts were then further parsed so that only officers assigned to patrol were selected. This excluded officers working in administrative or other non-patrol positions. After these cases were selected the number of hours each officer worked was calculated. These officer-hours were then aggregated by district to produce a district level measure of officer staffing.

While this measure of officer staffing captures the majority of patrol resources it does not address officers that may be working overtime or during times when they are not normally scheduled. In order to capture these officers a separate measure was constructed measuring the number of over-time hours officers were working in each district. One complication here was the difficulty in parsing out exactly why someone was receiving overtime. Overtime hours were calculated for activities that could be related to patrol but excluded hours earned for appearing in court or other non-patrol related capacity. The ability to clearly identify how officer overtime was being utilized may have had an unknown impact on the relationship between overtime hours and vigor, an issue addressed in the final chapter. Figure 6 illustrates city-wide trends for officer-hour and overtime-hour.

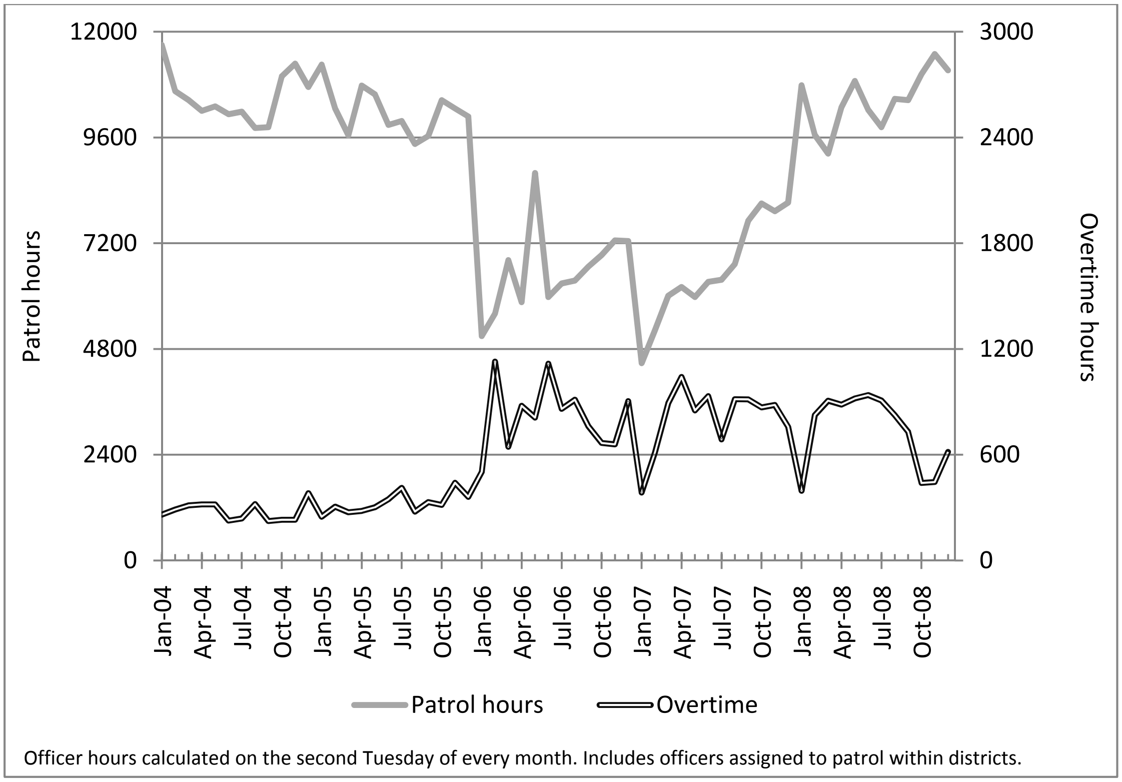

Figure 6: Officer-hour and overtime-hour trends

Several limitations to these measures must be kept in consideration. First, because the dataset is limited in geographic identifiers it was not possible to account for special units (such as the narcotics strike force or highway patrol) that are not assigned to a single district[22]. Second, the use of one day to represent each month's officer staffing level presents the possibility that things may change substantially day to day. Ideally each daily activity measure would be averaged over the entire month. Given the time consuming nature of requesting data

[22] Officers working in the strike force or highway patrol are assigned to divisions which are aggregated units of police districts. Unfortunately because these officers move freely between districts it was not possible to assign these officer hours to a single district. The potential importance of this limitation is explored more fully in the discussion section.

(a rather substantial imposition on the PPD) and the necessary data processing, this was not feasible within the study timeline.

Spatial Effects

Crime is an inherently spatial process (Griffiths & Chavez, 2004; Unwin & Unwin, 1998) and any analysis conducted must explicitly control for this spatial patterning or run the risk of false indicators of significance and biased parameter estimates (Anselin, 1999; Messner et al., 1999). Spatial effects for two levels of spatial resolution, block groups and police districts, were considered independently. Moran's I values for the dependent variables at the block group level (table 9) of aggregation demonstrated weak but significant spatial clustering.

Table 9: Global Moran's I values of dependent variables at the census block group level

Variable	Moran's I	Z
Unfounded 2004	0.18	48.49*
Unfounded 2005	0.16	43.18*
Unfounded 2006	0.22	60.15*
Unfounded 2007	0.27	73.51*
Unfounded 2008	0.29	79.48*
Unfounded 2004-2008 Average	0.21	58.39*
Low Seriousness Arrests 2004	0.27	75.40*
Low Seriousness Arrests 2005	0.25	70.69*
Low Seriousness Arrests 2006	0.22	61.80*
Low Seriousness Arrests 2007	0.27	74.72*
Low Seriousness Arrests 2008	0.22	59.55*
Low Seriousness Arrests 2004-2008 Average	0.27	74.39*
Traffic Stops 2004	0.05	15.81*
Traffic Stops 2005	0.06	16.92*
Traffic Stops 2006	0.07	18.90*
Traffic Stops 2007	0.06	18.57*
Traffic Stops 2008	0.05	14.95*
Traffic Stops 2004-2008 Average	0.06	16.05*

* $p < .01$

Note: Moran's I values calculated with a Euclidean based inverse distance weights matrix. The default neighborhood search threshold was calculated to be 7,475 feet (the minimum distance required to ensure that all census block groups had at least one neighbor).

The significant spatial autocorrelation found in the cross-sectional dependent variables was corrected through a two-stage least-squares spatial lag variable (Land & Deane, 1992). The method used to construct the spatial lag variable can be found in Appendix D. This variable captured the effect of two spatial processes. First, the spatial lag variable may have been representing a diffusion process whereby crime from one block group impacts crime levels in nearby block groups. This explanation would be consistent with a large body of literature suggesting a spatial diffusion process of crime and disorder (Cahill & Mulligan, 2007; Chainey & Ratcliffe, 2005; Cohen & Tita, 1999; Tita & Greenbaum, 2009). Second, this variable could be demonstrating the effects of other unmeasured processes that influence the vigor of police actions. For example, specialized police units operate around the city and are not constrained by district boundaries. Insofar as these officers generate unfounded events, low seriousness arrests, or traffic stops, or insofar as these officers are able to free up resources of officers on regular patrol duties they may have had an impact on the dependent variables that would be measured by the spatial lag variable.

Because of issues related to the modifiable areal unit problem (an issue that impacted a number of facets of the current study; see pages 74, 76, and 77), it was necessary to calculate separate measures of spatial association for police districts. Calculation of the measure of spatial association must be conducted on the monthly count of events in each district. Table 10 presents the Moran's I values of the dependent variables by month at the police district level.

Table 10: Global Moran's I values of dependent variables at the police district level

	Unfounded Events		LS Arrests		Traffic Stops	
	Moran's I	Z	Moran's I	Z	Moran's I	Z
January 2004	0.00	0.30	0.29	2.47*	0.33	2.78**
February 2004	0.06	0.77	0.33	3.04**	0.26	2.23*
March 2004	0.03	0.55	0.18	1.98*	0.25	2.16*
April 2004	0.10	1.06	0.23	2.18*	0.06	0.79
May 2004	0.11	1.11	0.34	2.94**	0.09	0.96
June 2004	0.08	0.89	0.30	2.74**	0.20	1.76
July 2004	0.05	0.70	0.18	1.77	0.09	1.00
August 2004	0.05	0.67	0.19	2.01*	0.14	1.34
September 2004	0.03	0.54	0.29	2.78**	0.14	1.33
October 2004	0.06	0.77	0.31	2.74**	0.12	1.16
November 2004	0.05	0.69	0.37	3.19**	0.15	1.44
December 2004	0.06	0.80	0.35	3.07**	0.19	1.69
January 2005	0.08	0.89	0.24	2.12*	0.21	1.87
February 2005	0.05	0.69	0.30	2.63**	0.19	1.69
March 2005	0.07	0.84	0.30	2.63**	0.17	1.56
April 2005	0.05	0.69	0.28	2.44*	0.20	1.77
May 2005	0.09	0.98	0.31	2.66**	0.12	1.18
June 2005	0.03	0.53	0.26	2.43*	0.20	1.76
July 2005	0.04	0.04	0.28	2.63**	0.33	2.74**
August 2005	0.08	0.27	0.24	2.25*	0.25	2.18*
September 2005	0.02	0.13	0.24	2.34*	0.36	3.02**
October 2005	0.02	0.43	0.26	2.52*	0.32	2.68**
November 2005	0.04	0.57	0.21	2.07*	0.21	1.86
December 2005	0.09	0.99	0.18	1.62	0.10	1.07
January 2006	0.08	0.90	0.20	1.80	0.17	1.57
February 2006	0.10	1.07	0.22	2.05*	0.11	1.16
March 2006	0.11	1.09	0.23	2.14*	0.12	1.17
April 2006	0.14	1.39	0.18	1.71	0.14	1.31
May 2006	0.18	1.68	0.17	1.60	0.13	1.28
June 2006	0.19	1.72	0.29	2.61**	0.21	1.84
July 2006	0.16	1.53	0.18	1.73	0.26	2.27*
August 2006	0.16	1.52	0.21	1.89	0.27	2.33*
September 2006	0.18	1.66	0.21	1.88	0.22	1.96*
October 2006	0.20	1.81	0.19	1.86	0.03	0.55
November 2006	0.15	1.46	0.22	2.08*	0.13	1.29
December 2006	0.13	1.31	0.24	2.18*	0.07	0.99
January 2007	0.16	1.53	0.14	1.49	0.09	0.98
February 2007	0.16	1.50	0.19	2.06*	0.17	1.63
March 2007	0.13	1.31	0.18	1.75	0.03	0.56
April 2007	0.09	1.01	0.13	1.41	0.12	1.20
May 2007	0.15	1.47	0.17	1.58	0.14	1.37
June 2007	0.21	1.92	0.22	2.04*	0.15	1.48
July 2007	0.20	1.79	0.21	1.90*	0.05	0.69

Table 10: Global Moran's I values of dependent variables at the police district level (cont.)

	Unfounded Events		LS Arrests		Traffic Stops	
	Moran's I	Z	Moran's I	Z	Moran's I	Z
August 2007	0.22	1.97*	0.29	2.54*	0.01	0.37
September 2007	0.23	2.00*	0.16	1.52	0.10	1.05
October 2007	0.24	2.15*	0.25	2.22*	0.07	0.80
November 2007	0.27	2.32*	0.21	1.93	0.01	0.24
December 2007	0.24	2.13*	0.29	2.63**	0.12	0.57
January 2008	0.25	2.21*	0.23	2.07*	0.02	0.18
February 2008	0.23	2.01*	0.21	1.93	0.05	0.04
March 2008	0.24	2.08*	0.28	2.46*	0.06	0.73
April 2008	0.23	2.01*	0.17	1.60	0.02	0.45
May 2008	0.25	2.15*	0.14	1.34	0.09	0.32
June 2008	0.22	1.93	0.09	0.94	0.09	0.98
July 2008	0.19	1.69	0.19	1.55	0.05	0.70
August 2008	0.19	1.69	0.12	1.17	0.06	0.79
September 2008	0.20	1.79	0.13	1.32	0.07	0.87
October 2008	0.22	1.98*	0.18	1.60	0.09	1.04
November 2008	0.23	2.02*	0.25	2.27*	0.05	0.68
December 2008	0.23	2.04*	0.27	2.37*	0.02	0.44

N = 25
* p < .05
** p < .01
Note: Moran's I values calculated with a Euclidean based inverse distance weights matrix. The default neighborhood search threshold was calculated to be 13,947 feet (the minimum distance required to ensure that all police districts had at least one neighbor).

The pattern of spatial clustering found in the longitudinal dataset was complicated by several factors. Generally Moran's I values were low and non-significant indicating that spatial clustering could be ignored without significantly biasing results or parameter estimates. However, these values changed over time and varied by outcome with low seriousness arrests showing the greatest number of months with significant spatial clustering.

The temporal patterning demonstrated by the spatial clustering raised numerous concerns regarding the most appropriate course of corrective action. In May 2009 a question was posted to two email listservs, the CRIMEMAP[23] listserv operated by the National Institute of

[23] The CRIMEMAP listserv has since been renamed "Geography and Crime" and can be found at http://groups.google.com/group/geography-and-crime.

Justice Crime Mapping Program and the Openspace[24] listserv, inquiring about the optimal method of controlling for spatial effects in longitudinal models. Two suggestions showed the most promise. One approach involved using a Bayesian analytic method that employed Markov chain Monte Carlo (MCMC) methods through the program WinBUGS (Lunn, Thomas, Best, & Spiegelhalter, 2000). This method was capable of simultaneously modeling both the spatial as well as the temporal trends found in these data. This method, while presenting several analytic advantages, was not adopted. The implications and limitations of this decision are discussed more fully in the final chapter of this work.

An alternative approach, and the one adopted for this analysis, used a three nearest neighbor spatial lag variable created using the spatial data analysis program GeoDa (Anselin, 2004). The three nearest neighbor approach creates a spatial lag value from the crime counts of the three police districts which are closest to the target district. A unique spatial lag variable was created for each month and each dependent variable. In order to prevent the artificial creation of isolated police districts all 25 districts were included in this calculation. This spatial lag variable was then entered into the statistical models discussed below.

Temporal Dissociation between Key Variables

As discussed previously the key dependent and independent variables come from a number of sources over a considerable period of time. This creates issues for both the cross-

[24] The Openspace listserv is described as "…a list to discuss all aspects of developing methods for spatial data analysis and their implementation in the form of open source software tools. It is a forum for support of spatial tools such as GeoDa, R-Geo, and PySAL." and can be found at http://groups.google.com/group/openspace-list. This list is dedicated to discussing issues at the cutting edge of spatial analysis and is monitored by some of the best researchers involved with spatial econometrics.

sectional as well as the longitudinal models which are fully discussed in the final chapter of this dissertation. Table 11 list the source and time periods of key dependent and independent variables.

Table 11: Source and time period of dependent and independent variables

Data	Source	Periodicity	Time period
Demographics	U.S. Census	Once	2000
Estimated demographics	GeoLytics	Yearly	2004-2008
Land use			
Zoning	City of Philadelphia	Once	2009
State liquor	Pennsylvania Liquor Control Board	Once	2005
Liquor / beer	Pennsylvania Liquor Control Board	Once	2005
Clubs	Pennsylvania Liquor Control Board	Once	2005
Pawn shops	Yellow pages; Online listings	Once	2005
Check cashing	Yellow pages; Online listings	Once	2005
Homeless	Yellow pages; Online listings	Once	2005
Drug treatment	Yellow pages; Online listings	Once	2005
Halfway houses	Yellow pages; Online listings	Once	2005
Regional rail stations	SEPTA website	Once	2005*
Subway	SEPTA website	Once	2005*
Bus route	SEPTA	Once	Fall 2008
Other			
Officer survey data	Hickman, Piquero, & Piquero, 2004	Once	2000
Officer staffing	Philadelphia Police Department	Monthly	2004-2008
Crime			
Incident data	Philadelphia Police Department	Monthly	2004-2008
Arrest data	Philadelphia Police Department	Monthly	2004-2008

* These locations did not change during the study period 2004-2008.

The ecological theory of policing suggests that a wide range of community demographic, environmental, and police organizational factors impact upon the level of vigor that officers expend. Table 12 specifies dependent and independent variables that capture the various dimensions of Klinger's theory.

Table 12: Specification of dependent and independent variables

Construct	Effect	Method to quantify
Vigor	*"…variation in the degree to which police officers extend their formal legal authority in encounters with citizens by making arrests, taking reports, conducting investigations…"* (p 279).	Unfounded events Arrests for low seriousness events Traffic stops
Normal crime	Officers in high crime areas see more crime; therefore they view more crimes as normal and not warranting a vigorous response.	Number of homicides (cross-sectional model) Number of more serious crimes (longitudinal model)
Deservedness of victims	Victims often bring crime upon themselves and many crime victims are themselves criminal. Higher crime districts have more victims that are also criminals. Officers believe that these people are worthy of less vigorous police responses. In high crime areas victims are seen as less worthy of vigorous police response.	Socio-economic status Median home value Median income % greater than high school education Stability % Living in same home 5 years previous % Owner occupied % people age 20-24 Race / Ethnicity % Households linguistically isolated % Population foreign born % Hispanic % African American
Police cynicism	Officers will come into contact with repeat offenders more frequently in high crime districts resulting in higher cynicism. Higher cynicism results in less vigor.	Survey data on officer cynicism
Workload	Higher workload leads to call prioritization; more incidents are pushed to lower level responses which is most pronounced in less serious offenses.	Number of officer hours assigned to patrol Number of overtime hours
Other	Officer safety Spatial dependency Land use and facilities	Assaults on police officers Spatial lag Commercial land use Alcohol establishments Check cashing / pawn shops Social services Mass transit
	Control variable	Population

Processing Spatial Data

Spatial data of various types and resolution were necessary for this analysis. The first step in using these data was to turn the records into electronic “points” – a process known as geocoding - that can be displayed on a map or spatially analyzed. A hit refers to a match between the address of the table file and a location with a known spatial extent. Therefore the hit rate refers to the percentage of incidents that can be assigned a spatial location. Under ideal circumstances all incidents would be accurately geocoded. This, however, is rarely the case when working with large administrative datasets. Match failure can result from a number of common issues including a lack of standardization in address format, user error (both from the people entering the original address and from the people responsible for the geocoding process), and electronic records that do not reflect real world conditions. Monte Carlo simulations of degrading hit rates suggests that match rates in excess of 85% are sufficient to provide reliable results (Ratcliffe, 2004). Incident level data were geocoded by the Philadelphia Police Department to a hit rate in excess of 97%. Arrest data (geocoded by the researcher) were matched to a level in excess of 97.7%. No obvious pattern was found among the cases that failed to match properly. This suggests that while there may be missing data it would not hinder further analyses.

Substantial efforts were undertaken to combine datasets that were originally collected at a variety of spatial resolutions and for a multitude of different uses. Three spatial join processes needed to be performed in order to combine these various data sources. First crime data, stored as point locations, needed to be aggregated to the block group level. Second, block groups needed to be joined with police districts. Third, monthly crime data needed to be joined to police districts.

The first spatial processing event was to join crime points to census block groups. This was necessary for the creation of both the dependent and independent variables in the cross-sectional models. A spatial join process was used to count the total number of events falling within each block group. In a small number of cases (0.05% - 0.20% depending upon event type) the event would fall exactly on the concordant boundary between two block groups. Two solutions to this problem were possible: (1) count the event twice, essentially allocating a single point to both geographies or (2) allow the system to allocate the point to only one of the geographies. The former approach was problematic because double counting an event creates issues with statistical techniques that assume independence of observations. The second approach was limited by the fact that incidents were allocated to the first census geography encountered by the system. Therefore, if multiple crime incidents occurred on the same spot that straddled a block group boundary all incidents would be allocated to the same block group. Additionally this allocation method was not random; the process systematically assigned the events to the first geography it encountered. Regardless of these limitations the second approach was adopted. While not ideal this method maintains the total number of events. Given the small number of cases impacted by this problem it was unlikely that the method of allocation would have any impact on the overall results.

The second spatial process involved determining the police district in which a block group was located. This was done through a process in a geographic information system called a spatial join. This spatial join was done based on the centroid, or geometric center, of the census block group. In general block group boundaries align with the district boundaries established by the PPD. In other words, census block groups generally nest cleanly within a single police district. However, a few census block groups (n = 77; 4.24%) span across multiple police districts. These census block groups were allocated using the same centroid method. While Philadelphia has 1,816 census block groups only 1,810 block groups are included in this analysis. The six block groups that were removed cover police districts 77 and 92, special operations districts providing police services for the Philadelphia International Airport and Fairmount Park, respectively. The lack of reliable population and demographic data found in these block groups combined with their unique role within the police department place them at odds with the main focus of this analysis. These districts perhaps represent an avenue for future research but their impact is not explored in the current study.

The final spatial operation performed involved joining crime data to the police districts. It was necessary to first separate out event data by month and then spatially join these monthly data to the police districts. This process needed to be done 60 times for each dependent and certain independent variables. This process yielded a file with monthly event counts aggregated to the police district level.

Analytical Plan

Two sets of census variables were used in this analysis: actual census values obtained in 2000 and postcensal estimates for the years 2004 – 2008. The estimated census dataset had a more limited selection of variables available than what could be found in the 2000 dataset. Given the limitations to census estimates and the difficulties inherent in working with multiple years of data, data reduction techniques were performed on the original data from the 2000 census. The closest corollaries to these variables were then selected from the estimated census data.

Principal components analysis with varimax rotation (results omitted) was performed on numerous census variables (drawn from the 2000 census) in order to explore the independent dimensions of demographic variables at the census block group level[25]. Three conceptually distinct dimensions emerged: socio-economic status, race and ethnicity, and stability. All scales were created by z-scoring and mean averaging the individual variables. These scales were created at both the census block group level and the police district level (using areally weighted census data; see Appendix C).

The socio-economic status index was comprised of median household income, median home value, and the percent of people with greater than a high school diploma (Cronbach's alpha: block groups = 0.79; police districts = 0.94). The ethnicity index was comprised of the

[25] The census block group was selected over the police district as the primary spatial unit for data reduction techniques. This was done for a number of reasons. First, block groups were more homogeneous spatial units than police districts. Therefore relationships that existed at the block group level were likely to persist at the district level. This helped to ensure suitably high reliability ratings for scales created at multiple levels of aggregation. From a more pragmatic perspective, creating areally weighted census data for the districts is extremely time consuming. Attempting to do so with dozens of potentially relevant variables would have been a near futile task.

percent of households linguistically isolated, the percent of the population foreign born, and the percent of the population that was Hispanic (Cronbach's alpha: block groups = 0.66; police districts = 0.74). The stability index was comprised of the percent of people living in the same house five years previously, the percent of housing units that were owner occupied, and the reverse coded percent of the population between the ages of 20 and 24 (Cronbach's alpha: block groups = 0.71; police districts = 0.88). One other census variables, the percent African American was also included in the analysis. Variance inflation factors and tolerance values were within acceptable levels at both the census block group level (VIF < 1.6; tolerance > 0.6) and the police district level (VIF < 2.0; tolerance > 0.49).

These variable and scales, of course, only apply to data derived directly from the 2000 U.S. census. Ideally the variables from the 2000 census would have been replicated with estimated data for the intervening years. Unfortunately, due to limitations of the estimated dataset this was not possible. Several variables in the 2000 census were not available in the postcensal estimates. The following variables were available in the estimated dataset: percent of people age 20-24, the percent African American, the percent Hispanic, the percent owner occupied, the percent of people with greater than high school education, and median household income. The education and income variables were z-scored and mean averaged to create a socio-economic scale (Cronbach's alpha: 2004 = 0.710; 2005 = 0.712; 2006 = 0.711; 2007 = 0.710; 2008 = 0.708). Variance inflation factor and tolerance values were within acceptable levels at the census block group level for all years (VIF < 1.5; tolerance > 0.60). Areally weighted estimated census data for the police district produced similarly acceptable VIF and tolerance values (VIF < 4.5; tolerance > 0.22).

Exploratory spatial data analysis (ESDA) was utilized to investigate the spatial distribution of the outcome measures. Both global measures (Moran's I; presented above in Table 9 and Table 10) and local measures (local indicators of spatial association, LISA; presented in the following chapter) were used to identify significant clusters of high and low vigor activity (Anselin, 1999; Anselin, Cohen, Cook, Gorr, & Tita, 2000; Cliff & Ord, 1973; Cohen & Tita, 1999).

This study was conducted with two separate analyses: a cross-sectional multi-level non-linear model (MLM) and a repeated-measures MLM design (Laird & Ware, 1982; Raudenbush & Bryk, 2002; Snijders & Bosker, 1999). This methodology had a number of benefits. MLM allowed for the investigation of both cross-sectional differences and longitudinal changes while respecting the district as the appropriate ecological unit of analysis. Using both a cross-sectional model and a repeated measures model provided the opportunity to investigate the relationship between district crime and vigor in conceptually distinct ways.

For the cross-sectional analysis the level-1 unit of analysis were census block group (n = 1,810). The level-2 unit of analysis was the police district (n = 23). Two sets of cross-sectional analyses were performed. The first set of cross-sectional analyses was performed on crime data for one year periods from 2004 through 2008. Structuring analyses in such a way allowed for comparisons across the five years of data. The use of multiple yearly cross-sectional models works as a test-retest reliability assessment of the findings. Consistency of findings across years helped to bolster confidence in the results. Estimated census data for the temporal period corresponding to the crime data were used as controls over local demographic characteristics.

The second set of cross-sectional analyses were performed using crime data averaged over the five year period, 2004 through 2008. This model was useful because it was less sensitive to transient crime reduction initiatives that are periodically and irregularly implemented by the police department. For example, in the summer of 2008 the Philadelphia Police Department implemented a program that placed officers on foot patrol in high crime areas in several districts. Operations like these have the potential to impact the relationship between workload and vigor towards minor crimes. The use of data averaged over five years helped to ameliorate the effects of these short-term programs. Finding consistent results across the five individual model years and the five year averaged model helped to bolster confidence in findings. The five year averaged models used actual census data from the 2000 U.S. Census.

Longitudinal models were employed to investigate the relationship between changing crime trends and their impact upon officer vigor. In this set of analyses the level-1 unit was months. This level of analysis included time varying covariates such as the district level homicide count and the availability of police resources. This analysis was conducted on five years (2004 through 2008) of monthly (n = 60) crime data. The level-2 unit of analysis was police districts (n=23).

The use of longitudinal models, however, did not fully clarify the relationship between time-varying predictors and the outcome of interest. The relationship between these variables may still suffer from reciprocal causation or endogeneity (Singer & Willet, 2003). For example, it was not possible to determine if the district workload was temporally prior to the level of vigor or if the level of vigor was temporally prior to the district workload. Further clarification of the temporal relationship between vigor and workload was accomplished by constructing both contemporary and time-lagged models within the longitudinal framework.

Contemporary and time-lagged models represent functional differences between the dependent and independent variables. The contemporary model evaluates instant causality[26] where "elements in the system react without any measurable time delay to changes in some other elements" (Cromwell et al., 1994: 32). In the contemporary models all variables were from the same time period so that $vigor_t$ was compared to $workload_t$. Lagged models, on the other hand, predict some meaningful time delay between the independent variable and its impact on the dependent variable. In these models, the independent variables were lagged *n* time units compared to the dependent variable so that $vigor_t$ was compared to $workload_{t-n}$ (StataCorp, 2005). The effects of a one and two month time lag were explored. A one and two month time lag provided enough time for the police to identify changing crime trends and implement appropriate changes to work patterns, formally or informally.

For both the cross-sectional and repeated measures models all three dependent variables were considered providing three separate parallel analyses. Conducting multiple statistical tests on correlated dependent variables has long been recognized as problematic (Holm, 1979; Rice, 1989). Increasing the number of statistical tests raises the possibility of incorrectly rejecting the null hypothesis (Type I error). One common approach to this issue is to adjust the alpha level at which we would call a variable significant. This method of controlling for alpha inflation has been criticized as overly conservative and was not adopted. A complete discussion about the impact of adjusting alpha levels can be found in Appendix E.

[26] Causality as employed here refers to the definition established by Granger (1969). *Granger-causality* has been summarized as "variable *x(t)* Granger-causes another variable *y(t)*, if given information of both *x(t)* and *y(t)* , the variable *y(t)* can be better predicted in the mean square error sense by using only past values of *x(t)* than by not doing so" (Cromwell, Hannan, Labys, & Terraza, 1994: 32). This definition of causality speaks more to the temporal ordering of the relationship between variables and has less to do with cause and effect.

All multi-level models were specified so that the predictor variables were group mean centered (subtracting the level-2 mean value from the level-1 value). Group mean centering all level-1 predictors had different implications in the cross-sectional and longitudinal models. Broadly, the cross-sectional models address the following question: does the vigor of police action vary by a spatial unit smaller than the police district. By group mean centering all level-1 predictors this question essentially became: does the vigor of police action vary *within* a district. The cross-sectional models investigated the spatial variation of vigor and operationalized the district as a potentially differentiated surface over which vigor could vary. Group mean centering within the longitudinal models produced a slightly different effect. The longitudinal models were conducted to investigate the temporally dynamic trends of officer vigor. By group mean centering the independent variables the models are really investigating the change in officer vigor *within each district* over time. Group mean centering in the longitudinal models allowed for investigating changing dynamics within the district.

Investigating the power of an analytical plan is useful in assessing the likelihood of finding statistically significant results. Power, in multi-level modeling, is sensitive to four factors: (1) the number of level-1 and level-2 units, (2) the effect size, (3) the alpha level, and (4) the intraclass correlation coefficient (ICC) (Raudenbush, 1997; Raudenbush & Liu, 2000; Spybrook, Raudenbush, Liu, Congdon, & Martinez, 2008). A priori analysis of power was conducted using Optimal Design for Multi-level and Longitudinal Research (Version 1.77) (Liu, Spybrook, Congdon, Martinez, & Raudenbush, 2006). Separate power analyses were conducted for the cross-sectional and longitudinal models.

A number of compromises and assumptions regarding parameter selection were made for this analysis. First, in the cross-sectional model, although the number of level-1 units per level-2 units varies from 41 to 158, power was calculated using the mean number (n = 79) of census block groups per police district. This fluctuation in the number of level-1 units should not pose a problem to estimating power (Snijders & Bosker, 1993). The number of level-1 units in the longitudinal model was consistent across all level-2 units (n = 60). Second, consistent with Cohen (1992), effect sizes (Cohen's *d*) of 0.20, 0.50, and 0.80 were selected to represent small, medium, and large effects, respectively. Third, notwithstanding the discussion of alpha correction found in Appendix E, an alpha level of 0.05 was adopted. Fourth, following Raudenbush and Liu (2000), ICC values of 0.05, 0.10, and 0.15 were adopted to represent small, medium, and large variances, respectively.

Utilizing these assumptions about effect size, alpha levels, and ICC values, it was found that power was adequate (greater than 0.80) in the cross-sectional models when effect size was medium or large regardless of variance size. When effect size was small, power remained below 0.50 regardless of variance size. Power for the longitudinal model was found to be similarly acceptable under large and medium effect sizes. These results indicate that power was adequate to find statistically significant results for some effect sizes.

CHAPTER 4:

RESULTS

This section covers, in order, univariate statistics separated by time invariant / time variant variables, spatial statistics, results from the cross-sectional models, and results from the longitudinal models. This section begins with a univariate description of the data.

Univariate Statistics

For clarity, variables were separated into time-varying and time invariant variables. Time invariant variables (those that do not vary over time during the study period) are discussed first. Univariate statistics for time invariant variables can be found in Table 13.

Table 13: Univariate statistics for time invariant variables

Variable	Geographic Unit	Mean	Median	Min	Max	SD
Controls						
Area[1]	Census BG	2.06	1.02	0.17	84.44	4.43
	Police District	164.55	144.60	38.90	474.21	115.36
Population[†]	Census BG	838.24	759.00	0.00	4012.00	518.20
	Police District	65,896.80	63,547.55	25,266.36	124,705.82	30,174.69
Police organizational						
Officer cynicism	Census BG	---	---	---	---	---
	Police District	59.04	59.35	54.00	62.74	2.23
Demographics						
Socio-economic status[2, †]	Census BG (n = 1,781)	0.02	-0.06	-2.33	8.47	0.83
	Police District	0.00	-0.09	-1.24	1.88	0.94
Ethnicity[3, †]	Census BG (n = 1,772)	0.00	-0.29	-0.65	5.70	0.77
	Police District	0.00	-0.31	-1.00	1.98	0.81
Percent African American						
Stability[4, †]	Census BG (n = 1,772)	0.01	0.15	-6.36	1.66	0.78
	Police District	0.00	0.17	-2.33	1.01	0.90
Land use						
% Commercial land use	Census BG	9.14	4.80	0.00	72.00	12.19
	Police District	9.66	7.62	3.25	29.61	6.58
% Rail	Census BG	0.69	0.00	0.00	42.88	3.75
	Police District	0.59	0.44	0.00	2.62	0.66
% Subway	Census BG	1.29	0.00	0.00	63.03	5.47
	Police District	1.22	0.84	0.00	6.63	1.50
Length of bus route[5]	Census BG	0.22	0.20	0.00	0.71	0.15
	Police District	0.20	0.18	0.09	0.43	0.09
% Club	Census BG	4.29	0.00	0.00	100.00	11.98
	Police District	3.35	2.08	0.78	9.60	2.65
% Liquor / beer eating	Census BG	27.96	19.85	0.00	100.00	27.73
	Police District	21.59	16.02	3.55	55.21	14.31
% State liquor	Census BG	1.12	0.00	0.00	60.47	5.15
	Police District	0.61	0.35	0.00	2.18	0.67
% Pawn shop	Census BG	0.74	0.00	0.00	62.04	4.58
	Police District	0.61	0.35	0.00	2.18	0.67
% Check cashing	Census BG	2.08	0.00	0.00	77.12	7.75
	Police District	2.02	1.15	0.00	8.33	2.45
% Homeless shelter	Census BG	1.28	0.00	0.00	98.73	6.75
	Police District	1.00	0.42	0.00	5.22	1.39

Table 13: Univariate statistics for time invariant variables (cont.)

Variable	Geographic Unit	Mean	Median	Min	Max	SD
Land use (cont.)						
% Halfway house	Census BG	1.19	0.00	0.00	90.01	7.01
	Police District	0.96	0.41	0.00	4.85	1.39
% Drug treatment	Census BG	0.80	0.00	0.00	58.72	4.63
	Police District	0.67	0.35	0.00	3.67	0.90

Census block groups: N = 1,810 (unless otherwise noted)
Police districts: N = 23 (excluding districts 77 and 92)
† From 2000 census data

1. Million sq./ft.
2. Socio-economic status index was comprised of median household income, median home value, and the percent of people with greater than a high school diploma (Cronbach's alpha: block groups = 0.79, police districts = 0.94). Values for each variable were z-scored and averaged.
3. The ethnicity index was comprised of the percent of households linguistically isolated, the percent of the population foreign born, the percent of the population that is Hispanic (Cronbach's alpha: block groups = 0.66, police districts = 0.74). Values for each variable were z-scored and averaged.
4. The stability index was comprised of the percent of people living in the same house five years previously, the percent of housing units that were owner occupied, and the reverse coded percent of the population between the ages of 20 and 24 (Cronbach's alpha: block groups = 0.71, police districts = 0.88). Values for each variable were z-scored and averaged.
5. Length of bus route within the geography normalized by area

The average residential population of a census block group during the 2000 census was 838. The average residential population at the police district level (using areally weighted 2000 census data) was nearly 66,000. The most frequent land use was eating establishments that serve liquor and beer. On average, a buffer generated from this facility type covered nearly 28% of the land of a census block group. A large standard deviation on this variable (and most other land uses) suggests that the distribution of these facilities is not equal throughout the city.

The cross-sectional and longitudinal models also take advantage of crime data, police records, and estimated census data from the years 2004 through 2008. Univariate values for the estimated census data show relatively small changes over time and can be found in Table 14.

Table 14: Univariate statistics for time-varying variables (cross-sectional models)

	2004					2005					2006				
	Mean	Median	SD	Min	Max	Mean	Median	SD	Min	Max	Mean	Median	SD	Min	Max
Dependent variables															
Unfounded events	210.65	172	159.65	3	1329	188.56	151.50	145.46	1	1207	177.24	140	146.84	2	1280
Low seriousness arrests	25.19	13	42.09	0	762	24.22	14	38.28	0	716	24.97	13	41.19	0	798
Traffic stops	161.79	120	149.39	2	1863	184.32	134	178.20	3	2586	178.22	130	167.34	2	2161
Independent variables															
Serious incidents	49.86	41.00	42.85	0	615	49.67	40	42.99	0	662	51.00	41	45.00	0	703
Homicides	0.23	0	0.51	0	3	0.24	0	0.55	0	7	0.26	0	0.56	0	4
Officer assaults	0.17	0	0.51	0	5	0.17	0	0.58	1	10	0.16	0	0.55	0	7
Officer hours†	457:35	465:35	96:59	270:36	624:19	442:56	447:30	102:03	274:59	623:20	285:53	263:19	70:56	190:08	408:14
Overtime hours†	14:20	11:39	9:16	4:01	44:18	15:33	12:48	9:21	5:43	38:10	35:41	34:14	8:16	22:08	54:01
Unfounded lag[1]	0.00	0.17	1.00	-5.08	2.21	0.00	0.18	1.00	-4.97	2.23	0.00	0.16	1.00	-4.69	2.35
LS arrest lag[1]	0.00	-0.04	1.00	-3.80	2.91	0.00	0.01	1.00	-4.08	2.81	0.00	0.02	1.00	-4.14	2.78
Traffic stop lag[1]	0.00	0.04	1.00	-4.22	2.59	0.00	0.03	1.00	-4.33	2.55	0.00	0.05	1.00	-4.38	2.48
Population	809.52	728.50	516.84	0	3938	804.48	724.50	513.18	0	3915	800.09	718.00	511.38	0.00	3899
% Age 20 – 24 (N = 1,783)	0.07	0.07	0.03	0.00	0.37	0.07	0.07	0.03	0.00	0.35	0.07	0.07	0.03	0.00	0.32
% Af. Am. (N = 1,783)	0.50	0.43	0.40	0.00	1.00	0.50	0.44	0.40	0.00	1.00	0.50	0.44	0.39	0.00	1.00
% Hispanic (N = 1,783)	0.09	0.03	0.17	0.00	1.00	0.10	0.03	0.18	0.00	1.00	0.10	0.03	0.18	0.00	1.00
% Owner occupied (N = 1,772)	0.60	0.64	0.23	0	1.00	0.60	0.64	0.23	0.00	1.00	0.60	0.64	0.23	0.00	1.00
SES[2] (N = 1,776)	0.01	-0.12	0.86	-1.78	6.52	0.01	-0.12	0.86	-1.79	6.54	0.01	-0.12	0.86	-1.79	6.54

Unit of analysis is census block groups (N = 1,810) unless noted otherwise.
Demographic variables based on yearly estimates (see Appendix B).
1. Lag variables created by saving the standardized residual values of an OLS regression (see Appendix D, page 241 for further details).
2. SES scale comprised of z-scored and averaged median household income and the percent with greater than high school education.
† Officer hours and over time hours calculated at the police district level.

Table 14: Univariate statistics for time-varying variables (cross-sectional models (cont.))

	2007					2008					Five Year Average				
	Mean	Median	SD	Min	Max	Mean	Median	SD	Min	Max	Mean	Median	SD	Min	Max
Dependent variables															
Unfounded events	167.21	129	141.06	1	1158	171.41	134	145.40	2	1183	183.01	146.80	140.23	2.80	1053.40
Low seriousness arrests	27.40	15	43.46	0	698	26.53	14	42.69	0	593	25.66	14.90	39.24	0	685.40
Traffic stops	178.22	130	167.34	2	2161	218.48	155	210.96	3	2114	182.56	135.60	165.28	4.80	1968
Independent variables															
Serious incidents	49.33	40	46.29	0	770	48.45	40	46.29	1	722	49.67	40.20	43.13	3	686.20
Homicides	0.26	0	0.56	0	5	0.22	0	0.51	0	4	0.24	0.20	0.30	0	2.40
Officer assaults	0.19	0	0.65	0	15	0.22	0	0.65	0	7	0.18	0	0.34	0	7.60
Officer hours†	286:55	264:30	65:04	211:17	399:07	454:41	469:30	103:40	278:20	674:26	385:36	375:48	79:30	249:53	490:46
Overtime hours†	35:18	34:00	7:14	21:32	49:19	33:08	30:48	14:40	14:10	76:33	26:48	24:55	5:35	18:05	38:19
Unfounded lag[1]	0.00	0.07	1.00	-4.38	2.43	0.00	0.03	1.00	-4.35	2.58	0.00	0.12	1.00	-4.72	2.58
LS arrest lag[1]	0.00	0.03	1.00	-4.14	2.87	0.00	0.05	1.00	-4.37	2.80	0.00	0.02	1.00	-4.10	2.81
Traffic stop lag[1]	0.00	0.12	1.00	-4.44	2.66	0.00	0.16	1.00	-4.71	2.80	0.00	0.08	1.00	-4.43	2.59
Population	794.89	713.50	508.82	0.00	3862	790.14	710.00	506.57	0.00	3824	---	---	---	---	---
% Age 20 – 24 (N = 1,783)	0.07	0.07	0.02	0.00	0.29	0.07	0.07	0.02	0.00	0.25	---	---	---	---	---
% Af. Am. (N = 1,783)	0.50	0.44	0.40	0.00	1.00	0.50	0.45	0.40	0.00	1.00	---	---	---	---	---
% Hispanic (N = 1,783)	0.10	0.03	0.18	0.00	1.00	0.10	0.03	0.18	0.00	1.00	---	---	---	---	---
% Owner occupied (N = 1,772)	0.60	0.64	0.23	0.00	1.00	0.60	0.64	0.23	0.00	1.00	---	---	---	---	---
SES[2] (N = 1,776)	0.01	-0.12	0.86	-1.79	6.52	0.01	-0.12	0.86	-1.78	6.49	---	---	---	---	---

Unit of analysis is census block groups (N = 1,810) unless noted otherwise.

Demographic variables based on yearly estimates (see Appendix B).

1. Lag variables created by saving the standardized residual values of an OLS regression (see Appendix D, page 241 for further details).

2. SES scale comprised of z-scored and averaged median household income and the percent with greater than high school education.

† Officer hours and over time hours calculated at the police district level.

Unfounded events and traffic stops showed a steady decline from the start of the study period through 2007, with a slight uptick in 2008. Low seriousness arrests appeared to be relatively stable during the study period. The number of serious incidents also appeared to be stable during this time. Demographic variables constructed from postcensal estimates appeared to be relatively stable during the study period as well. The estimates also indicated that there was a steady decline in the average block group population from 2004 through 2008. Figure 7 illustrates the temporal trends of the outcome variables.

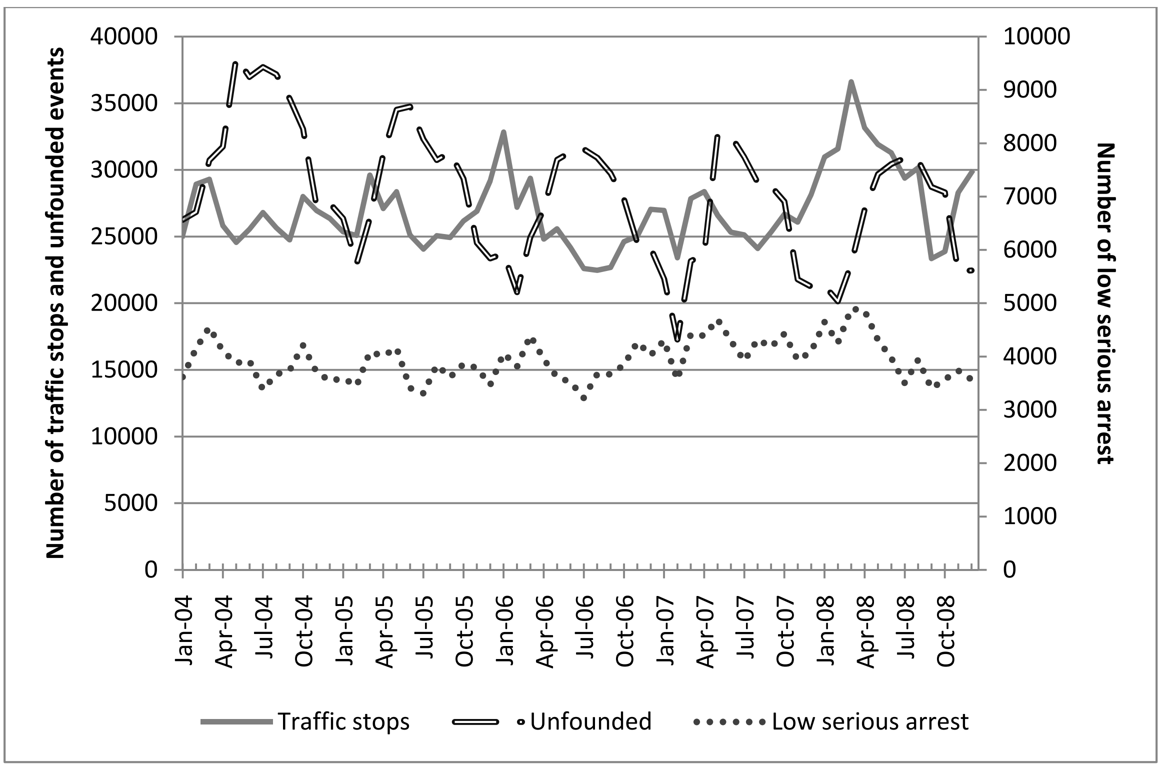

Figure 7: Citywide temporal trends of dependent variables by month

Unfounded events, low seriousness arrests, and traffic stops appeared to follow different temporal trends. Unfounded events demonstrated clear patterns of seasonality with the greatest volume of events peaking during summer months. The volume of arrest for low seriousness events was more stable during the study period and showed less dramatic seasonal trends. Traffic stops, by contrast, peaked during periods of low unfounded events. This suggests, perhaps, that officers were conducting traffic stops when not occupied by responding to calls for service. These temporal trends were more fully explored with the longitudinal models. Table 15 presents descriptive statistics for the monthly outcome variables.

Table 15: Descriptive statistics for monthly varying variables

	Mean	Median	Std. Deviation	Variance	Skewness	Minimum	Maximum
Unfounded Events	1,219.04	1066	690.44	476,711.60	1.08	63	4,059
Low Seriousness Arrests	171.26	144	127.70	16,307.69	1.686	15	847
Traffic Stops	1,133.27	1064	445.23	198,230.25	0.91	334	3,671
Serious Incidents	328.22	324	133.29	17,765.43	0.34	71	803
Officer Assaults	1.22	1	133.29	2.70	2.06	0	10
Patrol Hours	411:01	408:06	20:53	13,944.52	0.22	155:45	753:30
Overtime Hours	26:13	23:00	20:53	436.22	1.11	0:00	166:39

N = 1,380

On average there were 1,219 unfounded events, 171 low seriousness arrests, and 1,133 traffic stops per district per month during the study period. For all three outcome variables, in both the cross-sectional and the longitudinal models, the variance is greater than two times the mean indicating that models would be most appropriately specified as Poisson with overdispersion. Figure 8 displays the frequency distributions for the outcome variables in the longitudinal models.

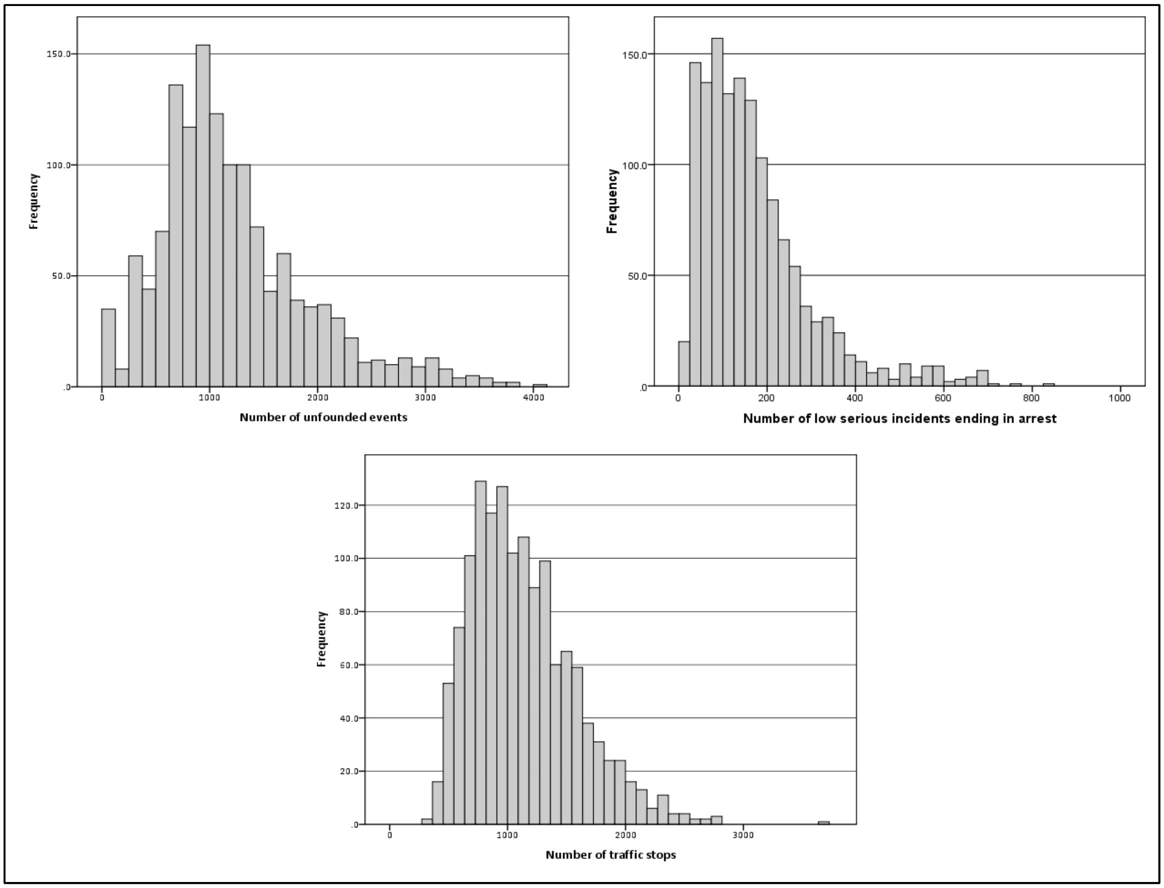

Figure 8: Histogram of unfounded events, low seriousness arrests, and traffic stops by month

Spatial Statistics

Measures of global spatial association (Table 9, above) indicated that, at the block group level, the dependent variables (unfounded events, arrests for low seriousness incidents, and traffic stops) demonstrated weak but significant spatial clustering. Indicators of global spatial clustering at the police district level (Table 10, above) were not as clear. The significance of the clustering varied by both the dependent variable and by the time period under consideration.

Spatial clustering in the cross-sectional modals was also explored through a univariate local indicator of spatial association (LISA) analysis. Unlike the global measures of spatial clustering presented earlier, LISA analysis looks for clustering of similar values in smaller areas throughout the city. All clusters shown were significant at $p < .05$ (based on 999 permutations). For visual clarity clusters of high areas surrounded by low areas, low areas surrounded by high areas, and non-significant clusters have been omitted from display. This analysis was conducted on the count values averaged over the 5 year study period (2004-2008). Figure 9 presents the LISA results for unfounded events.

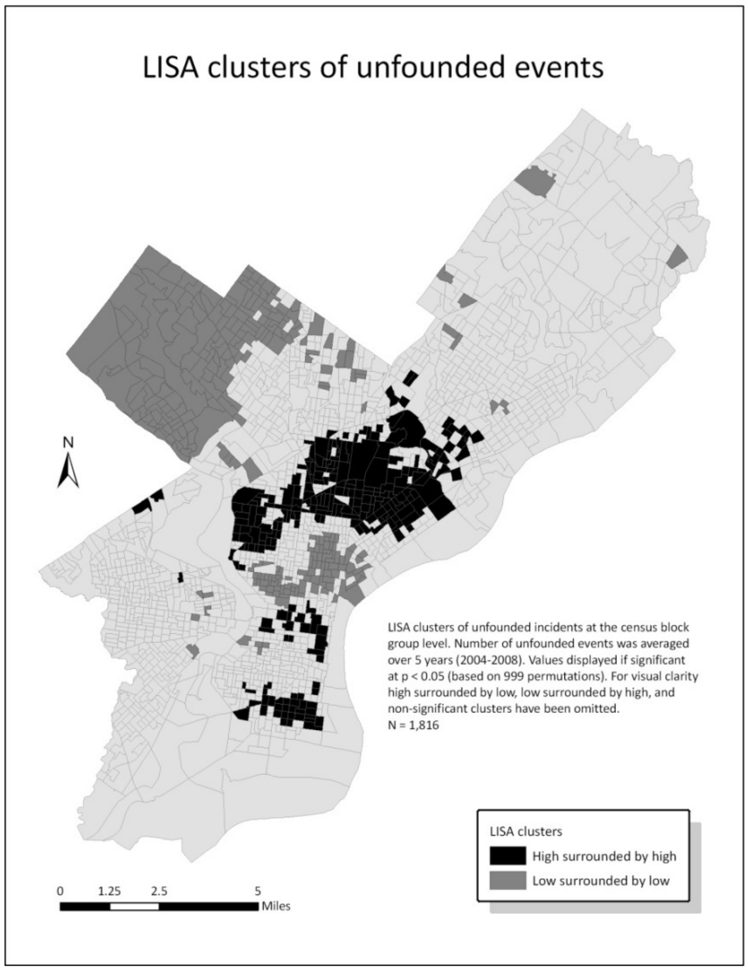

Figure 9: LISA map of unfounded incidents

LISA values indicated high levels of unfounded events clustered (high-high) in North Philadelphia with smaller clusters located in the south. Significant low-low clusters could be found in the northwest section (Chestnut Hill, Mt. Airy, Manayunk, and Roxborough regions) of Philadelphia along with a smaller clusters located near Center City (the central business district of Philadelphia). Figure 10 displays the LISA results for low seriousness arrests.

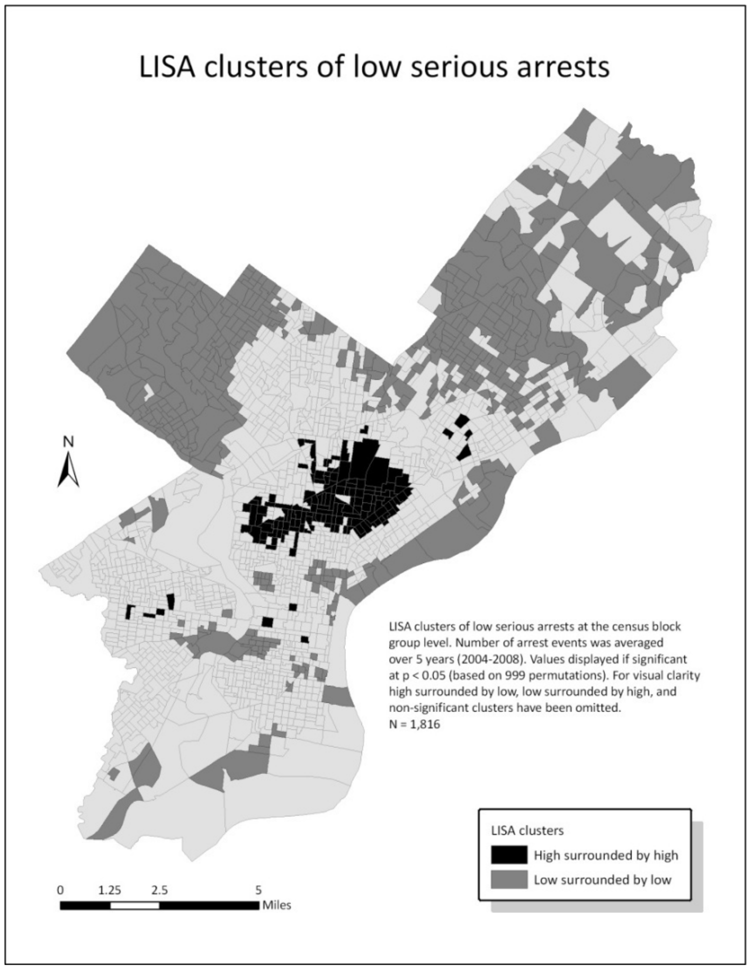

Figure 10: LISA map of low seriousness arrests

Clustering patterns were similar between unfounded events and arrests for low seriousness crimes. Strong clustering of high-high block groups was found in North Philadelphia.

City center, found to be a location of high-high clustering of unfounded events, was largely non-significant when considering arrests for low seriousness events. Low-low clusters persist through the northwest sections of the city with additional low-low clustering exhibiting itself throughout much of Northeast Philadelphia. Figure 11 illustrates the LISA results for traffic stops.

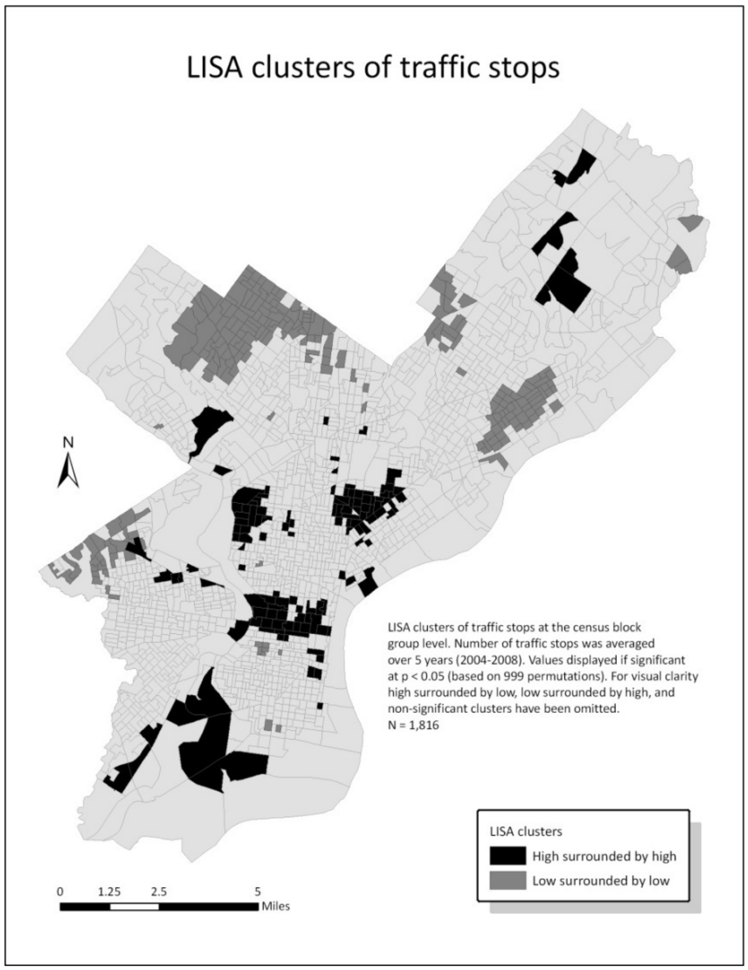

Figure 11: LISA map of traffic stops

Clustering patterns of traffic stops were noticeably different than the pattern demonstrated by either unfounded events or low seriousness arrests. High-high clustering was found in numerous sections of the city. The figure also indicates that clusters in North

Philadelphia were not as dramatic as found for the other outcome measures. Furthermore, areas of low-low clusters covered a much smaller area of the city. In comparison to the other events under consideration it would appear that traffic stops exhibited a much more diffuse spatial pattern. While there were some similar high-high areas between traffic stops and unfounded events and traffic stops and low seriousness arrest locations it was clear that traffic stops were occurring throughout much of the city. These patterns suggested that the three outcome variables may have been driven by distinct organizational or environmental characteristics. The potential processes driving these differences were explored in greater detail in the cross-sectional and longitudinal models. These different spatial patterns have implications for the construct validity of operationalizing vigor through different measures and may suggest that vigor was a multi-dimensional construct. This issue is addressed in further detail in the following chapter.

Cross-Sectional Models

Six cross-sectional models were conducted to investigate the impact of workload, demographics, and land use upon officer vigor. This model building process was undertaken so that it would be possible to monitor changes in the strength, direction, and significance of independent variables under different model specifications. Model 1 was an ANOVA model and explores the variance within and between districts. Model 2 added population and spatial lag variables. Model 3 added the workload variables (operationalized as the number of homicides and the number of officer assaults). Model 4 added demographic data to the previously entered workload, population, and spatial effects variables. Model 5 built upon model 4 by adding land use indicators. Model 6 substituted serious incidents in place of the homicide variable. The level of serious incidents served as an alternative indicator of officer workload that was consistent with the operationalization of the workload construct in the longitudinal models.

A separate series of models were also specified using crime data from a single year beginning with 2004 and concluding with 2008. These models used estimated census data corresponding to the year of the crime data. These models helped to assess the stability of the relationship between demographics and land use over time.

All variables entered into the models were group mean centered. This forces all level-1 variables to explain only variations within a district; they do not attempt to account for variance between the districts. The cross-sectional models, therefore, only investigate how sub-district variation in workload, spatial effects, demographic, and land use effect patterns of unfounding events, arresting for low seriousness offenses, and conducting traffic stops. Assessments of model fit were undertaken and can be found in Appendix F.

Cross-sectional Models of Unfounded Events

Table 16 presents the results of a two-level multilevel regression analysis of the count of unfounded events averaged over the five year study period. Parameter estimates of the final full model specification are discussed unless noteworthy differences were found in the model building process.

Table 16: Cross-sectional analyses of unfounded events (five year average)

	Model 1			Model 2		
Fixed effects	Coefficient (S.E.)	Event rate ratio	Confidence interval	Coefficient (S.E.)	Event rate ratio	Confidence interval
Intercept	5.161900*** (0.083608)	174.495633	146.752 - 207.484	5.121384***(0.084476)	167.567148	140.672 - 199.604
Spatial lag[1]				0.234817***(0.026666)	1.264678	1.200 - 1.333
Population				0.000523***(0.000028)	1.000523	1.000 - 1.001
Homicide						
Serious incidents						
Officer assaults						
SES[2]						
Stability[3]						
Ethnicity[4]						
% Af. Am.						
% Commercial						
% State Liquor						
% Liquor						
% Club						
% Pawn						
% Check cashing						
% Homeless shelter						
% Drug treatment						
% Halfway house						
% Rail						
% Subway						
Bus[5]						
Random effects	Variance component	Chi-Square	*Df*			
Between district (Level-2)						
Intercept	0.15390***	605.24540	22			
Within-district (Level-1)						
Residual Variation	76.40853					

1. Spatial lag variable created through a two-stage least squares approach (see Appendix D for details).
2. Socio-economic status index was comprised of median household income, median home value, and the percent of people with greater than a high school diploma (Cronbach's alpha = 0.79). Values for each variable were z-scored and averaged.
3. The stability index was comprised of the percent of people living in the same house five years previously, the percent of housing units that were owner occupied, and the reverse coded percent of the population between the ages of 20 and 24 (Cronbach's alpha = 0.71). Values for each variable were z-scored and averaged.
4. The ethnicity index was comprised of the percent of households linguistically isolated, the percent of the population foreign born, the percent of the population that is Hispanic (Cronbach's alpha = 0.66). Values for each variable were z-scored and averaged.
5. Length of bus route within the geography normalized by area

Table 16: Cross-sectional analyses of unfounded events (five year average) (cont.)

	Model 3			Model 4		
Fixed effects	Coefficient (S.E.)	Event rate ratio	Confidence interval	Coefficient (S.E.)	Event rate ratio	Confidence interval
Intercept	5.103974*** (0.081705)	164.674988	139.040 - 195.036	5.093763*** (0.084251)	163.002122	136.904 - 194.075
Spatial lag[1]	0.143528*** (0.023455)	1.154340	1.102 - 1.209	0.093339*** (0.024934)	1.097834	1.045 - 1.153
Population	0.000393*** (0.000025)	1.000393	1.000 - 1.000	0.000420*** (0.000025)	1.000420	1.000 - 1.000
Homicide	0.624670*** (0.035262)	1.867630	1.743 - 2.001	0.501320*** (0.035659)	1.650899	1.539 - 1.770
Serious incidents	--- ---	---	---	--- ---	---	---
Officer assaults	0.168326*** (0.024490)	1.183323	1.128 - 1.242	0.272742*** (0.034018)	1.313561	1.229 - 1.404
SES[2]				-0.105544*** (0.026084)	0.899835	0.855 - 0.947
Stability[3]				-0.048614** (0.017833)	0.952549	0.920 - 0.986
Ethnicity[4]				0.017929 (0.020844)	1.018091	0.977 - 1.061
% Af. Am.				0.144551* (0.064126)	1.155521	1.019 - 1.310
% Commercial						
% State Liquor						
% Liquor						
% Club						
% Pawn						
% Check cashing						
% Homeless shelter						
% Drug treatment						
% Halfway house						
% Rail						
% Subway						
Bus[5]						
Random effects						
Between district (Level-2)						
Intercept						
Within-district (Level-1)						
Residual Variation						

1. Spatial lag variable created through a two-stage least squares approach (see Appendix D for details).
2. Socio-economic status index was comprised of median household income, median home value, and the percent of people with greater than a high school diploma (Cronbach's alpha = 0.79). Values for each variable were z-scored and averaged.
3. The stability index was comprised of the percent of people living in the same house five years previously, the percent of housing units that were owner occupied, and the reverse coded percent of the population between the ages of 20 and 24 (Cronbach's alpha = 0.71). Values for each variable were z-scored and averaged.
4. The ethnicity index was comprised of the percent of households linguistically isolated, the percent of the population foreign born, the percent of the population that is Hispanic (Cronbach's alpha = 0.66). Values for each variable were z-scored and averaged.
5. Length of bus route within the geography normalized by area

Table 16: Cross-sectional analyses of unfounded events (five year average) (cont.)

	Model 5			Model 6		
Fixed effects	Coefficient (S.E.)	Event rate ratio	Confidence interval	Coefficient (S.E.)	Event rate ratio	Confidence interval
Intercept	5.075360*** (0.085829)	160.029814	133.969 - 191.160	5.059430*** (0.088279)	157.500792	131.184 - 189.096
Spatial lag[1]	0.075728*** (0.022949)	1.078669	1.031 - 1.128	0.119656*** (0.021085)	1.127109	1.081 - 1.175
Population	0.000488*** (0.000023)	1.000488	1.000 - 1.001	0.000410*** (0.000022)	1.000410	1.000 - 1.000
Homicide	0.427039*** (0.033277)	1.532713	1.436 - 1.636	--- ---	---	---
Serious incidents	--- ---	---	---	0.004619*** (0.000186)	1.004630	1.004 - 1.005
Officer assaults	0.263312*** (0.031117)	1.301233	1.224 - 1.383	0.261484*** (0.027692)	1.298856	1.230 - 1.371
SES[2]	-0.107170*** (0.023780)	0.898373	0.857 - 0.941	-0.144711*** (0.021983)	0.865273	0.829 - 0.903
Stability[3]	0.006200 (0.016780)	1.006220	0.974 - 1.040	0.002731 (0.015092)	1.002735	0.974 - 1.033
Ethnicity[4]	-0.010567 (0.019093)	0.989489	0.953 - 1.027	0.020024 (0.017410)	1.020226	0.986 - 1.056
% Af. Am.	0.138989* (0.059745)	1.149112	1.022 - 1.292	0.283204*** (0.054086)	1.327376	1.194 - 1.476
% Commercial	0.011136*** (0.001048)	1.011198	1.009 - 1.013	0.000628 (0.001068)	1.000628	0.999 - 1.003
% State Liquor	0.001556 (0.002033)	1.001557	0.998 - 1.006	-0.000323 (0.001934)	0.999677	0.996 - 1.003
% Liquor	0.000504 (0.000475)	1.000504	1.000 - 1.001	0.001750*** (0.000435)	1.001751	1.001 - 1.003
% Club	0.000042 (0.000874)	1.000042	0.998 - 1.002	0.000149 (0.000800)	1.000149	0.999 - 1.002
% Pawn	0.002917 (0.001865)	1.002921	0.999 - 1.007	0.004061* (0.001685)	1.004069	1.001 - 1.007
% Check cashing	0.003063* (0.001268)	1.003068	1.001 - 1.006	0.000224 (0.001209)	1.000224	0.998 - 1.003
% Homeless shelter	-0.001981 (0.001735)	0.998021	0.995 - 1.001	0.001531 (0.001584)	1.001532	0.998 - 1.005
% Drug treatment	-0.000843 (0.002135)	0.999158	0.995 - 1.003	-0.002779 (0.001988)	0.997225	0.993 - 1.001
% Halfway house	0.001408 (0.001319)	1.001409	0.999 - 1.004	0.002006 (0.001188)	1.002008	1.000 - 1.004
% Rail	0.006079* (0.002879)	1.006097	1.000 - 1.012	-0.004382 (0.002712)	0.995628	0.990 - 1.001
% Subway	0.007854*** (0.001733)	1.007885	1.004 - 1.011	0.007237*** (0.001580)	1.007263	1.004 - 1.010
Bus[5]	0.105815 (0.088976)	1.111617	0.934 - 1.323	0.155012 (0.081434)	1.167672	0.995 - 1.370
Random effects						
Between district (Level-2)						
Intercept						
Within-district (Level-1)						
Residual Variation						

1. Spatial lag variable created through a two-stage least squares approach (see Appendix D for details).
2. Socio-economic status index was comprised of median household income, median home value, and the percent of people with greater than a high school diploma (Cronbach's alpha = 0.79). Values for each variable were z-scored and averaged.
3. The stability index was comprised of the percent of people living in the same house five years previously, the percent of housing units that were owner occupied, and the reverse coded percent of the population between the ages of 20 and 24 (Cronbach's alpha = 0.71). Values for each variable were z-scored and averaged.
4. The ethnicity index was comprised of the percent of households linguistically isolated, the percent of the population foreign born, the percent of the population that is Hispanic (Cronbach's alpha = 0.66). Values for each variable were z-scored and averaged.
5. Length of bus route within the geography normalized by area

The ANOVA model (model 1) indicates that there are, on average, 174 unfounded events per block group.

Population & spatial effects: Residential population was significantly related to the number of unfounded events in a block group. A 100 unit increase in residential population of a block group was associated with a 4.9% increase in the expected count of unfounded events (model 5). The spatial lag variable was also positively associated with the count of unfounded events. A one standard deviation increase in the instrumented lag variable was associated with a 7.9% increase in the expected count of unfounded events, after controlling for other relevant block group characteristics (model 5). These effects were relatively stable through the model building process (model 1 through model 5).

Workload: Officer workload, as operationalized through the number of homicides and the number of officer assaults, was consistently associated with the number of unfounded events. On average, every additional homicide increased the expected count of unfounded events by 53.3%, after controlling for demographics, land use, and spatial effects (model 5). The direction and significance of this variable was consistent in models 3 through model 5. Also consistent with theoretical expectations, a one unit increase in the number of officer assaults was associated with a 30.1% increase in the number of unfounded events (consistent from model 3 through model 6). Using serious incidents in place of homicides as a workload indicator (model 6) found that every 10 additional serious incidents were related to a 4.6% increase in the expected count of unfounded events.

Demographics: Socioeconomic status was consistently related to the count of unfounded events. A one standard deviation increase in the socioeconomic scale was associated with a 10.2% decrease in the expected count of unfounded events, after controlling for workload, other demographic characteristics, spatial effects, and land use (model 5).

Stability had a negative relationship with the count of unfounded events (model 4). This impact, however, was reduced to non-significance after controlling for relevant land use characteristics of the block group (model 5). The ethnicity scale failed to attain significance in any of the models (model 4 or model 5). The percent African American, however, was significantly associated with unfounded events. A 1% increase in the African American residential population was associated with a 14.9% increase in the count of unfounded events after controlling for workload, other demographics, land use, and spatial effects (model 4).

Land use: A number of land use indicators had significant relationships with unfounded events. Beginning with commercial land use, a 10% increase in the area of a block group zoned as commercial was associated with an 11.2% increase in the expected count of unfounded events, while controlling for other relevant block group characteristics (model 5). Check cashing locations were also significantly related to the count of unfounded events with a 10% increase in the area of a block group under the buffer of a check cashing location being associated with a 3% increase in the count of unfounded events (model 5). Similarly, a 10% increase in the regional rail measure was associated with a 6.1% increase in the count of unfounded events, after controlling for other relevant block group characteristics (model 5). Finally, subway stops were associated with the count of unfounded events. A 10% increase in the subway stops buffer was associated with a 7.9% increase in the expected count of unfounded events, after controlling for other relevant characteristics (model 5).

Using serious incidents as the workload measure produced some changes to the strength and significance of several of the facility variables. Substituting serious incidents for homicides rendered the commercial land use, check cashing, and rail indicators non-significant.

The opposite effect was true for liquor and pawn shop measures; these variables became significant after substituting serious incidents for homicides.

To summarize, the relationship between unfounded events and officer workload was consistent with theoretical predictions: higher levels of workload was associated with higher levels of unfounded events. This relationship was consistent across the different methods of operationalizing officer workload. The relationship between demographics, land use, and the count of unfounded events was generally, but not always, in the expected direction. The next set of analyses set out to determine the temporal stability of these relationships across the five year study period.

Temporal Variation on Cross-Sectional Unfounded Models

The proceeding models used crime data averaged over the five year study period and census data from the 2000 U.S. Census. It is, of course, possible that these dynamics may have changed over time and using averaged data may have been masking important temporal variability. To assess this possibility models were re-specified using crime data from one year periods starting in 2004 and working through 2008. These models used census data created from postcensal estimates generated by Geolytics (see Appendix B for a review of the methodology used to create these estimates). Table 17 provides the estimates of yearly cross-sectional models for unfounded events.

Table 17: Temporal variation on cross-sectional unfounded models

	2004			2005		
Fixed effects	Coefficient (S.E.)	Event rate ratio	Confidence interval	Coefficient (S.E.)	Event rate ratio	Confidence interval
Intercept	5.234247*** (0.084192)	187.587865	157.573 - 223.321	5.129731*** (0.083356)	168.971664	142.181 - 200.810
Spatial lag[1]	0.071708** (0.025628)	1.074342	1.022 - 1.130	0.063181* (0.026450)	1.065220	1.011 - 1.122
Population[2]	0.000535*** (0.000024)	1.000535	1.000 - 1.001	0.000513*** (0.000024)	1.000513	1.000 - 1.001
Homicide	0.137970*** (0.020732)	1.147941	1.102 - 1.196	0.098724*** (0.017081)	1.103762	1.067 - 1.141
Officer assaults	0.099042*** (0.018912)	1.104112	1.064 - 1.146	0.103169*** (0.019435)	1.108679	1.067 - 1.152
% Age 20-24[2]	-0.944128* (0.483117)	0.389019	0.151 - 1.003	-0.810137 (0.521471)	0.444797	0.160 - 1.236
% Owner occupied[2]	-0.142666* (0.067464)	0.867044	0.760 - 0.990	-0.170233** (0.067606)	0.843469	0.739 - 0.963
SES[2]	-0.087501*** (0.025266)	0.916218	0.872 - 0.963	-0.104499*** (0.025274)	0.900776	0.857 - 0.947
% Hispanic[2]	0.160084 (0.115052)	1.173609	0.937 - 1.470	0.302986** (0.112050)	1.353895	1.087 - 1.686
% Af. Am.[2]	0.395567*** (0.066684)	1.485227	1.303 - 1.693	0.367696*** (0.066793)	1.444403	1.267 - 1.646
% Commercial	0.009998*** (0.001240)	1.010048	1.008 - 1.013	0.010773*** (0.001232)	1.010831	1.008 - 1.013
% State Liquor	0.001443 (0.002391)	1.001444	0.997 - 1.006	0.001197 (0.002427)	1.001198	0.996 - 1.006
% Liquor	0.001392** (0.000552)	1.001393	1.000 - 1.002	0.001130* (0.000556)	1.001130	1.000 - 1.002
% Club	-0.000334 (0.001038)	0.999666	0.998 - 1.002	0.000058 (0.001037)	1.000058	0.998 - 1.002
% Pawn	0.005261* (0.002209)	1.005275	1.001 - 1.010	0.004437* (0.002180)	1.004447	1.000 - 1.009
% Check cashing	0.002473 (0.001548)	1.002476	0.999 - 1.006	0.002737 (0.001534)	1.002740	1.000 - 1.006
% Homeless shelter	-0.001541 (0.001987)	0.998460	0.995 - 1.002	-0.003235 (0.001984)	0.996770	0.993 - 1.001
% Drug treatment	-0.000785 (0.002591)	0.999216	0.994 - 1.004	-0.000604 (0.002472)	0.999397	0.995 - 1.004
% Halfway house	0.000492 (0.001571)	1.000492	0.997 - 1.004	0.001315 (0.001522)	1.001316	0.998 - 1.004
% Rail	-0.001931 (0.003806)	0.998071	0.991 - 1.006	0.000929 (0.003741)	1.000929	0.994 - 1.008
% Subway	0.006696** (0.002080)	1.006718	1.003 - 1.011	0.008175*** (0.002046)	1.008208	1.004 - 1.012
Bus[3]	0.096613 (0.102388)	1.101434	0.901 - 1.346	0.071824 (0.103403)	1.074467	0.877 - 1.316
Random effects	Variance component	Chi-Square	*Df*	Variance component	Chi-Square	*Df*
Between district (Level-2)						
Intercept	0.15849	855.18752	22	0.15524	815.44741	22
Within-district (Level-1)						
Residual Variation	51.48832			46.69256		

1. Spatial lag variable created through a two-stage least squares approach (see Appendix D for details).
2. Based on yearly census estimates created by Geolytics. See Appendix B for methodological details.
3. Length of bus route within the geography normalized by area

Table 17: Temporal variation on cross-sectional unfounded models (cont.)

	2006			2007		
Fixed effects	Coefficient (S.E.)	Event rate ratio	Confidence interval	Coefficient (S.E.)	Event rate ratio	Confidence interval
Intercept	5.017581*** (0.112133)	151.045409	119.744 - 190.530	4.938887*** (0.115788)	139.614718	109.847 - 177.449
Spatial lag[1]	0.063805* (0.028027)	1.065884	1.009 - 1.126	0.059102* (0.027902)	1.060883	1.004 - 1.121
Population[2]	0.000522*** (0.000025)	1.000522	1.000 - 1.001	0.000508*** (0.000025)	1.000508	1.000 - 1.001
Homicide	0.109732*** (0.019943)	1.115979	1.073 - 1.160	0.128417*** (0.017622)	1.137027	1.098 - 1.177
Officer assaults	0.083425*** (0.019576)	1.087004	1.046 - 1.130	0.091677*** (0.018896)	1.096011	1.056 - 1.137
% Age 20-24[2]	-1.092248 (0.623135)	0.335462	0.099 - 1.138	-0.812980 (0.657118)	0.443535	0.122 - 1.608
% Owner occupied[2]	-0.112303 (0.071021)	0.893773	0.778 - 1.027	-0.075427 (0.067789)	0.927347	0.812 - 1.059
SES[2]	-0.099623*** (0.026625)	0.905179	0.859 - 0.954	-0.098479*** (0.025575)	0.906215	0.862 - 0.953
% Hispanic[2]	0.315478** (0.107700)	1.370915	1.110 - 1.693	0.232388* (0.096290)	1.261609	1.045 - 1.524
% Af. Am.[2]	0.298135*** (0.068357)	1.347344	1.178 - 1.541	0.246258*** (0.063918)	1.279229	1.129 - 1.450
% Commercial	0.011361*** (0.001284)	1.011425	1.009 - 1.014	0.009418*** (0.001215)	1.009462	1.007 - 1.012
% State Liquor	0.001489 (0.002481)	1.001490	0.997 - 1.006	0.001626 (0.002300)	1.001627	0.997 - 1.006
% Liquor	0.000643 (0.000569)	1.000643	1.000 - 1.002	0.001052* (0.000532)	1.001053	1.000 - 1.002
% Club	0.000374 (0.001058)	1.000374	0.998 - 1.002	-0.000430 (0.000993)	0.999570	0.998 - 1.002
% Pawn	0.006431** (0.002184)	1.006452	1.002 - 1.011	0.006530** (0.002024)	1.006551	1.003 - 1.011
% Check cashing	0.003270* (0.001578)	1.003276	1.000 - 1.006	0.003390* (0.001448)	1.003396	1.001 - 1.006
% Homeless shelter	-0.003000 (0.002152)	0.997004	0.993 - 1.001	-0.001803 (0.002030)	0.998199	0.994 - 1.002
% Drug treatment	-0.001499 (0.002574)	0.998502	0.993 - 1.004	-0.000422 (0.002420)	0.999578	0.995 - 1.004
% Halfway house	0.001938 (0.001528)	1.001940	0.999 - 1.005	-0.000046 (0.001489)	0.999954	0.997 - 1.003
% Rail	-0.001116 (0.004323)	0.998884	0.990 - 1.007	-0.002552 (0.004146)	0.997451	0.989 - 1.006
% Subway	0.010025*** (0.002078)	1.010075	1.006 - 1.014	0.010531*** (0.001937)	1.010587	1.007 - 1.014
Bus[3]	0.107860 (0.105676)	1.113892	0.906 - 1.370	0.158781* (0.099720)	1.172081	0.964 - 1.425
Random effects	Variance component	Chi-Square	*Df*	Variance component	Chi-Square	*Df*
Between district (Level-2)						
Intercept	0.28339	1262.00650	22	0.30288	1631.33113	22
Within-district (Level-1)						
Residual Variation	47.26161			40.70397		

1. Spatial lag variable created through a two-stage least squares approach (see Appendix D for details).
2. Based on yearly census estimates created by Geolytics. See Appendix B for methodological details.
3. Length of bus route within the geography normalized by area

Table 17: Temporal variation on cross-sectional unfounded models (cont.)

	2008			
Fixed effects	Coefficient (S.E.)		Event rate ratio	Confidence interval
Intercept	4.951010***	(0.113799)	141.317574	111.646 - 178.875
Spatial lag[1]	0.040585	(0.025529)	1.041420	0.991 - 1.095
Population[2]	0.000498***	(0.000024)	1.000498	1.000 - 1.001
Homicide	0.089571***	(0.018742)	1.093704	1.054 - 1.135
Officer assaults	0.106110***	(0.013862)	1.111944	1.082 - 1.143
% Age 20-24[2]	-0.354690	(0.713505)	0.701391	0.173 - 2.840
% Owner occupied[2]	-0.029894	(0.065082)	0.970549	0.854 - 1.103
SES[2]	-0.130485***	(0.025108)	0.877670	0.836 - 0.922
% Hispanic[2]	0.250532**	(0.091468)	1.284709	1.074 - 1.537
% Af. Am.[2]	0.222006***	(0.062292)	1.248579	1.105 - 1.411
% Commercial	0.010227***	(0.001159)	1.010279	1.008 - 1.013
% State Liquor	0.000602	(0.002233)	1.000602	0.996 - 1.005
% Liquor	0.001244*	(0.000518)	1.001245	1.000 - 1.002
% Club	-0.000841	(0.000974)	0.999159	0.997 - 1.001
% Pawn	0.006190**	(0.001952)	1.006209	1.002 - 1.010
% Check cashing	0.003220*	(0.001382)	1.003225	1.001 - 1.006
% Homeless shelter	-0.001981	(0.001964)	0.998021	0.994 - 1.002
% Drug treatment	-0.000904	(0.002327)	0.999096	0.995 - 1.004
% Halfway house	-0.000404	(0.001422)	0.999596	0.997 - 1.002
% Rail	-0.003759	(0.003934)	0.996248	0.989 - 1.004
% Subway	0.011585***	(0.001868)	1.011652	1.008 - 1.015
Bus[3]	0.245736**	(0.097209)	1.278562	1.057 - 1.547
Random effects	Variance component		Chi-Square	*Df*
Between district (Level-2)				
Intercept	0.29261		1858.98761	22
Within-district (Level-1)				
Residual Variation	39.02290			

1. Spatial lag variable created through a two-stage least squares approach (see Appendix D for details).
2. Based on yearly census estimates created by Geolytics. See Appendix B for methodological details.
3. Length of bus route within the geography normalized by area

The relationship between officer workload and the count of unfounded events remained stable throughout the five yearly cross-sectional models. Higher counts of homicides and higher counts of officer assaults were related to higher counts of unfounding. Population was also consistent across the five year study periods.

The spatial lag variable followed a noticeable degrading trend during the study period. The spatial lag was significant in early years but weakens to non-significance by the end of the series. This was an unexpected finding given the consistency of the spatial lag terms in other models using other methods of quantifying officer vigor. This finding suggests that the level of unfounded events became less clustered as time passed. Some potential explanations for this finding are given in the following chapter.

Some demographic variables were significant and maintained significance throughout the five years. Socioeconomic status was the strongest and most consistent predictor of unfounded events with higher levels of socioeconomic status being associated with fewer unfounded events. This relationship was consistent with theoretical predictions and a wider body of literature surrounding social stratification of urban services (Stone, 1980). This finding suggests at least the possibility that less police service was available in lower income areas. Percent African American was also consistently significant across years. Percent Hispanic (significant in all years except 2004) was similarly related to unfounded events. Higher levels of Hispanic population were related to higher levels of unfounded events. Generally the relationships found with the five year averaged models were consistent across the yearly estimates. A number of demographic variables showed significant relationships with unfounded events that varied over time. Percent owner occupied was significant in early years; however, by the end of the series the relationship had deteriorated to non-significance.

A number of land use variables were consistently related to the count of unfounded events throughout the study period. The percent of commercial land use, the subway indicator, and the pawn shop indicator were significant, positive, and consistent across the study period. A number of land uses were consistently *not* related to unfounded events. Indicators for rail, homeless shelters, drug treatment facilities, halfway houses, state liquor stores, and clubs were all non-significant during the study period.

Several land use indicators demonstrated a relationship with unfounded events that varied over time. The bus route indicator was only significant in 2008. The liquor outlet indicator was inconsistent across the study period. Significant relationships were found for four out of the five years. Similarly, the check cashing variable was significant and positive in only three of the five years.

To summarize, the cross-sectional unfounded models investigated the relationship between unfounded events, workload, socio-demographics, and land use characteristics. This was conducted on values averaged over five years and on individual yearly event counts. Consistent with theoretical expectations, these models suggested that officer workload, as operationalized by the number of homicides, officer assaults, and serious incidents, was consistently related to the number of unfounded events. Demographics and land use frequently had significant relationships with the count of unfounded events, although this relationship was not always in the expected direction. The most consistent socio-demographic characteristic related to unfounded events was socioeconomic status. This relationship was consistent with predictions made by the ecological theory of policing and was stable regardless of model specification. The next set of analyses operationalized vigor as the count of arrests for low seriousness offenses.

Cross-Sectional Models of Low Seriousness Arrests

Turning to low seriousness arrests, the analysis format followes the same path laid out in analyzing unfounded events. The results of the five year average are presented first. The complete models are then re-specified to look at yearly crime data from 2004 through 2008. Table 18 presents the findings of the cross-sectional analyses of low seriousness arrests averaged over the 5 year study period.

Table 18: Cross-sectional analyses of low seriousness arrests (five year average)

	Model 1			Model 2		
Fixed effects	Coefficient (S.E.)	Event rate ratio	Confidence interval	Coefficient (S.E.)	Event rate ratio	Confidence interval
Intercept	3.100919*** (0.119645)	22.218357	17.342 - 28.466	3.015362***(0.125536)	20.396481	16.227 - 25.637
Spatial lag[1]				0.561480***(0.048048)	1.753266	1.448 - 2.122
Population				0.000556***(0.000051)	1.000556	1.000 - 1.001
Homicide						
Serious incidents						
Officer assaults						
SES[2]						
Stability[3]						
Ethnicity[4]						
% Af. Am.						
% Commercial						
% State Liquor						
% Liquor						
% Club						
% Pawn						
% Check cashing						
% Homeless shelter						
% Drug treatment						
% Halfway house						
% Rail						
% Subway						
Bus[5]						

Random effects	Variance component	Chi-Square	*Df*
Between district (Level-2)			
Intercept	0.30396***	604.61281	22
Within-district (Level-1)			
Residual Variation	33.94626		

1. Spatial lag variable created through a two-stage least squares approach (see Appendix D for details).
2. Socio-economic status index was comprised of median household income, median home value, and the percent of people with greater than a high school diploma (Cronbach's alpha = 0.79). Values for each variable were z-scored and averaged.
3. The stability index was comprised of the percent of people living in the same house five years previously, the percent of housing units that were owner occupied, and the reverse coded percent of the population between the ages of 20 and 24 (Cronbach's alpha = 0.71). Values for each variable were z-scored and averaged.
4. The ethnicity index was comprised of the percent of households linguistically isolated, the percent of the population foreign born, the percent of the population that is Hispanic (Cronbach's alpha = 0.66). Values for each variable were z-scored and averaged.
5. Length of bus route within the geography normalized by area

Table 18: Cross-sectional analyses of low seriousness arrests (five year average) (cont.)

	Model 3			Model 4		
Fixed effects	Coefficient (S.E.)	Event rate ratio	Confidence interval	Coefficient (S.E.)	Event rate ratio	Confidence interval
Intercept	2.971037*** (0.124581)	19.512143	15.075 - 25.256	2.948025*** (0.121545)	19.068253	14.825 - 24.526
Spatial lag[1]	0.426691*** (0.041063)	1.532179	1.414 - 1.661	0.198766*** (0.043003)	1.219897	1.121 - 1.327
Population	0.000305*** (0.000046)	1.000305	1.000 - 1.000	0.000272*** (0.000045)	1.000272	1.000 - 1.000
Homicide	0.758786*** (0.055282)	2.135681	1.916 - 2.380	0.536347*** (0.054382)	1.709750	1.537 - 1.902
Serious incidents	--- ---	---	---	--- ---	---	---
Officer assaults	0.393916*** (0.037206)	1.482775	1.378 - 1.595	0.670558*** (0.051131)	1.955328	1.769 - 2.161
SES[2]				-0.353417*** (0.049562)	0.702284	0.637 - 0.774
Stability[3]				0.006223 (0.031649)	1.006243	0.946 - 1.071
Ethnicity[4]				0.153872*** (0.033380)	1.166342	1.092 - 1.245
% Af. Am.				0.278203** (0.111475)	1.320755	1.062 - 1.643
% Commercial						
% State Liquor						
% Liquor						
% Club						
% Pawn						
% Check cashing						
% Homeless shelter						
% Drug treatment						
% Halfway house						
% Rail						
% Subway						
Bus[5]						
Random effects						
Between district (Level-2)						
Intercept						
Within-district (Level-1)						
Residual Variation						

1. Spatial lag variable created through a two-stage least squares approach (see Appendix D for details).
2. Socio-economic status index was comprised of median household income, median home value, and the percent of people with greater than a high school diploma (Cronbach's alpha = 0.79). Values for each variable were z-scored and averaged.
3. The stability index was comprised of the percent of people living in the same house five years previously, the percent of housing units that were owner occupied, and the reverse coded percent of the population between the ages of 20 and 24 (Cronbach's alpha = 0.71). Values for each variable were z-scored and averaged.
4. The ethnicity index was comprised of the percent of households linguistically isolated, the percent of the population foreign born, the percent of the population that is Hispanic (Cronbach's alpha = 0.66). Values for each variable were z-scored and averaged.
5. Length of bus route within the geography normalized by area

Table 18: Cross-sectional analyses of low seriousness arrests (five year average) (cont.)

	Model 5			Model 6		
Fixed effects	Coefficient (S.E.)	Event rate ratio	Confidence interval	Coefficient (S.E.)	Event rate ratio	Confidence interval
Intercept	2.929762*** (0.120664)	18.723181	14.583 - 24.039	2.895411*** (0.128369)	18.090939	13.868 - 23.600
Spatial lag[1]	0.167233*** (0.041271)	1.182029	1.090 - 1.282	0.195393*** (0.040554)	1.215788	1.123 - 1.316
Population	0.000329*** (0.000044)	1.000329	1.000 - 1.000	0.000249*** (0.000043)	1.000249	1.000 - 1.000
Homicide	0.448664*** (0.053452)	1.566219	1.410 - 1.739	--- ---	---	---
Serious incidents	--- ---	---	---	0.005399*** (0.000416)	1.005414	1.005 - 1.006
Officer assaults	0.639624*** (0.048699)	1.895769	1.723 - 2.086	0.633680*** (0.045751)	1.884533	1.723 - 2.061
SES[2]	-0.358973*** (0.046447)	0.698393	0.638 - 0.765	-0.410718*** (0.045080)	0.663174	0.607 - 0.724
Stability[3]	0.064792* (0.031074)	1.066937	1.004 - 1.134	0.070588* (0.030092)	1.073139	1.012 - 1.138
Ethnicity[4]	0.114578*** (0.032466)	1.121400	1.052 - 1.195	0.146607*** (0.031818)	1.157899	1.088 - 1.232
% Af. Am.	0.275460** (0.107486)	1.317136	1.067 - 1.626	0.480789*** (0.105471)	1.617350	1.315 - 1.989
% Commercial	0.006438*** (0.001896)	1.006459	1.003 - 1.010	-0.002681 (0.001999)	0.997322	0.993 - 1.001
% State Liquor	0.010853*** (0.002915)	1.010912	1.005 - 1.017	0.008849** (0.002939)	1.008888	1.003 - 1.015
% Liquor	0.001825* (0.000807)	1.001827	1.000 - 1.003	0.003469*** (0.000793)	1.003475	1.002 - 1.005
% Club	-0.003242* (0.001638)	0.996763	0.994 - 1.000	-0.003076 (0.001599)	0.996929	0.994 - 1.000
% Pawn	0.000251 (0.002988)	1.000251	0.994 - 1.006	0.001720 (0.002879)	1.001721	0.996 - 1.007
% Check cashing	-0.001558 (0.002150)	0.998443	0.994 - 1.003	-0.004270* (0.002166)	0.995739	0.992 - 1.000
% Homeless shelter	-0.001533 (0.002886)	0.998468	0.993 - 1.004	0.001941 (0.002841)	1.001943	0.996 - 1.008
% Drug treatment	0.015998*** (0.002633)	1.016127	1.011 - 1.021	0.014419*** (0.002610)	1.014523	1.009 - 1.020
% Halfway house	-0.000022 (0.002185)	0.999978	0.996 - 1.004	0.000134 (0.002114)	1.000134	0.996 - 1.004
% Rail	-0.007170 (0.006139)	0.992856	0.981 - 1.005	-0.016785** (0.006047)	0.983356	0.972 - 0.995
% Subway	0.012230*** (0.002940)	1.012305	1.006 - 1.018	0.010890*** (0.002866)	1.010949	1.005 - 1.017
Bus[5]	0.336328* (0.155505)	1.399797	1.032 - 1.899	0.370249* (0.152859)	1.448096	1.073 - 1.954
Random effects						
Between district (Level-2)						
Intercept						
Within-district (Level-1)						
Residual Variation						

1. Spatial lag variable created through a two-stage least squares approach (see Appendix D for details).
2. Socio-economic status index was comprised of median household income, median home value, and the percent of people with greater than a high school diploma (Cronbach's alpha = 0.79). Values for each variable were z-scored and averaged.
3. The stability index was comprised of the percent of people living in the same house five years previously, the percent of housing units that were owner occupied, and the reverse coded percent of the population between the ages of 20 and 24 (Cronbach's alpha = 0.71). Values for each variable were z-scored and averaged.
4. The ethnicity index was comprised of the percent of households linguistically isolated, the percent of the population foreign born, the percent of the population that is Hispanic (Cronbach's alpha = 0.66). Values for each variable were z-scored and averaged.
5. Length of bus route within the geography normalized by area

The ANOVA model (model 1) indicated that there were, on average, 22 low seriousness arrests per block group when averaging crime over the five year study period.

Population & spatial effects: Population had a positive and significant relationship with low seriousness arrests counts. A 100 unit increase in the residential population of a block group was associated with a 3.3% increase in the expected count of low seriousness arrests (model 5). The spatial lag variable was also significantly associated with the count of low seriousness arrests. A one unit increase in the instrumented lag variable was associated with an 18% increase in the expected count of low seriousness arrests (model 5). These results were stable across various model specifications (model 1 through model 5).

Workload: Counter to theoretical expectations both workload indicators were significantly positively associated with the count of low seriousness arrests. Counter to theoretical expectations, every additional homicide was associated with a 113% increase in the expected count of low seriousness arrests (when ignoring demographics and land use; model 3) to a 57% increase under the full model specification (model 5). Every additional officer assault was associated with an 89% increase in the expected count of low seriousness arrests. Model 6 was specified using serious incidents instead of homicides as a control over officer workload. Serious incidents were significantly associated with the number of low seriousness arrests (a finding that was again counter to theoretical expectations). Ten additional serious incidents were associated with a 5.4% increase in the expected count of low seriousness arrests (model 6). Recall that Klinger's ecological theory would have predicted *less* vigor towards low seriousness arrests in areas with higher levels of workload. When workload was operationalized as homicides, officer assaults, or serious crimes the results suggested a relationship that was opposite to theoretical predictions.

Demographics: A number of demographic variables were associated with the count of low seriousness arrests. A one unit increase in the socioeconomic scale was associated with a 30% decrease in the count of low seriousness arrests, after controlling for workload, other demographics, and land use (model 5). Given that the low seriousness arrests variable was largely comprised of drug offenses this finding suggests that there were less arrests for drug offenses in areas with higher levels of socio-economic status. Stability had a weak and inconsistent relationship with low seriousness arrests. Considered in the model omitting land use, stability was not significantly associated with low seriousness arrests (model 4). After controlling for land use, however, a one unit increase in the stability scale was associated with a 6.7% increase in the expected count of low seriousness arrests. The ethnicity scale was also significantly associated with low seriousness arrests. A one unit increase in the ethnicity scale was associated with a 12% increase in the expected count of low seriousness arrests. Finally, a one percent increase in the African American population was associated with a 31% increase in the expected count of low seriousness arrests, after controlling for workload, spatial effects, and land use (model 5).

Land use: Beginning with commercial land use, a 10% increase in the land of a block group zoned as commercial was associated with a 6.5% increase in the expected count of low seriousness arrests after controlling for demographics, workload, and spatial effects (model 5). Alcohol distributing facilities had an inconsistent relationship with low seriousness arrests. Two indicators (state liquor store and liquor serving facilities) were associated with higher levels of low seriousness arrests. A 10% increase in the state liquor store measure was associated with 10.9% increase in the expected count of low seriousness arrests whereas a 10% increase in the liquor store measure was associated with a much smaller 1.8% increase in the expected count of low seriousness arrests (model 5). One alcohol distributing facility, clubs, was associated with lower levels of arrests for low seriousness events. A 10% increase in the club buffer measure was associated with a 3.2% decrease in the number of low seriousness arrests.

No money providing facilities (pawn shops or check cashing locations) were significantly associated with the count of low seriousness arrests. Of the three service facility variables (homeless shelters, drug treatment facilities, and halfway houses) only drug treatment centers were significantly associated with the count of low seriousness arrests. A 1% increase in the block group area falling under the buffer of a drug treatment facility was associated with a 1.6% increase in the excepted count of low seriousness arrests after controlling for demographics, other land use, workload, and spatial effects (model 5). Two transit variables were associated with the count of low seriousness arrests. A one percent increase in a block group area covered by a buffer generated from a subway stop was associated with a 1.2% increase in the expected count of low seriousness arrests after controlling for other relevant variables (model 5). Bus routes also had a significant relationship with low seriousness arrests. A one unit increase in the distance/area based bus measure was associated with a 40% increase in the expected count of low seriousness arrests.

A few noteworthy changes among facility variables were seen after re-specifying the model with serious incidents instead of homicides as the measure of officer workload. Commercial land use, significant in model 5, was no longer significant after the substitution of serious incidents. The club indicator was also rendered non-significant in model 6. Two variables, check cashing and regional rail, became significant after the addition of serious incidents. A 10% increase in the amount of land falling under a buffer generated by a club was related to a 3.1% decrease in the expected count of low seriousness arrests. Also counter to theoretical expectations, a 10% increase in the amount of land falling under a check cashing buffer was associated with a 4.3% reduction in the count of low seriousness arrests.

The preceding models investigated the relationship between the count of low seriousness arrests, workload, socio-demographics, and land use. The relationship between low seriousness arrests and workload was positive and significant, suggesting that areas of higher workload were associated with higher levels of arrests for low seriousness events. This was counter to theoretical predictions and counter to the results seen when operationalizing vigor through the count of unfounded events. These findings suggest that vigor may have been multidimensional and that the method of operationalizing vigor is important. This finding is discussed in greater detail in the following chapter. The next section uses yearly counts at the block group level to explore any potential temporal dynamics that may have been occurring during the study period.

Temporal Variation on Cross-Sectional Low Seriousness Arrest Models

Table 19 displays models that were re-specified using yearly low seriousness arrest counts (instead of five year averages) and estimated census data corresponding to the year of the dependent variable (in place of data from the 2000 U.S. census).

Table 19: Temporal variation on cross-sectional low seriousness arrest models

	2004			2005		
Fixed effects	Coefficient (S.E.)	Event rate ratio	Confidence interval	Coefficient (S.E.)	Event rate ratio	Confidence interval
Intercept	2.888007*** (0.131169)	17.957480	13.686 - 23.563	2.879469*** (0.116029)	17.804820	14.002 - 22.641
Spatial lag[1]	0.107481* (0.048271)	1.113470	1.013 - 1.224	0.139150** (0.050073)	1.149296	1.042 - 1.268
Population[2]	0.000426*** (0.000045)	1.000426	1.000 - 1.001	0.000451*** (0.000045)	1.000451	1.000 - 1.001
Homicide	0.150816*** (0.033669)	1.162783	1.089 - 1.242	0.144483*** (0.025672)	1.155442	1.099 - 1.215
Officer assaults	0.176450*** (0.028642)	1.192974	1.128 - 1.262	0.172533*** (0.029363)	1.188311	1.122 - 1.259
% Age 20-24[2]	-0.632236 (0.922351)	0.531402	0.087 - 3.240	-0.255121 (1.023387)	0.774823	0.104 - 5.759
% Owner occupied[2]	-0.128885 (0.126142)	0.879075	0.687 - 1.126	-0.303437 (0.051160)	0.913958	0.713 - 1.172
SES[2]	-0.304883*** (0.051528)	0.737209	0.666 - 0.816	-0.089970*** (0.127027)	0.738276	0.668 - 0.816
% Hispanic[2]	1.392043*** (0.168188)	4.023062	2.893 - 5.594	1.656385*** (0.177099)	5.240331	3.703 - 7.415
% Af. Am.[2]	0.690132*** (0.125497)	1.993979	1.559 - 2.550	0.748774*** (0.126169)	2.114406	1.651 - 2.708
% Commercial	0.008705*** (0.002189)	1.008743	1.004 - 1.013	0.006714** (0.002262)	1.006737	1.002 - 1.011
% State Liquor	0.012083*** (0.003310)	1.012156	1.006 - 1.019	0.008818** (0.003483)	1.008857	1.002 - 1.016
% Liquor	0.002409** (0.000928)	1.002412	1.001 - 1.004	0.004188*** (0.000932)	1.004197	1.002 - 1.006
% Club	-0.000862 (0.001894)	0.999139	0.995 - 1.003	-0.001229*** (0.001916)	0.998772	0.995 - 1.003
% Pawn	0.008333** (0.003157)	1.008367	1.002 - 1.015	0.006341 (0.003362)	1.006361	1.000 - 1.013
% Check cashing	-0.001760 (0.002469)	0.998242	0.993 - 1.003	-0.003564 (0.002560)	0.996442	0.991 - 1.001
% Homeless shelter	-0.000954 (0.003361)	0.999046	0.992 - 1.006	-0.003451 (0.003477)	0.996555	0.990 - 1.003
% Drug treatment	0.019859*** (0.002990)	1.020057	1.014 - 1.026	0.015817*** (0.003044)	1.015943	1.010 - 1.022
% Halfway house	0.000282 (0.002385)	1.000282	0.996 - 1.005	-0.001889 (0.002582)	0.998112	0.993 - 1.003
% Rail	-0.016848* (0.008365)	0.983293	0.967 - 1.000	-0.018049* (0.008816)	0.982113	0.965 - 0.999
% Subway	0.009793** (0.003322)	1.009841	1.003 - 1.016	0.011677*** (0.003405)	1.011746	1.005 - 1.019
Bus[3]	0.375581* (0.178268)	1.455837	1.027 - 2.065	0.458960** (0.179219)	1.582427	1.114 - 2.248
Random effects	Variance component	Chi-Square	*Df*	Variance component	Chi-Square	*Df*
Between district (Level-2)						
Intercept	0.37534***	1267.30160	22	0.29011***	893.40297	22
Within-district (Level-1)						
Residual Variation	19.85625			19.36544		

1. Spatial lag variable created through a two-stage least squares approach (see Appendix D for details).
2. Based on yearly census estimates created by Geolytics. See Appendix B for methodological details.
3. Length of bus route within the geography normalized by area

Table 19: Temporal variation on cross-sectional low seriousness arrest models (cont.)

	2006			2007		
Fixed effects	Coefficient (S.E.)	Event rate ratio	Confidence interval	Coefficient (S.E.)	Event rate ratio	Confidence interval
Intercept	2.916451*** (0.119362)	18.475603	14.429 - 23.657	2.980354*** (0.125785)	19.694793	15.178 - 25.556
Spatial lag[1]	0.111172* (0.055524)	1.117587	1.002 - 1.246	0.101748* (0.049338)	1.107104	1.005 - 1.220
Population[2]	0.000506*** (0.000049)	1.000506	1.000 - 1.001	0.000425*** (0.000044)	1.000425	1.000 - 1.001
Homicide	0.085447* (0.037114)	1.089204	1.013 - 1.171	0.195092*** (0.027787)	1.215423	1.151 - 1.283
Officer assaults	0.197383*** (0.031200)	1.218211	1.146 - 1.295	0.184502*** (0.030118)	1.202619	1.134 - 1.276
% Age 20-24[2]	-0.106616 (1.262262)	0.898871	0.076 - 10.670	-0.028698 (1.313306)	0.971710	0.074 - 12.748
% Owner occupied[2]	-0.023716 (0.142515)	0.976563	0.739 - 1.291	-0.096419 (0.126057)	0.908083	0.709 - 1.163
SES[2]	-0.312674*** (0.057713)	0.731488	0.653 - 0.819	-0.233085*** (0.052062)	0.792087	0.715 - 0.877
% Hispanic[2]	1.697547*** (0.204250)	5.460537	3.659 - 8.149	1.712452*** (0.180537)	5.542534	3.891 - 7.896
% Af. Am.[2]	0.745972*** (0.142186)	2.108490	1.596 - 2.786	0.824371*** (0.126709)	2.280447	1.779 - 2.923
% Commercial	0.006601** (0.002566)	1.006622	1.002 - 1.012	0.008777*** (0.002313)	1.008816	1.004 - 1.013
% State Liquor	0.011333** (0.003983)	1.011398	1.004 - 1.019	0.010544** (0.003534)	1.010600	1.004 - 1.018
% Liquor	0.001565 (0.001073)	1.001566	0.999 - 1.004	0.002056* (0.000947)	1.002058	1.000 - 1.004
% Club	-0.001837 (0.002188)	0.998165	0.994 - 1.002	-0.002073 (0.001982)	0.997929	0.994 - 1.002
% Pawn	0.008188* (0.003712)	1.008222	1.001 - 1.016	0.003390 (0.003526)	1.003396	0.996 - 1.010
% Check cashing	-0.002998 (0.002987)	0.997007	0.991 - 1.003	-0.002966 (0.002631)	0.997039	0.992 - 1.002
% Homeless shelter	0.002196 (0.003732)	1.002199	0.995 - 1.010	-0.002153 (0.003569)	0.997850	0.991 - 1.005
% Drug treatment	0.017186*** (0.003505)	1.017335	1.010 - 1.024	0.015517*** (0.003185)	1.015638	1.009 - 1.022
% Halfway house	0.001045 (0.002735)	1.001046	0.996 - 1.006	-0.001599 (0.002636)	0.998402	0.993 - 1.004
% Rail	-0.013163 (0.009034)	0.986923	0.970 - 1.005	-0.017816* (0.008868)	0.982342	0.965 - 1.000
% Subway	0.016775*** (0.003751)	1.016917	1.009 - 1.024	0.015072*** (0.003448)	1.015186	1.008 - 1.022
Bus[3]	0.500951** (0.203604)	1.650289	1.107 - 2.460	0.453981** (0.181374)	1.574569	1.104 - 2.247

Random effects	Variance component	Chi-Square	*Df*	Variance component	Chi-Square	*Df*
Between district (Level-2)						
Intercept	0.30323***	715.87090	22	0.34340***	1056.25786	22
Within-district (Level-1)						
Residual Variation	25.53328			22.14546		

1. Spatial lag variable created through a two-stage least squares approach (see Appendix D for details).
2. Based on yearly census estimates created by Geolytics. See Appendix B for methodological details.
3. Length of bus route within the geography normalized by area

Table 19: Temporal variation on cross-sectional low seriousness arrest models (cont.)

		2008		
Fixed effects	Coefficient (S.E.)		Event rate ratio	Confidence interval
Intercept	2.989879***	(0.120306)	19.883268	15.498 - 25.509
Spatial lag[1]	0.148573**	(0.056106)	1.160178	1.039 - 1.295
Population[2]	0.000430***	(0.000050)	1.000430	1.000 - 1.001
Homicide	0.078495*	(0.037041)	1.081658	1.006 - 1.163
Officer assaults	0.195961***	(0.025590)	1.216479	1.157 - 1.279
% Age 20-24[2]	-0.224470	(1.604303)	0.798940	0.034 - 18.541
% Owner occupied[2]	0.025868	(0.139462)	1.026205	0.781 - 1.349
SES[2]	-0.280290***	(0.057739)	0.755564	0.675 - 0.846
% Hispanic[2]	1.661584***	(0.207483)	5.267646	3.508 - 7.911
% Af. Am.[2]	0.580664***	(0.139428)	1.787224	1.360 - 2.349
% Commercial	0.005354*	(0.002538)	1.005368	1.000 - 1.010
% State Liquor	0.012912***	(0.003803)	1.012995	1.005 - 1.021
% Liquor	0.002676**	(0.001084)	1.002679	1.001 - 1.005
% Club	-0.000241	(0.002154)	0.999759	0.996 - 1.004
% Pawn	0.008252*	(0.003895)	1.008286	1.001 - 1.016
% Check cashing	-0.002775	(0.002972)	0.997229	0.991 - 1.003
% Homeless shelter	-0.003029	(0.004057)	0.996976	0.989 - 1.005
% Drug treatment	0.013016***	(0.003713)	1.013101	1.006 - 1.021
% Halfway house	-0.007108*	(0.003282)	0.992917	0.987 - 0.999
% Rail	-0.016001	(0.009493)	0.984126	0.966 - 1.003
% Subway	0.014526***	(0.003874)	1.014632	1.007 - 1.022
Bus[3]	0.358742	(0.205365)	1.431528	0.957 - 2.141
Random effects	Variance component		Chi-Square	*Df*
Between district (Level-2)				
Intercept	0.30887***		638.74908	22
Within-district (Level-1)				
Residual Variation	26.86089			

1. Spatial lag variable created through a two-stage least squares approach (see Appendix D for details).
2. Based on yearly census estimates created by Geolytics. See Appendix B for methodological details.
3. Length of bus route within the geography normalized by area

The workload indicators, spatial lag, and population were consistent across the years of analysis. Counter to theoretical expectations, a higher count of homicides or a higher count of officer assaults was significantly associated with higher counts of low seriousness arrests regardless of the year under study.

The spatial lag variable and population controls were positive, significant, and consistent across model years. Higher population or higher values on the spatial lag variable were associated with higher counts of low serious arrests. Demographic characteristics were also consistent throughout the years of analysis. Socioeconomic status had a consistent negative and significant relationship with low serious arrests. The percent African American and percent Hispanic were consistent and positive across all years suggesting that higher levels of African American or Hispanic population were associated with higher levels of low serious arrests.

Turning to land use, the percent of land zoned as commercial was significant across all years of study. The same was true of state liquor stores, drug treatment centers, and subway stops. Check cashing and homeless shelters were consistently *not* related to low serious arrests.

Consistent with unfounded events, relationships between arrests for low serious offenses and land use variables were stable from 2004 through 2008. Only a few land uses had relationships with low seriousness arrests that varied over time. Length of bus route was significant in all years except 2008[27]. Similarly, the liquor outlet variable was significant in all years except 2006. The rail stop indicator was negative and significant in three out of the five

[27] This is particularly interesting given the fact that the bus route data were collected in 2008 and should therefore have the strongest relationship with the outcome variable of the same year. The lack of significance between the bus route variable and the low serious arrest count for the year 2008 may be indicative of a spurious relationship in other years of analysis.

years. Pawn shops were positive and significant in three out of the five years. Finally the indicator for halfway houses was significant in only 2008.

The preceding models evaluated the relationship between arrests for low seriousness crimes, workload, socio-demographics, and land use. On the key theoretical relationship, that between low seriousness arrests and workload, these analyses found a relationship that was counter-theoretical with higher levels of workload being associated with higher levels of vigor. This relationship was stable across the five years of analysis. Regarding socio-demographic characteristics, only socio-economic status, the percent African American, and the percent Hispanic were consistently related to the count of traffic stops. The relationship between arrests and land use was more variable with only some land uses demonstrating theoretically consistent relationship. The remainder of this section is devoted to assessing key relationships when vigor is operationalized as traffic stops.

Cross-Sectional Models of Traffic Stops

The next section turns to the final outcome variable, traffic stops. Recall that, according to theoretical predictions, higher counts of traffic stops is indicative of greater officer vigor. Table 20 presents the findings from the cross-sectional analyses of traffic stops averaged over the five year study period.

Table 20: Cross-sectional analyses of traffic stops (five year average)

	Model 1			Model 2		
Fixed effects	Coefficient (S.E.)	Event rate ratio	Confidence interval	Coefficient (S.E.)	Event rate ratio	Confidence interval
Intercept	5.164368*** (0.059984)	174.926821	154.492 - 198.065	5.152202*** (0.060591)	172.811666	151.933 - 196.559
Spatial lag[1]				0.274762*** (0.057992)	1.316217	1.080 - 1.605
Population				0.000186** (0.000057)	1.000186	1.000 - 1.000
Homicide						
Serious incidents						
Officer assaults						
SES[2]						
Stability[3]						
Ethnicity[4]						
% Af. Am.						
% Commercial						
% State Liquor						
% Liquor						
% Club						
% Pawn						
% Check cashing						
% Homeless shelter						
% Drug treatment						
% Halfway house						
% Rail						
% Subway						
Bus[5]						

Random effects	Variance component	Chi-Square	*Df*
Between district (Level-2)			
Intercept	0.06625***	124.73421	22
Within-district (Level-1)			
Residual Variation	204.31248		

1. Spatial lag variable created through a two-stage least squares approach (see Appendix D for details).
2. Socio-economic status index was comprised of median household income, median home value, and the percent of people with greater than a high school diploma (Cronbach's alpha = 0.79). Values for each variable were z-scored and averaged.
3. The stability index was comprised of the percent of people living in the same house five years previously, the percent of housing units that were owner occupied, and the reverse coded percent of the population between the ages of 20 and 24 (Cronbach's alpha = 0.71). Values for each variable were z-scored and averaged.
4. The ethnicity index was comprised of the percent of households linguistically isolated, the percent of the population foreign born, the percent of the population that is Hispanic (Cronbach's alpha = 0.66). Values for each variable were z-scored and averaged.
5. Length of bus route within the geography normalized by area

Table 20: Cross-sectional analyses of traffic stops (five year average) (cont.)

	Model 3			Model 4		
Fixed effects	Coefficient (S.E.)	Event rate ratio	Confidence interval	Coefficient (S.E.)	Event rate ratio	Confidence interval
Intercept	5.091106*** (0.057401)	162.569496	144.348 - 183.091	5.061057*** (0.056443)	157.757119	140.353 - 177.319
Spatial lag[1]	0.128166*** (0.041756)	1.136741	1.047 - 1.234	0.206084*** (0.042929)	1.228856	1.130 - 1.337
Population	-0.000030 (0.000042)	0.999970	1.000 - 1.000	0.000067 (0.000040)	1.000067	1.000 - 1.000
Homicide	1.006899*** (0.053478)	2.737101	2.465 - 3.040	0.737211*** (0.053931)	2.090098	1.880 - 2.323
Serious incidents	--- ---	---	---	--- ---	---	---
Officer assaults	0.323823*** (0.030711)	1.382403	1.302 - 1.468	0.598220*** (0.049680)	1.818878	1.650 - 2.005
SES[2]				-0.056584 (0.035792)	0.944987	0.881 - 1.014
Stability[3]				-0.026240 (0.026626)	0.974101	0.925 - 1.026
Ethnicity[4]				0.053313 (0.029846)	1.054760	0.995 - 1.118
% Af. Am.				-0.113514 (0.097595)	0.892692	0.737 - 1.081
% Commercial						
% State Liquor						
% Liquor						
% Club						
% Pawn						
% Check cashing						
% Homeless shelter						
% Drug treatment						
% Halfway house						
% Rail						
% Subway						
Bus[5]						
Random effects						
Between district (Level-2)						
Intercept						
Within-district (Level-1)						
Residual Variation						

1. Spatial lag variable created through a two-stage least squares approach (see Appendix D for details).
2. Socio-economic status index was comprised of median household income, median home value, and the percent of people with greater than a high school diploma (Cronbach's alpha = 0.79). Values for each variable were z-scored and averaged.
3. The stability index was comprised of the percent of people living in the same house five years previously, the percent of housing units that were owner occupied, and the reverse coded percent of the population between the ages of 20 and 24 (Cronbach's alpha = 0.71). Values for each variable were z-scored and averaged.
4. The ethnicity index was comprised of the percent of households linguistically isolated, the percent of the population foreign born, the percent of the population that is Hispanic (Cronbach's alpha = 0.66). Values for each variable were z-scored and averaged.
5. Length of bus route within the geography normalized by area

Table 20: Cross-sectional analyses of traffic stops (five year average) (cont.)

	Model 5			Model 6		
Fixed effects	Coefficient (S.E.)	Event rate ratio	Confidence interval	Coefficient (S.E.)	Event rate ratio	Confidence interval
Intercept	5.040729*** (0.053358)	154.582685	138.410 - 172.644	5.025395*** (0.057953)	152.230364	135.014 - 171.643
Spatial lag[1]	0.188804*** (0.040899)	1.207804	1.115 - 1.309	0.248933*** (0.039497)	1.282656	1.187 - 1.386
Population	0.000148*** (0.000038)	1.000148	1.000 - 1.000	0.000067 (0.000037)	1.000067	1.000 - 1.000
Homicide	0.652413*** (0.052939)	1.920168	1.731 - 2.130	--- ---	---	---
Serious incidents	--- ---	---	---	0.005644*** (0.000309)	1.005660	1.005 - 1.006
Officer assaults	0.581420*** (0.047899)	1.788576	1.628 - 1.965	0.592224*** (0.044682)	1.808004	1.656 - 1.973
SES[2]	-0.077827* (0.034291)	0.925124	0.865 - 0.989	-0.138269 (0.033933)	0.870864	0.815 - 0.931
Stability[3]	0.032535 (0.026049)	1.033070	0.982 - 1.087	0.029150 (0.024975)	1.029579	0.980 - 1.081
Ethnicity[4]	0.010774 (0.029352)	1.010832	0.954 - 1.071	0.053165 (0.028379)	1.054604	0.998 - 1.115
% Af. Am.	-0.161609 (0.094911)	0.850774	0.706 - 1.025	0.079985 (0.091131)	1.083271	0.906 - 1.295
% Commercial	0.011159*** (0.001609)	1.011222	1.008 - 1.014	-0.001947 (0.001749)	0.998055	0.995 - 1.001
% State Liquor	0.005877* (0.003008)	1.005895	1.000 - 1.012	0.003491 (0.003059)	1.003497	0.997 - 1.010
% Liquor	-0.001715* (0.000776)	0.998286	0.997 - 1.000	0.000148 (0.000754)	1.000148	0.999 - 1.002
% Club	-0.002653 (0.001472)	0.997350	0.994 - 1.000	-0.002615 (0.001422)	0.997388	0.995 - 1.000
% Pawn	0.003157 (0.002696)	1.003162	0.998 - 1.008	0.005592* (0.002567)	1.005608	1.001 - 1.011
% Check cashing	0.008270*** (0.001886)	1.008304	1.005 - 1.012	0.003551 (0.001965)	1.003557	1.000 - 1.007
% Homeless shelter	-0.005361 (0.002819)	0.994654	0.989 - 1.000	-0.000473 (0.002718)	0.999527	0.994 - 1.005
% Drug treatment	-0.000673 (0.003274)	0.999327	0.993 - 1.006	-0.003482 (0.003232)	0.996524	0.990 - 1.003
% Halfway house	0.000438 (0.002304)	1.000438	0.996 - 1.005	0.001078 (0.002161)	1.001078	0.997 - 1.005
% Rail	0.002676 (0.004288)	1.002680	0.994 - 1.011	-0.016110*** (0.004534)	0.984019	0.975 - 0.993
% Subway	0.006945** (0.002645)	1.006969	1.002 - 1.012	0.006200* (0.002568)	1.006219	1.001 - 1.011
Bus[5]	0.314473* (0.143424)	1.369538	1.034 - 1.814	0.339197* (0.138580)	1.403820	1.070 - 1.842
Random effects						
Between district (Level-2)						
Intercept						
Within-district (Level-1)						
Residual Variation						

1. Spatial lag variable created through a two-stage least squares approach (see Appendix D for details).
2. Socio-economic status index was comprised of median household income, median home value, and the percent of people with greater than a high school diploma (Cronbach's alpha = 0.79). Values for each variable were z-scored and averaged.
3. The stability index was comprised of the percent of people living in the same house five years previously, the percent of housing units that were owner occupied, and the reverse coded percent of the population between the ages of 20 and 24 (Cronbach's alpha = 0.71). Values for each variable were z-scored and averaged.
4. The ethnicity index was comprised of the percent of households linguistically isolated, the percent of the population foreign born, the percent of the population that is Hispanic (Cronbach's alpha = 0.66). Values for each variable were z-scored and averaged.
5. Length of bus route within the geography normalized by area

The ANOVA model (model 1) indicated that there were, on average 175 traffic stops per block group when data were averaged over the five year study period.

Population & spatial effects: Population had a varying relationship with the count of traffic stops. When only considering spatial effects, population was significantly associated with the count of traffic stops (model 2). The addition of workload (model 3), and subsequently demographic characteristics (model 4) rendered the residential population non-significant. However, in the final model (model 5), controlling for land use, demographics, workload, and spatial effects the residential population was again significant with a 100 unit increase in the residential population being associated with a 1.5% increase in the expected count of traffic stops. The spatial lag variable was consistently related to the count of traffic stops. A one unit increase in the instrumented lag variable was associated with a 21% increase in the expected count of traffic stops, controlling for other relevant variables (model 5).

Workload: Counter to theoretical predictions, both workload indicators were positively associated with traffic stops. Each additional homicide was associated with a 92% increase in the expected count of traffic stops (model 5). The strength of the relationship but neither the significance nor direction was altered by the inclusion of land use and demographics (model 3 compared to models 4 and 5). Every additional officer assault was associated with a 79% increase in the expected count of traffic stops net of other relevant variables (model 5). Models were re-specified using serious incidents in place of homicides as the primary indicator of officer workload. Under these models a 10 unit increase in the number of serious incidents was associated with a 5.7% increase in the expected count of traffic stops, controlling for other relevant variables (model 6). One explanation may be that officers use traffic stops as investigative techniques to search for more serious crimes, an explanation that is explored more fully in the following chapter.

Demographics: Under the specifications of model 4 no demographic variables attained significance. After controlling for relevant land use characteristics, however, the level of socioeconomic status was significantly associated with the count of traffic stops. A one unit increase in the socioeconomic scale was associated with a 7.5% decrease in the expected count of traffic stops. Under the alternative workload specification (model 6), however, this effect was non-significant. The stability scale, the ethnicity scale, and the percent African American did not achieve statistical significance in any of the models.

Land use: Land use patterns have a strong ability to structure vehicular traffic. It was no surprise then that a number of land use variables were significantly related to the count of traffic stops. A 10% increase in the amount of land zoned as commercial in a block group was related to an 11.2% increase in the expected count of traffic stops, net of other relevant variables (model 5). Two out of three alcohol establishment related variables were significantly associated with the count of traffic stops. A 10% increase in the state liquor store variable was associated with an 11.2% increase in the expected count of traffic stops, net of other relevant variables (model 5). Conversely, a 10% increase in the liquor distributing outlets variable was associated with a 1.7% *decrease* in the expected count of traffic stops, after controlling for other relevant variables (model 5). One of the two money providing facilities was associated with the count of traffic stops. A 10% increase in the check cashing buffer measure was associated with an 8.3% increase in the expected count of traffic stops (model 5). No significant relationship was found between service facilities (homeless shelters, drug treatment facilities, and halfway houses) and the count of traffic stops. Finally two transit variables, subways and bus routes, were significantly associated with traffic stops. A 10% increase in the quantity of land falling under the buffer of a subway stop was associated with a 7.0% increase in the expected count of traffic stops, net of other relevant variables. A one unit increase in the bus route variable was associated with a 37% increase in the expected count of traffic stops after controlling for other relevant variables (model 5). Railway stops were not significantly associated with the count of traffic stops.

Re-specifying workload using serious incidents in place of homicides produced several noteworthy changes in the relationship between traffic stops and land use. Commercial land use, state liquor stores, liquor distributing facilities, and check cashing facilities were rendered non-significant (model 5 compared to model 6). Pawn shops and rail stops attained significance in model 6. A 10% increase in the area of a block group under a pawn shop buffer was associated with a 5.6% increase in the expected count of traffic stops, controlling for other relevant variables. A 10% increase in the area of a block group under a buffer generated by a train stop was associated with a 16% decrease in the expected count of traffic stops.

The cross-sectional results (measuring vigor through the count of traffic stops) produced a number of results that were inconsistent with theoretical predictions. All three methods of operationalizing workload produced results that suggested higher levels of homicides, officer assaults, and serious incidents resulted in higher counts of traffic stops. This was inconsistent with theoretical predictions which postulates that vigor will be reduced as workload increases. Generally no demographic variables were significantly associated with the count of traffic stops. The exception was socio-economic status which was only significantly related to the count of traffic stops after considering land use. A number of land uses had significant relationships with the count of traffic stops. These relationships were found to be both consistent and inconsistent to theoretical predictions.

Temporal Variation on Cross-Sectional Traffic Stop Models

The next set of models explored potential differences across the study years by examining each year independently. Table 21 presents the results of models run with yearly crime data and estimated census data corresponding to the crime data year.

Table 21: Temporal variation on cross-sectional traffic stop models

	2004			2005		
Fixed effects	Coefficient (S.E.)	Event rate ratio	Confidence interval	Coefficient (S.E.)	Event rate ratio	Confidence interval
Intercept	5.008842*** (0.073676)	149.731304	128.542 - 174.413	5.027544*** (0.066897)	152.557866	132.821 - 175.228
Spatial lag[1]	0.233389*** (0.055013)	1.262873	1.134 - 1.407	0.219089*** (0.051863)	1.244942	1.125 - 1.378
Population[2]	0.000242*** (0.000046)	1.000242	1.000 - 1.000	0.000304*** (0.000043)	1.000304	1.000 - 1.000
Homicide	0.254736*** (0.036399)	1.290122	1.201 - 1.386	0.172861*** (0.026571)	1.188701	1.128 - 1.252
Officer assaults	0.213091*** (0.031609)	1.237497	1.163 - 1.317	0.188104*** (0.030502)	1.206959	1.137 - 1.281
% Age 20-24[2]	0.275750 (0.778122)	1.317518	0.287 - 6.055	0.173786 (0.827802)	1.189801	0.235 - 6.027
% Owner occupied[2]	-0.046648 (0.122290)	0.954423	0.751 - 1.213	-0.002300 (0.115677)	0.997702	0.795 - 1.252
SES[2]	-0.030397 (0.042081)	0.970060	0.893 - 1.053	-0.082894* (0.040301)	0.920449	0.851 - 0.996
% Hispanic[2]	0.265398 (0.185883)	1.303949	0.906 - 1.877	0.313565 (0.172543)	1.368294	0.976 - 1.919
% Af. Am.[2]	0.071250 (0.117184)	1.073849	0.853 - 1.351	0.100052 (0.109690)	1.105228	0.891 - 1.370
% Commercial	0.012920*** (0.002019)	1.013004	1.009 - 1.017	0.011144*** (0.001942)	1.011206	1.007 - 1.015
% State Liquor	0.006224 (0.003863)	1.006243	0.999 - 1.014	0.007181* (0.003618)	1.007207	1.000 - 1.014
% Liquor	-0.001858 (0.000991)	0.998143	0.996 - 1.000	-0.000541 (0.000934)	0.999459	0.998 - 1.001
% Club	-0.004853** (0.001888)	0.995159	0.991 - 0.999	-0.003223 (0.001779)	0.996782	0.993 - 1.000
% Pawn	0.009170** (0.003232)	1.009213	1.003 - 1.016	0.006949* (0.003239)	1.006973	1.001 - 1.013
% Check cashing	0.008670*** (0.002512)	1.008708	1.004 - 1.014	0.007384** (0.002370)	1.007411	1.003 - 1.012
% Homeless shelter	-0.010017** (0.003811)	0.990033	0.983 - 0.997	-0.007980* (0.003476)	0.992052	0.985 - 0.999
% Drug treatment	0.001686 (0.004389)	1.001688	0.993 - 1.010	-0.002228 (0.004178)	0.997775	0.990 - 1.006
% Halfway house	-0.001011 (0.002797)	0.998989	0.994 - 1.004	-0.001607 (0.002819)	0.998394	0.993 - 1.004
% Rail	-0.003201 (0.007343)	0.996804	0.983 - 1.011	-0.003783 (0.006772)	0.996224	0.983 - 1.010
% Subway	0.005636 (0.003304)	1.005652	0.999 - 1.012	0.008160* (0.003185)	1.008193	1.002 - 1.015
Bus[3]	0.168735 (0.182738)	1.183806	0.827 - 1.694	0.259784 (0.172107)	1.296650	0.925 - 1.817
Random effects	Variance component	Chi-Square	*Df*	Variance component	Chi-Square	*Df*
Between district (Level-2)						
Intercept	0.11148***	266.27440	22	0.09094***	236.83214	22
Within-district (Level-1)						
Residual Variation	130.23391			118.97566		

1. Spatial lag variable created through a two-stage least squares approach (see Appendix D for details).
2. Based on yearly census estimates created by Geolytics. See Appendix B for methodological details.
3. Length of bus route within the geography normalized by area

Table 21: Temporal variation on cross-sectional traffic stop models (cont.)

	2006			2007		
Fixed effects	Coefficient (S.E.)	Event rate ratio	Confidence interval	Coefficient (S.E.)	Event rate ratio	Confidence interval
Intercept	4.986154*** (0.059425)	146.372333	129.423 - 165.541	5.023921*** (0.063418)	152.006128	133.297 - 173.341
Spatial lag[1]	0.238984*** (0.048566)	1.269958	1.155 - 1.397	0.158618*** (0.046325)	1.171890	1.070 - 1.283
Population[2]	0.000345*** (0.000042)	1.000345	1.000 - 1.000	0.000279*** (0.000040)	1.000279	1.000 - 1.000
Homicide	0.187318*** (0.031659)	1.206010	1.133 - 1.283	0.211360*** (0.028240)	1.235357	1.169 - 1.306
Officer assaults	0.235813*** (0.027440)	1.265937	1.200 - 1.336	0.176042*** (0.027854)	1.192488	1.129 - 1.259
% Age 20-24[2]	-0.533524 (0.915402)	0.586535	0.098 - 3.528	0.195476 (0.992500)	1.215890	0.174 - 8.506
% Owner occupied[2]	0.003748 (0.110607)	1.003755	0.808 - 1.247	-0.037808 (0.105121)	0.962898	0.784 - 1.183
SES[2]	-0.095769* (0.039754)	0.908674	0.841 - 0.982	-0.068139 (0.038187)	0.934130	0.867 - 1.007
% Hispanic[2]	0.203792 (0.159408)	1.226043	0.897 - 1.676	0.350583* (0.162137)	1.419895	1.033 - 1.951
% Af. Am.[2]	0.030024 (0.105074)	1.030480	0.839 - 1.266	0.063881 (0.101108)	1.065966	0.874 - 1.300
% Commercial	0.008541*** (0.001947)	1.008578	1.005 - 1.012	0.010586*** (0.001864)	1.010642	1.007 - 1.014
% State Liquor	0.006307 (0.003557)	1.006327	0.999 - 1.013	0.004774 (0.003496)	1.004786	0.998 - 1.012
% Liquor	-0.000623 (0.000908)	0.999377	0.998 - 1.001	-0.000084 (0.000870)	0.999916	0.998 - 1.002
% Club	-0.004151* (0.001779)	0.995857	0.992 - 0.999	-0.003382* (0.001683)	0.996624	0.993 - 1.000
% Pawn	0.007470** (0.003021)	1.007498	1.002 - 1.013	0.007093* (0.002937)	1.007118	1.001 - 1.013
% Check cashing	0.008381*** (0.002279)	1.008416	1.004 - 1.013	0.007544*** (0.002184)	1.007573	1.003 - 1.012
% Homeless shelter	-0.002906 (0.003367)	0.997098	0.991 - 1.004	-0.005059 (0.003232)	0.994954	0.989 - 1.001
% Drug treatment	0.001461 (0.003884)	1.001463	0.994 - 1.009	0.002275 (0.003582)	1.002278	0.995 - 1.009
% Halfway house	-0.003867 (0.002872)	0.996141	0.991 - 1.002	-0.001277 (0.002664)	0.998724	0.994 - 1.004
% Rail	-0.003134 (0.006299)	0.996870	0.985 - 1.009	-0.004189 (0.006345)	0.995819	0.984 - 1.008
% Subway	0.011264*** (0.003086)	1.011327	1.005 - 1.017	0.010382*** (0.002913)	1.010436	1.005 - 1.016
Bus[3]	0.435228** (0.167417)	1.545315	1.113 - 2.145	0.422366** (0.159942)	1.525566	1.115 - 2.087
Random effects	Variance component	Chi-Square	*Df*	Variance component	Chi-Square	*Df*
Between district (Level-2)						
Intercept	0.06966***	228.76904	22	0.08234***	264.72685	22
Within-district (Level-1)						
Residual Variation	109.43233			100.58568		

1. Spatial lag variable created through a two-stage least squares approach (see Appendix D for details).
2. Based on yearly census estimates created by Geolytics. See Appendix B for methodological details.
3. Length of bus route within the geography normalized by area

Table 21: Temporal variation on cross-sectional traffic stop models (cont.)

	2008			
Fixed effects	Coefficient	(S.E.)	Event rate ratio	Confidence interval
Intercept	5.188703***	(0.062416)	179.235886	157.502 - 203.969
Spatial lag[1]	0.132945**	(0.046347)	1.142187	1.043 - 1.251
Population[2]	0.000260***	(0.000042)	1.000260	1.000 - 1.000
Homicide	0.147649***	(0.032913)	1.159106	1.087 - 1.236
Officer assaults	0.128889***	(0.023985)	1.137564	1.085 - 1.192
% Age 20-24[2]	-0.466781	(1.191252)	0.627018	0.061 - 6.476
% Owner occupied[2]	-0.208547	(0.109250)	0.811763	0.655 - 1.006
SES[2]	-0.083676*	(0.041642)	0.919729	0.848 - 0.998
% Hispanic[2]	0.681624***	(0.188465)	1.977087	1.366 - 2.861
% Af. Am.[2]	0.190000	(0.109833)	1.209249	0.975 - 1.500
% Commercial	0.011399***	(0.001946)	1.011464	1.008 - 1.015
% State Liquor	0.004885	(0.003677)	1.004897	0.998 - 1.012
% Liquor	-0.000821	(0.000928)	0.999180	0.997 - 1.001
% Club	-0.001934	(0.001773)	0.998068	0.995 - 1.002
% Pawn	0.006640*	(0.003203)	1.006662	1.000 - 1.013
% Check cashing	0.006861**	(0.002308)	1.006885	1.002 - 1.011
% Homeless shelter	-0.003837	(0.003263)	0.996170	0.990 - 1.003
% Drug treatment	0.003046	(0.003741)	1.003051	0.996 - 1.010
% Halfway house	0.001220	(0.002608)	1.001221	0.996 - 1.006
% Rail	-0.005443	(0.006307)	0.994572	0.982 - 1.007
% Subway	0.011095***	(0.003118)	1.011157	1.005 - 1.017
Bus[3]	0.453810**	(0.169042)	1.574300	1.130 - 2.193
Random effects	Variance component		Chi-Square	*Df*
Between district (Level-2)				
Intercept	0.07873***		240.26676	22
Within-district (Level-1)				
Residual Variation	128.19047			

1. Spatial lag variable created through a two-stage least squares approach (see Appendix D for details).
2. Based on yearly census estimates created by Geolytics. See Appendix B for methodological details.
3. Length of bus route within the geography normalized by area

Officer workload, as operationalized through homicide and officer assault incidents, was positive, significant, and consistent throughout the study years. Population and the spatial lag variables follow the same trend.

The relationship between demographic variables and traffic stops differed from the relative stability of findings from the other outcome measures. Most notably, socioeconomic status, one of the strongest and most consistent predictors of unfounded events and low seriousness arrests, was only significantly related to traffic stops during 2005, 2006, and 2008. In these years, a higher level of socioeconomic status was associated with lower counts of traffic stops. The tenuous relationship between socioeconomic status and traffic stops may have to do with the variables selected to control for population effects. It may be that for traffic stops the level of residential population does not correlate highly with the level of vehicular traffic. This negative relationship may be demonstrating a relationship between socioeconomic status and the level of vehicular traffic (possibly because higher socioeconomic status translates to lower population density or because it translates to land uses with less vehicular traffic). Only one other demographic variable, percent Hispanic, was significantly related to traffic stops, and again only in a few years (2007 and 2008). The percent African American, the percent owner occupied housing, and the percent of people age 20-24 did not attain statistical significance in any of the study years.

Consistent with the unfounded events and low serious arrests, the percentage of land zoned as commercial was consistently positively related to the number of traffic stops occurring in a block group. The only other land use indicator that was consistently related to traffic stops was pawn shops. Indicators for liquor stores, drug treatment centers, halfway houses, and rail stations were consistently non-significant throughout the study period.

Several land use variables had inconsistent relationships with traffic stops. The subway stop indicator was significant and positive in four out of the five years (2005-2008). Clubs were significantly associated with lower traffic stop counts in three out of the five years (2004, 2006, and 2007). The length of bus routes was significantly associated with more traffic stops in three of the five years (2006, 2007, and 2008). The homeless shelter indicator was significantly associated with lower levels of traffic stops in 2004 and 2005, but was non-significant in other years. Finally, the indicator for state run liquor stores was positively associated with higher levels of traffic stops in only one year, 2005.

These cross-sectional models have demonstrated that, at least under certain conditions, variation in vigor existed at the sub-district level. These variations were driven by workload, demographics, and land uses.

Cross-Sectional Summary

The cross-sectional models looked at officer vigor at the census block group level of analysis. In doing so these models investigated how socio-demographics, land use, and officer workload impacted the level of officer vigor at a sub-district unit of analysis. While a comprehensive discussion can be found in the following chapter it is worthwhile to undertake a brief review of the key findings from these models.

The cross-sectional models suggested that the method of operationalizing vigor was critically important. Depending upon how vigor was operationalized the vigor-workload hypothesis was both supported and not supported. This suggested that vigor may have been multi-dimensional and attempting to measure vigor with a single construct would have missed this critical component. The strongest support for Klinger’s hypothesis came from operationalizing vigor through measuring unfounded events. Recall that when workload (homicides, officer assaults, or serious incidents) increased the level of unfounded events also increased suggesting that officers may be shedding work in order to concentrate on more serious, time consuming, crime issues. The two other measures of vigor, low seriousness arrests and traffic stops, did not behave in the theoretically expected direction. For both of these outcomes higher levels of workload was associated with *greater* levels of vigor.

The relationship between demographics, land use, and officer vigor was less clear. Once again, differences were found between outcome measures and their relationship to demographics and land use. These differences further reinforced the understanding that vigor was multidimensional. The most consistent demographic predictor of officer vigor was socio-economic status which fits in well with broader literature suggesting that socio-economic status is frequently associated with crime and the distribution of social services (literature cited in the previous sections). The most consistent land use predictor of crime was commercial land use. This was perhaps not surprising given the rather general nature of this land use measure compared to the individual measures of facility proximity.

One other result is worth briefly discussing here. The spatial lag term was generally significant across all models. The exception to this finding was the spatial lag term in the yearly unfounded models which was significant in 2005 but decreased monotonically to non-significance by 2008. The general significance of the spatial lag term, however, suggested that officer vigor followed a spatial diffusion pattern. This may be indicative of broader spatial patterns, perhaps suggestive of district norms as hypothesized by Klinger. Spatial patterns along with a greater discussion of workload, demographics, and land use can be found in the following chapter. The remainder of this section is devoted to further exploring district level dynamics through longitudinal analyses of unfounded events, low seriousness arrests, and traffic stops.

Longitudinal Models

The remainder of this section is devoted to the longitudinal models conducted to investigate the temporal dynamics of officer vigor. These models were conducted at the district level (level-1 units being temporally varying months and level-2 units being time invariant districts). These longitudinal models help to expand Klinger's theory by investigating the proposed relationships in a longitudinal framework. Specifically the longitudinal models investigated how officer workload (in the form of serious crimes) and officer staffing levels impacted the level of officer vigor.

Five longitudinal models were conducted on each of the three outcome variables. These models were constructed in order to monitor changes in the direction, magnitude, or significance of the independent variables as models were respecified. No predictor variables were entered into model 1. This model served to test the significance of the variance at level-2 (between districts). Model 2 entered variables representing linear trends, quadratic (non-linear) trends, temperature[28], and the number of days in the month of the observation. This model attempted to model the on-going, long term, persistent trends found in the outcome variables. Model 3 added two variables, the spatial lag term and population, to the temporal trend variables found in model 2. This model explored the impact of spatial effects and population, two factors that have strong ties to the outcome variables. Model 4 added officer workload (measured through the number of serious incidents) and the number of officer assaults. These two variables represent two key constructs in the ecological theory. Model 5 added the number

[28] Temperature was used as a control over seasonality, a factor that can have substantial influence on crime and disorder. Temperature was measured as the average monthly temperature (generated by averaging the maximum and minimum daily temperature for every day in the month) and was gathered from historical weather archives located at www.wunderground.com.

of officer hours assigned to patrol as well as the number of overtime hours allocated to patrol related positions. These two variables represent officer resources, a key aspect to Klinger's theory and an issue that could not be addressed in the cross-sectional models. Finally, model 6 and model 7 used temporally lagged workload and officer staffing variables to further explore the temporal sequencing between key theoretical predictors and the outcome variables. Assessments of model fit were undertaken and can be found in Appendix F.

All variables were group mean centered before entering. Group mean centering means that the coefficients only measure changes within the district over time. These longitudinal models, therefore, do not explore differences between districts; they are used only to logitudinalize the dynamics discussed in Klinger's theory and explore the ongoing changes and trends within each district. The results of models for each outcome are discussed individually beginning with unfounded events (Table 22).

Longitudinal Models of Unfounded Events

Table 22: Longitudinal models of unfounded events

	Model 1			Model 2		
Fixed effects	Coefficient (S.E.)	Event rate ratio	Confidence interval	Coefficient (S.E.)	Event rate ratio	Confidence interval
Intercept	6.972781***(0.118277)	1067.186769	835.332 - 1363.394	6.958887*** (0.118552)	1052.461140	823.338 - 1345.346
Linear				-0.012898*** (0.001318)	0.987184	0.985 - 0.990
Quadratic				0.000136*** (0.000021)	1.000136	1.000 - 1.000
Temp[1]				0.008477*** (0.000367)	1.008513	1.008 - 1.009
Days				0.035359*** (0.007976)	1.035991	1.020 - 1.052
Spatial lag[2]						
Population[3]						
Serious incidents						
Officer assaults						
Officer hours[4]						
Overtime hours[5]						

Random effects	Variance component	Chi-Square	*Df*
Between district (Level-2)			
Intercept	0.32***	5422.59	22
Within-district (Level-1)			
Residual Variation	86.88		

* p < .05, ** p < .01, *** p < .001

1. Average daily, average monthly temperature. Collected from www.wunderground.com
2. Spatial lag calculated for monthly dependent variable event counts based on a three nearest neighbors weight matrix.
3. Population data drawn from estimated census data created by Geolytics. See Appendix B for comprehensive discussion of the estimation technique used.
4. Officer hours calculated based on data drawn from the Philadelphia Police Department's personnel management system. Data for each month was calculated from officer staffing on the second Wednesday of the month. Only officers assigned to districts in patrol capacity were included in this calculation.
5. Overtime hours calculated based on data drawn from the Philadelphia Police Department's personnel management system. Data for each month was calculated from officer staffing on the second Wednesday of the month. Only officers working overtime for patrol related duties were included in this analysis.

Table 22: Longitudinal models of unfounded events (cont.)

	Model 3			Model 4		
Fixed effects	Coefficient (S.E.)	Event rate ratio	Confidence interval	Coefficient (S.E.)	Event rate ratio	Confidence interval
Intercept	6.714886*** (0.109879)	824.589786	656.765 - 1035.299	6.719928*** (0.109937)	828.757573	660.005 - 1040.657
Linear	-0.007116*** (0.001310)	0.992909	0.990 - 0.995	-0.007889*** (0.001314)	0.992142	0.990 - 0.995
Quadratic	0.000063** (0.000021)	1.000063	1.000 - 1.000	0.000076*** (0.000021)	1.000076	1.000 - 1.000
Temp[1]	0.006140*** (0.000399)	1.006159	1.005 - 1.007	0.005303*** (0.000444)	1.005317	1.004 - 1.006
Days	0.02739*** (0.007476)	1.027773	1.013 - 1.043	0.017000* (0.007839)	1.017145	1.002 - 1.033
Spatial lag[2]	0.000199*** (0.000018)	1.000199	1.000 - 1.000	0.000195*** (0.000018)	1.000195	1.000 - 1.000
Population[3]	0.000040*** (0.000006)	1.000040	1.000 - 1.000	0.000039*** (0.000006)	1.000039	1.000 - 1.000
Serious incidents				0.000594*** (0.000141)	1.000595	1.000 - 1.001
Officer assaults				-0.002265 (0.003241)	0.997737	0.991 - 1.004
Officer hours[4]						
Overtime hours[5]						
Random effects						
Between district (Level-2)						
Intercept						
Within-district (Level-1)						
Residual Variation						

* p < .05, ** p < .01, *** p < .001

1. Average daily, average monthly temperature. Collected from www.wunderground.com
2. Spatial lag calculated for monthly dependent variable event counts based on a three nearest neighbors weight matrix.
3. Population data drawn from estimated census data created by Geolytics. See Appendix B for comprehensive discussion of the estimation technique used.
4. Officer hours calculated based on data drawn from the Philadelphia Police Department's personnel management system. Data for each month was calculated from officer staffing on the second Wednesday of the month. Only officers assigned to districts in patrol capacity were included in this calculation.
5. Overtime hours calculated based on data drawn from the Philadelphia Police Department's personnel management system. Data for each month was calculated from officer staffing on the second Wednesday of the month. Only officers working overtime for patrol related duties were included in this analysis.

Table 22: Longitudinal models of unfounded events (cont.)

	Model 5			
Fixed effects	Coefficient (S.E.)		Event rate ratio	Confidence interval
Intercept	6.955206***	0.118745	1048.594664	819.984 - 1340.942
Linear	-0.011994***	0.001434	0.988078	0.985 - 0.991
Quadratic	0.000142***	0.000023	1.000142	1.000 - 1.000
Temp[1]	0.005306***	0.000442	1.005321	1.004 - 1.006
Days	0.020666**	0.007747	1.020881	1.005 - 1.036
Spatial lag[2]	0.000193***	0.000017	1.000193	1.000 - 1.000
Population[3]	0.000045***	0.000006	1.000045	1.000 - 1.000
Serious incidents	0.000547***	0.000140	1.000547	1.000 - 1.001
Officer assaults	-0.001814	0.003196	0.998188	0.992 - 1.004
Officer hours[4]	-0.000443***	0.000069	0.999557	0.999 - 1.000
Overtime hours[5]	0.000306	0.000241	1.000306	1.000 - 1.001
Random effects				
Between district (Level-2)				
Intercept				
Within-district (Level-1)				
Residual Variation				

* p < .05, ** p < .01, *** p < .001

1. Average daily, average monthly temperature. Collected from www.wunderground.com
2. Spatial lag calculated for monthly dependent variable event counts based on a three nearest neighbors weight matrix.
3. Population data drawn from estimated census data created by Geolytics. See Appendix B for comprehensive discussion of the estimation technique used.
4. Officer hours calculated based on data drawn from the Philadelphia Police Department's personnel management system. Data for each month was calculated from officer staffing on the second Wednesday of the month. Only officers assigned to districts in patrol capacity were included in this calculation.
5. Overtime hours calculated based on data drawn from the Philadelphia Police Department's personnel management system. Data for each month was calculated from officer staffing on the second Wednesday of the month. Only officers working overtime for patrol related duties were included in this analysis.

The ANOVA analysis (model 1) indicated that there were, on average, 1,067 unfounded events per month, per district during the study period.

Ongoing temporal trends: The linear time trend variable indicated that there was a significant decline in unfounded events during the study period. The number of unfounded events was decreasing roughly 1.2% per month across all districts (model 2). The quadratic variable was positive and significant indicating that there was an accelerating positive trend in the number of unfounded events during the study period. While the overall trend may be decreasing (as indicated by the linear trend variable) there appeared to have been a significant uptick in unfounded events towards the end of the study period. The temperature variable was significant and positive indicating that a 10 degree change in temperature was related to an 8.5% increase in the number of unfounded events per month, per district (model 2). The number of days was also associated with the number of unfounded events. Adding one additional day per month was associated with a 3.5% increase in the number of unfounded events per month, per district, net of other temporal trends (model 2). The direction, general magnitude, and significance of these variables were consistent across model specification (compare models 2 through 5).

Population & spatial effects: Population and spatial effects were added to the model specification beginning with model 3. The spatial lag term (recall that the spatial lag term was constructed with a 3-nearest neighbor contiguity matrix) was positive and significant indicating that higher levels of unfounded events in neighboring police districts was significantly associated with higher levels of unfounding in the target police district. Population was also positively and significantly related to the number of unfounded events. A 1,000 unit increase in the count of residential population was associated with a 4% increase in the expected count of unfounded events, net of ongoing temporal trends (model 3). Both population and the spatial lag terms were positive and significant across all model specifications.

Workload: Serious incidents were positively linked to the number of unfounded events. On average a 100 unit increase in the number of serious incidents per month, per district was associated with a 5.5% increase in the number of unfounded events per month, per district, net of spatial effects, population, and ongoing temporal trends (model 5). The number of officer assaults was not significantly related to the number of unfounded events (model 4 or model 5).

Officer staffing: Both the number of officer hours assigned to patrol and the number of overtime hours for patrol purposes were entered into model 5. Consistent with theoretical predictions a 100 unit increase in the number of officer-hours assigned to patrol was associated with a 4.4% decrease in the number of unfounded events, net of workload, population, spatial effects, and ongoing temporal trending, per month, per district. The number of overtime hours was not significantly related to the count of unfounded events (model 5).

It was argued earlier that key independent variables may not have an immediate impact upon the outcome variable. There may be a time lag between increases in workload and decreases in the level of patrol officer vigor. To further explore this temporal dimension a number of additional models were run with key independent variables temporally lagged by one and two months. Table 23 presents the results of these temporally lagged models.

Table 23: Longitudinal models of unfounded events with temporally lagged variables

	Model 6			Model 7		
Fixed effects	Coefficient (S.E.)	Event rate ratio	Confidence interval	Coefficient (S.E.)	Event rate ratio	Confidence interval
Intercept	6.955218*** (0.118832)	1048.606729	819.846 - 1341.198	6.955345*** (0.118719)	1048.740047	820.143 - 1341.054
Linear	-0.011841*** (0.001446)	0.988229	0.985 - 0.991	-0.011879*** (0.001432)	0.98819	0.985 - 0.991
Quadratic	0.000139*** (0.000023)	1.000139	1.000 - 1.000	0.000139*** (0.000023)	1.000139	1.000 - 1.000
Temp[1]	0.005843*** (0.000418)	1.005860	1.005 - 1.007	0.005261*** (0.000443)	1.005275	1.004 - 1.006
Days	0.031428*** (0.007405)	1.031927	1.017 - 1.047	0.021026*** (0.007783)	1.021249	1.006 - 1.037
Spatial lag[2]	0.000198*** (0.000017)	1.000198	1.000 - 1.000	0.000190*** (0.000017)	1.000190	1.000 - 1.000
Population[3]	0.000045*** (0.000006)	1.000045	1.000 - 1.000	0.000045*** (0.000006)	1.000045	1.000 - 1.000
Serious incidents	**0.000209* (0.000107)**	**1.000209**	**1.000 - 1.000**	0.000570*** (0.000139)	1.000570	1.000 - 1.001
Officer assaults	**-0.004415 (0.003283)**	**0.995595**	**0.989 - 1.002**	-0.002617 (0.003201)	0.997386	0.991 - 1.004
Officer hours[4]	-0.000460*** (0.000069)	0.999540	0.999 - 1.000	**-0.000437*** (0.000069)**	**0.999563**	**0.999 - 1.000**
Overtime hours[5]	0.000306 (0.000242)	1.000306	1.000 - 1.001	**0.000165 (0.000242)**	**1.000165**	**1.000 - 1.001**

Random effects	Variance component	Chi-Square	*Df*	Variance component	Chi-Square	*Df*
Between district (Level-2)						
Intercept	0.32***	10407.00	22	0.32***	10474.70	22
Within-district (Level-1)						
Residual Variation	45.27			44.87		

* p < .05, ** p < .01, *** p < .001

Bold variables indicate a one-unit temporal lag

1. Average daily, average monthly temperature. Collected from www.wunderground.com
2. Spatial lag calculated for monthly dependent variable event counts based on a three nearest neighbors weight matrix.
3. Population data drawn from estimated census data created by Geolytics. See Appendix B for comprehensive discussion of the estimation technique used.
4. Officer hours calculated based on data drawn from the Philadelphia Police Department's personnel management system. Data for each month was calculated from officer staffing on the second Wednesday of the month. Only officers assigned to districts in patrol capacity were included in this calculation.
5. Overtime hours calculated based on data drawn from the Philadelphia Police Department's personnel management system. Data for each month was calculated from officer staffing on the second Wednesday of the month. Only officers working overtime for patrol related duties were included in this analysis.

Model 6 explored the impact of temporally lagging workload variables. When serious incidents were lagged by one month their impact was reduced and the coefficient hovered at the edge of significance. At a two month lag (results not shown) the serious incident variable was non-significant indicating further degradation in the relationship between serious incidents and unfounded events. Officer assaults were largely unaffected by the temporal lagging. Neither a one month nor two month temporal lag resulted in any change to the coefficient or non-significance of officer assaults. Other variables in these models were largely unchanged with no substantial impact on the direction, magnitude, or significance of other predictors.

Time lagging officer staffing variables (model 7) resulted in very few changes to the time lagged variables or to other variables in the model. Specifically, lagging officer hours by one or two months resulted in minimal changes to the direction, magnitude, and significance of the coefficient. The number of officer hours was consistently significantly related to the number of unfounded events. Similarly, the number of overtime hours was not significantly related to the number of unfounded events. Once again, overall direction, magnitude, and significance of other variables in the model were largely unchanged.

Longitudinal Models of Low Seriousness Arrests

The next section details the results from the longitudinal analyses of low seriousness arrests (Table 24). Recall that higher levels of arrests for low seriousness incidents are indicative of greater officer vigor.

Table 24: Longitudinal models of low seriousness arrest events

	Model 1			Model 2		
Fixed effects	Coefficient (S.E.)	Event rate ratio	Confidence interval	Coefficient (S.E.)	Event rate ratio	Confidence interval
Intercept	4.911931***(0.150797)	135.901519	99.447 - 185.718	4.911200*** (0.150803)	135.802247	99.374 - 185.585
Linear				0.002505 (0.001503)	1.002508	1.000 - 1.005
Quadratic				-0.000017 (0.000024)	0.999983	1.000 - 1.000
Temp[1]				-0.001711*** (0.000411)	0.998290	0.997 - 0.999
Days				0.022245** (0.008385)	1.022494	1.006 - 1.039
Spatial lag[2]						
Population[3]						
Serious incidents						
Officer assaults						
Officer hours[4]						
Overtime hours[5]						

Random effects	Variance component	Chi-Square	*Df*
Between district (Level-2)			
Intercept	0.52***	14,327.05	22
Within-district (Level-1)			
Residual Variation	9.72		

* p < .05, ** p < .01, *** p < .001

1. Average daily, average monthly temperature. Collected from www.wunderground.com
2. Spatial lag calculated for monthly dependent variable event counts based on a three nearest neighbors weight matrix.
3. Population data drawn from estimated census data created by Geolytics. See Appendix B for comprehensive discussion of the estimation technique used.
4. Officer hours calculated based on data drawn from the Philadelphia Police Department's personnel management system. Data for each month was calculated from officer staffing on the second Wednesday of the month. Only officers assigned to districts in patrol capacity were included in this calculation.
5. Overtime hours calculated based on data drawn from the Philadelphia Police Department's personnel management system. Data for each month was calculated from officer staffing on the second Wednesday of the month. Only officers working overtime for patrol related duties were included in this analysis.

Table 24: Longitudinal models of low seriousness arrest events (cont.)

	Model 3			Model 4		
Fixed effects	Coefficient (S.E.)	Event rate ratio	Confidence interval	Coefficient (S.E.)	Event rate ratio	Confidence interval
Intercept	4.909157*** (0.150959)	135.525137	99.139 -185.266	4.909089*** (0.150941)	135.515881	99.136 - 185.246
Linear	0.002165 (0.001458)	1.002167	0.999 - 1.005	0.002456 (0.001476)	1.002459	1.000 - 1.005
Quadratic	-0.000025 (0.000023)	0.999975	1.000 - 1.000	-0.000031 (0.000023)	0.999969	1.000 - 1.000
Temp[1]	-0.001257** (0.000407)	0.998744	0.998 - 1.000	-0.001243** (0.000475)	0.998758	0.998 - 1.000
Days	0.018866* (0.008180)	1.019045	1.003 - 1.036	0.018936* (0.008760)	1.019117	1.002 - 1.037
Spatial lag[2]	0.001008*** (0.000182)	1.001008	1.001 - 1.001	0.001010*** (0.000183)	1.001010	1.001 - 1.001
Population[3]	-0.000057*** (0.000007)	0.999943	1.000 - 1.000	-0.000056*** (0.000007)	0.999944	1.000 - 1.000
Serious incidents				-0.000055 (0.000166)	0.999945	1.000 - 1.000
Officer assaults				0.008411* (0.003599)	1.008446	1.001 - 1.016
Officer hours[4]						
Overtime hours[5]						
Random effects						
Between district (Level-2)						
Intercept						
Within-district (Level-1)						
Residual Variation						

* p < .05, ** p < .01, *** p < .001

1. Average daily, average monthly temperature. Collected from www.wunderground.com
2. Spatial lag calculated for monthly dependent variable event counts based on a three nearest neighbors weight matrix.
3. Population data drawn from estimated census data created by Geolytics. See Appendix B for comprehensive discussion of the estimation technique used.
4. Officer hours calculated based on data drawn from the Philadelphia Police Department's personnel management system. Data for each month was calculated from officer staffing on the second Wednesday of the month. Only officers assigned to districts in patrol capacity were included in this calculation.
5. Overtime hours calculated based on data drawn from the Philadelphia Police Department's personnel management system. Data for each month was calculated from officer staffing on the second Wednesday of the month. Only officers working overtime for patrol related duties were included in this analysis.

Table 24: Longitudinal models of low seriousness arrest events (cont.)

	Model 5			
Fixed effects	Coefficient	(S.E.)	Event rate ratio	Confidence interval
Intercept	4.909057***	(0.150935)	135.511566	99.134 - 185.238
Linear	0.001091	(0.001670)	1.001091	0.998 - 1.004
Quadratic	-0.000008	(0.000027)	0.999992	1.000 - 1.000
Temp[1]	-0.001208**	(0.000479)	0.998793	0.998 - 1.000
Days	0.020175*	(0.008818)	1.020380	1.003 - 1.038
Spatial lag[2]	0.001030***	(0.000183)	1.001030	1.001 - 1.001
Population[3]	-0.000053***	(0.000007)	0.999947	1.000 - 1.000
Serious incidents	-0.000069	(0.000166)	0.999931	1.000 - 1.000
Officer assaults	0.008431*	(0.003598)	1.008466	1.001 - 1.016
Officer hours[4]	-0.000135	(0.000078)	0.999865	1.000 - 1.000
Overtime hours[5]	0.000055	(0.000295)	1.000055	0.999 - 1.001
Random effects				
Between district (Level-2)				
Intercept				
Within-district (Level-1)				
Residual Variation				

* p < .05, ** p < .01, *** p < .001

1. Average daily, average monthly temperature. Collected from www.wunderground.com
2. Spatial lag calculated for monthly dependent variable event counts based on a three nearest neighbors weight matrix.
3. Population data drawn from estimated census data created by Geolytics. See Appendix B for comprehensive discussion of the estimation technique used.
4. Officer hours calculated based on data drawn from the Philadelphia Police Department's personnel management system. Data for each month was calculated from officer staffing on the second Wednesday of the month. Only officers assigned to districts in patrol capacity were included in this calculation.
5. Overtime hours calculated based on data drawn from the Philadelphia Police Department's personnel management system. Data for each month was calculated from officer staffing on the second Wednesday of the month. Only officers working overtime for patrol related duties were included in this analysis.

The ANOVA analysis (Model 1) indicated that there were, on average, 136 arrests for low seriousness incidents per district per month during the study period with significant differences between districts.

Ongoing temporal trends: Both the linear and quadratic trends were non-significant regardless of model specification; during the study period there were no clear trends in the number of low seriousness events in each district per month. The temperature variable was significant and negative indicating that a 10 degree increase in temperature was associated with a 1.7% decrease in the number of low seriousness arrest events per month, per district (model 2). The number of days was significantly and positively associated with the number of low seriousness arrests. Every additional day per month was associated with a 2.2% increase in the number of low seriousness arrests per month, per district. These effects persisted regardless of model specification.

Population & spatial effects: Perhaps unexpectedly the residential population of a district was negatively associated with the number of low seriousness arrests. A 1,000 unit increase in the residential population was associated with a 5.7% decrease in the number of low seriousness arrests. Spatial effects were positively associated with the count of low seriousness arrests. A one unit increase in the lag variable was associated with a 1% increase in the monthly count of low seriousness arrests in the target police district (model 3). Models 4 and 5 demonstrated similar patterns.

Workload: Diverging from the results of unfounded events, serious incidents were not significantly associated with the number of low seriousness arrests (model 4 or model 5). Officer assaults, however, were positively associated with the monthly low seriousness arrest counts.

Every additional officer assault per month, per district was associated with a 0.84% increase in the number of low seriousness arrests per month, per district (model 4).

Officer staffing: Neither officer hours nor overtime hours were significantly associated with the number of low seriousness arrests.

To further explore this temporal dimension a number of additional models were run with key independent variables temporally lagged by one and two months (Table 25).

Table 25: Longitudinal models of low seriousness arrest events with temporally lagged variables

	Model 6				Model 7			
Fixed effects								
Intercept	4.909411***	(0.150875)	135.559600	99.181 - 185.281	4.909356***	(0.150872)	135.552084	99.176 - 185.270
Linear	0.001096	(0.001676)	1.001097	0.998 - 1.004	0.000458	(0.001661)	1.000458	0.997 - 1.004
Quadratic	-0.000008	(0.000027)	0.999992	1.000 - 1.000	0.000001	(0.000026)	1.000001	1.000 - 1.000
Temp[1]	-0.001303**	(0.000432)	0.998698	0.998 - 1.000	-0.001289**	(0.000477)	0.998712	0.998 - 1.000
Days	0.020216*	(0.008261)	1.020422	1.004 - 1.037	0.021462*	(0.008859)	1.021694	1.004 - 1.040
Spatial lag[2]	0.001032***	(0.000184)	1.001033	1.001 - 1.001	0.001035***	(0.000183)	1.001036	1.001 - 1.001
Population[3]	-0.000053***	(0.000007)	0.999947	1.000 - 1.000	-0.000052***	(0.000007)	0.999948	1.000 - 1.000
Serious incidents	**-0.000040**	**(0.000125)**	**0.999960**	**1.000 - 1.000**	-0.000059	(0.000166)	0.999941	1.000 - 1.000
Officer assaults	**0.008558***	**(0.003661)**	**1.008595**	**1.001 - 1.016**	0.008045*	(0.003597)	1.008078	1.001 - 1.015
Officer hours[4]	-0.000122	(0.000078)	0.999878	1.000 - 1.000	**-0.000192****	**(0.000078)**	**0.999808**	**1.000 - 1.000**
Overtime hours[5]	0.000093	(0.000295)	1.000093	1.000 - 1.001	**0.000106**	**(0.000296)**	**1.000106**	**1.000 - 1.001**

Random effects	Variance component	Chi-Square	*Df*	Variance component	Chi-Square	*Df*
Between district (Level-2)						
Intercept	0.52***	15614.42	22	0.52	15661.49	22
Within-district (Level-1)						
Residual Variation	8.92			8.89		

* p < .05, ** p < .01, *** p < .001

Bold variables indicate a one-unit temporal lag

1. Average daily, average monthly temperature. Collected from www.wunderground.com
2. Spatial lag calculated for monthly dependent variable event counts based on a three nearest neighbors weight matrix.
3. Population data drawn from estimated census data created by Geolytics. See Appendix B for comprehensive discussion of the estimation technique used.
4. Officer hours calculated based on data drawn from the Philadelphia Police Department's personnel management system. Data for each month was calculated from officer staffing on the second Wednesday of the month. Only officers assigned to districts in patrol capacity were included in this calculation.
5. Overtime hours calculated based on data drawn from the Philadelphia Police Department's personnel management system. Data for each month was calculated from officer staffing on the second Wednesday of the month. Only officers working overtime for patrol related duties were included in this analysis.

Model 6 explored the impact of a one month lag on the key workload variables, number of serious incidents and the number of officer assaults. The addition of these temporally lagged variables resulted in very few changes to the overall model. Serious incidents remained non-significant while officer assaults maintained significance. Other variables in the model were relatively unaffected by the addition of the lagged variables. A two month lag on key workload variables (results omitted) produced a single change to other variables in the model: officer assaults were no longer significantly associated with the number of low seriousness arrests. There were no other noteworthy changes to other variables in the model.

Model 7 explored the impacts of temporally lagged officer staffing variables. Officer hours, when entered with a one or two month (results omitted) lag, was a significant predictor of the number of low seriousness arrests. This variable, however, was going in the opposite direction than theoretically expected. A 100 unit increase in the number of officers assigned to patrol was expected to decrease the count of low seriousness arrests events by 1.9% controlling for other relevant factors.

Longitudinal Models of Traffic Stops

The next set of models explored the relationship between workload, resources, and traffic stops and can be found in Table 26. Higher levels of traffic stops would be indicative of greater levels of vigor.

Table 26: Longitudinal models of traffic stops

	Model 1			Model 2		
Fixed effects	Coefficient (S.E.)	Event rate ratio	Confidence interval	Coefficient (S.E.)	Event rate ratio	Confidence interval
Intercept	6.986148*** (0.066598)	1081.546830	942.204 - 1241.497	6.984328*** (0.066605)	1079.580783	940.478 - 1239.258
Linear				-0.003161* (0.001465)	0.996844	0.994 - 1.000
Quadratic				0.000083*** (0.000023)	1.000083	1.000 - 1.000
Temp[1]				-0.002669*** (0.000404)	0.997334	0.997 - 0.998
Days				0.027529*** (0.008238)	1.027911	1.011 - 1.045
Spatial lag[2]						
Population[3]						
Serious incidents						
Officer assaults						
Officer hours[4]						
Overtime hours[5]						

Random effects	Variance component	Chi-Square	*Df*
Between district (Level-2)			
Intercept	0.10***	2334.98	22
Within-district (Level-1)			
Residual Variation	65.74		

* p < .05, ** p < .01, *** p < .001

1. Average daily, average monthly temperature. Collected from www.wunderground.com
2. Spatial lag calculated for monthly dependent variable event counts based on a three nearest neighbors weight matrix.
3. Population data drawn from estimated census data created by Geolytics. See Appendix B for comprehensive discussion of the estimation technique used.
4. Officer hours calculated based on data drawn from the Philadelphia Police Department's personnel management system. Data for each month was calculated from officer staffing on the second Wednesday of the month. Only officers assigned to districts in patrol capacity were included in this calculation.
5. Overtime hours calculated based on data drawn from the Philadelphia Police Department's personnel management system. Data for each month was calculated from officer staffing on the second Wednesday of the month. Only officers working overtime for patrol related duties were included in this analysis.

Table 26: Longitudinal models of traffic stops (cont.)

	Model 3			Model 4		
Fixed effects	Coefficient (S.E.)	Event rate ratio	Confidence interval	Coefficient (S.E.)	Event rate ratio	Confidence interval
Intercept	6.983061*** (0.066549)	1078.213338	939.397 - 1237.542	6.982339*** (0.066463)	1077.435610	938.885 - 1236.432
Linear	-0.002129 (0.001449)	0.997874	0.995 - 1.001	-0.001131 (0.001436)	0.998870	0.996 - 1.002
Quadratic	0.000058* (0.000023)	1.000058	1.000 - 1.000	0.000042 (0.000023)	1.000042	1.000 - 1.000
Temp[1]	-0.001642*** (0.000412)	0.998359	0.998 - 0.999	-0.000085 (0.000470)	0.999915	0.999 - 1.001
Days	0.018810* (0.008102)	1.018988	1.003 - 1.035	0.038366*** (0.008488)	1.039112	1.022 - 1.057
Spatial lag[2]	0.000314*** (0.000037)	1.000314	1.000 - 1.000	0.000297*** (0.000037)	1.000297	1.000 - 1.000
Population[3]	-0.000006 (0.000007)	0.999994	1.000 - 1.000	-0.000002 (0.000007)	0.999998	1.000 - 1.000
Serious incidents				-0.001110*** (0.000166)	0.998890	0.999 - 0.999
Officer assaults				0.005394 (0.003784)	1.005409	0.998 - 1.013
Officer hours[4]						
Overtime hours[5]						
Random effects						
Between district (Level-2)						
Intercept						
Within-district (Level-1)						
Residual Variation						

* p < .05, ** p < .01, *** p < .001

1. Average daily, average monthly temperature. Collected from www.wunderground.com
2. Spatial lag calculated for monthly dependent variable event counts based on a three nearest neighbors weight matrix.
3. Population data drawn from estimated census data created by Geolytics. See Appendix B for comprehensive discussion of the estimation technique used.
4. Officer hours calculated based on data drawn from the Philadelphia Police Department's personnel management system. Data for each month was calculated from officer staffing on the second Wednesday of the month. Only officers assigned to districts in patrol capacity were included in this calculation.
5. Overtime hours calculated based on data drawn from the Philadelphia Police Department's personnel management system. Data for each month was calculated from officer staffing on the second Wednesday of the month. Only officers working overtime for patrol related duties were included in this analysis.

Table 26: Longitudinal models of traffic stops (cont.)

	Model 5		
Fixed effects	Coefficient (S.E.)	Event rate ratio	Confidence interval
Intercept	6.981903*** (0.066463)	1076.965472	938.476 - 1235.892
Linear	0.002571 (0.001624)	1.002574	0.999 - 1.006
Quadratic	-0.000017 (0.000026)	0.999983	1.000 - 1.000
Temp[1]	-0.000168 (0.000471)	0.999832	0.999 - 1.001
Days	0.035986*** (0.008495)	1.036641	1.020 - 1.054
Spatial lag[2]	0.000298*** (0.000037)	1.000298	1.000 - 1.000
Population[3]	-0.000008 (0.000007)	0.999992	1.000 - 1.000
Serious incidents	-0.001062*** (0.000165)	0.998938	0.999 - 0.999
Officer assaults	0.005253 (0.003764)	1.005267	0.998 - 1.013
Officer hours[4]	0.000381*** (0.000078)	1.000382	1.000 - 1.001
Overtime hours[5]	0.000253 (0.000295)	1.000253	1.000 - 1.001
Random effects			
Between district (Level-2)			
Intercept			
Within-district (Level-1)			
Residual Variation			

* p < .05, ** p < .01, *** p < .001

1. Average daily, average monthly temperature. Collected from www.wunderground.com
2. Spatial lag calculated for monthly dependent variable event counts based on a three nearest neighbors weight matrix.
3. Population data drawn from estimated census data created by Geolytics. See Appendix B for comprehensive discussion of the estimation technique used.
4. Officer hours calculated based on data drawn from the Philadelphia Police Department's personnel management system. Data for each month was calculated from officer staffing on the second Wednesday of the month. Only officers assigned to districts in patrol capacity were included in this calculation.
5. Overtime hours calculated based on data drawn from the Philadelphia Police Department's personnel management system. Data for each month was calculated from officer staffing on the second Wednesday of the month. Only officers working overtime for patrol related duties were included in this analysis.

The ANOVA analysis (model 1) indicated that there were, on average, 1,081 traffic stops per month, per district during the study period.

Ongoing temporal trends: When modeled independently of workload and resources (model 2) the findings suggest significant trends in the number of traffic stops. The linear trend variable indicated a significant decline in the number of traffic stops during the study period. Traffic stops were, on average, declining by 0.3% per month, per district. The quadratic term, however, indicated that there was a significant accelerating positive trend towards the end of the study period (a finding mirrored by the results of the low seriousness arrests models). Temperature was negatively related to the number of traffic stops. For every 10 degree increase in the average temperature there was an expected 2.6% decrease in the number of traffic stops per district per month. The number of days per month was positively associated with the number of traffic stops. On average, every additional day was associated with a 2.8% increase in the number of traffic stops per month, per district (model 2). The impact of these variables, however, was substantially altered by the inclusion of workload, officer staffing, population, and spatial effects variables. Only the number of days per month remained significant in the final model specification (model 5). It would appear that during the study period there were no linear, quadratic, or seasonality dependent trends in the number of traffic stops conducted per month, per district after controlling for other relevant organizational and environmental factors.

Population & spatial effects: Residential population was not significantly related to the number of traffic stops conducted in each district per month (model 3, 4, or 5). The spatial lag variable was significant and positive indicating that a one unit increase in the lagged crime variable was associated with a 0.03% increase in the traffic stop count per month, per district (model 3). This effect was consistent across model specifications.

Workload: Officer workload, as measured by the number of serious incidents, was negatively associated with the number of traffic stops. An increase of 10 additional serious incidents per month, per district was associated with a 1.1% decrease in the number of traffic stops per month, per district, net of ongoing temporal trends (model 4). The number of officer assaults was not significantly related to the number of traffic stops. These effects persisted even after controlling for the number of officer hours and the number of overtime hours (model 5).

Officer staffing: The number of officer hours assigned to patrol was positively associated with the number of traffic stops. For every additional 100 officer hours assigned to patrol per day, per district (note the change in temporal unit) the expected count of traffic stops would increase by 3.8% per month, per district. The relationship between the number of overtime hours and the number of traffic stops was non-significant.

Table 27 used temporally lagged variables to further explore the temporal relationship between traffic stops and key independent variables.

Table 27: Longitudinal models of traffic stops with temporally lagged variables

	Model 6				Model 7			
Fixed effects								
Intercept	6.982003***	(0.066476)	1077.073971	938.546 - 1236.048	6.981721***	(0.066432)	1076.770432	938.366 - 1235.589
Linear	0.002926	(0.001633)	1.002931	1.000 - 1.006	0.002874	(0.001599)	1.002878	1.000 - 1.006
Quadratic	-0.000021	(0.000026)	0.999979	1.000 - 1.000	-0.000020	(0.000025)	0.999980	1.000 - 1.000
Temp[1]	-0.001099**	(0.000429)	0.998902	0.998 - 1.000	-0.000162	(0.000468)	0.999838	0.999 - 1.001
Days	0.014312	(0.008015)	1.014415	0.999 - 1.030	0.031918***	(0.008497)	1.032433	1.015 - 1.050
Spatial lag[2]	0.000288***	(0.000037)	1.000288	1.000 - 1.000	0.000281***	(0.000036)	1.000281	1.000 - 1.000
Population[3]	-0.000008	(0.000007)	0.999992	1.000 - 1.000	-0.000009	(0.000007)	0.999991	1.000 - 1.000
Serious incidents	**-0.000658*** **	**(0.000125)**	**0.999342**	**0.999 - 1.000**	-0.001094***	(0.000164)	0.998907	0.999 - 0.999
Officer assaults	**0.013546*** **	**(0.003776)**	**1.013638**	**1.006 - 1.021**	0.005117	(0.003756)	1.005130	0.998 - 1.013
Officer hours[4]	0.000419***	(0.000078)	1.000419	1.000 - 1.001	**0.000447*** **	**(0.000077)**	**1.000447**	**1.000 - 1.001**
Overtime hours[5]	0.000229	(0.000296)	1.000229	1.000 - 1.001	**0.000736** **	**(0.000295)**	**1.000736**	**1.000 - 1.001**

Random effects	Variance component	Chi-Square	*Df*	Variance component	Chi-Square	*Df*
Between district (Level-2)						
Intercept	0.10	2750.17	22	0.10	2786.10	22
Within-district (Level-1)						
Residual Variation	55.56			54.76		

* p < .05, ** p < .01, *** p < .001

Bold variables indicate a one-unit temporal lag

1. Average daily, average monthly temperature. Collected from www.wunderground.com
2. Spatial lag calculated for monthly dependent variable event counts based on a three nearest neighbors weight matrix.
3. Population data drawn from estimated census data created by Geolytics. See Appendix B for comprehensive discussion of the estimation technique used.
4. Officer hours calculated based on data drawn from the Philadelphia Police Department's personnel management system. Data for each month was calculated from officer staffing on the second Wednesday of the month. Only officers assigned to districts in patrol capacity were included in this calculation.
5. Overtime hours calculated based on data drawn from the Philadelphia Police Department's personnel management system. Data for each month was calculated from officer staffing on the second Wednesday of the month. Only officers working overtime for patrol related duties were included in this analysis.

Model 6 lagged workload variables by one month. Some noteworthy changes were apparent. The serious incidents variable remained significant, in the same direction, and at about the same magnitude. Diverging from the contemporaneous models, the lagged models found that the number of officer assaults was significantly related to the count of traffic stops. Every additional officer assault per month, per district was expected to raise the count of traffic stops by 1.4% per month, per district. Officer staffing, spatial effects, and population remained consistent between contemporaneous and lagged models. These results were consistent across both one and two month (results omitted) lags.

Model 7 explored the effects of temporally lagging officer staffing variables. Unlike temporally lagging workload variables, lagging officer staffing only produced changes in the lagged variables; other variables in the model were consistent with the full contemporaneous model (model 5). Consistent with the contemporaneous model, the officer hours variable was significant and positive. However, unlike model 5, the temporally lagged model found that the number of overtime hours was significantly related to the number of traffic stops. Every additional 100 hours of overtime per day, per district was expected to increase the count of traffic stops by 7.4% per district per month, controlling for other relevant variables. These patterns of findings were consistent across both one and two unit temporal lags (results omitted).

Results Summary

Table 28 summarizes the significant results found between predictors and the various outcome measures in both the cross-sectional and longitudinal models. For the cross-sectional models only results that were generally significant across multiple years of analysis were included. This results summary suggests that officer vigor was related to workload, officer resources, demographics, and land use. These relationships were not always in the theoretically correct direction and for clarity key theoretical variables (workload and officer staffing) were highlighted so that **bold** results indicate the relationship was in the theoretically predicted direction while *italicized* results were in a direction not predicted by theory. Overall unfounded events were the most theoretically consistent with results being in the expected direction for both cross-sectional and longitudinal models. The relationship between traffic stops and workload and officer staffing varied based on the analysis methodology. The relationship was consistent with predictions in the longitudinal models but not the cross-sectional models. Finally, low seriousness arrests were not related to workload and staffing in the theoretically appropriate direction in either the cross-sectional or longitudinal models.

Table 28: Results summary

	Event Type		
Cross-sectional models (at the census block group level)	Unfounded events	Low seriousness arrests	Traffic stops
For every additional…			
100 unit increase in residential population…	+4.9%	+3.3%	+1.5%
Homicide…	**+53.3%**	*+56.6%*	*+92.0%*
Officer assault…	**+30.1%**	*+89.5%*	*+78.8%*
10 Serious incidents…	**+4.6%**	*+5.4%*	*+5.7%*
Standard deviation on the socioeconomic scale…	-10.2%	-30.2%	-7.5%
Standard deviation on ethnicity scale…	--	+12.1%	--
1% increase African American…	+14.9%	+31.7%	--
10% increase in commercial land use…	+11.2%	+6.5%	+11.2%
10% increase in state liquor…	--	+10.9	--
10% increase in liquor…	--	+1.8%	+1.7%
10% increase in check cashing…	--	--	+8.3%
10% increase in Drug treatment…	--	+16.1%	--
10% increase in Subway…	--	+12.3%	+7.0%
Bus length (standardized by area)…	--	+39.9%	+36.9%
Longitudinal models (monthly at the police district level)			
For every additional…			
1000 unit increase in residential population…	+4.5%	+5.7%	--
100 unit increase in serious incidents…	**+5.5%**	--	**-10.6**
1 unit increase in officer assaults…	--	*+0.8%*	--
100 unit increase in officer hours…	**-4.4%**	--	**+3.8%**

Key theoretical variables (workload and officer staffing) are highlighted to show consistency with theoretical predictions. Results in **bold** were consistent with theoretical predictions while results in *italics* were counter to theoretical expectations.

Note: Only effects that were relatively stable across multiple years of the cross-sectional models were included in this summary. Event rate ratios for the cross-sectional models were taken from the 5-year average models. All event rate ratios were taken from the final full model specification.

CHAPTER 5:

DISCUSSION

Using both cross-sectional and longitudinal multilevel modeling, the previous section explored key propositions relating to the relationship between vigor, workload, resources, and local environmental characteristics. Vigor was operationalized as the number of unfounded events, the number of low seriousness arrests, and the number of traffic stops at the block group level (cross-sectional) and at the police district level (longitudinal). By using cross-sectional models at the census block group level of aggregation this analysis expands the original scope of the theory by investigating organizational dynamics at the sub-district level. The longitudinal models expand the scope of the theory by positing that vigor is a temporally dynamic concept that is sensitive to changes in workload and officer resources. The result of these analyses suggests that key theoretical variables and officer vigor had relationships that were both consistent with and in opposition to theoretical predictions. This section will discuss key findings from both the cross-sectional and longitudinal models.

Before discussing the relationship between vigor and the independent variables it is worthwhile to spend a bit of time discussing the methods used to operationalize the vigor construct. These findings, taken as a whole, suggest that the method of operationalizing the concept of vigor had a substantial impact upon the relationships seen with key predictor variables.

Operationalizing Vigor

One apparent result from these analyses is that the method of quantifying vigor matters. The first indication that vigor was a multi-dimensional construct came from the descriptive spatial statistics. LISA indicators clearly demonstrated that unfounded events, low seriousness arrests, and traffic stops demonstrated different patterns of spatial clustering. Recall that unfounded events and low seriousness arrests showed significant clustering in North Philadelphia whereas traffic stops showed a much more disperse spatial pattern with several clusters in different locations throughout the city. These disparate spatial patterns suggested that vigor was not a unidimensional construct and that investigating vigor with multiple indicators would be a worthwhile endeavor.

Perhaps the most interesting finding from the spatial statistics was that unfounded events and low seriousness arrests showed similar patterns of clustering whereas traffic stops demonstrated a substantially different pattern. It was surprising then that the multi-level statistical models using unfounded events and low seriousness arrests produced substantially different results; unfounded events had results that were theoretically consistent with key theoretical variables whereas the relationship between low seriousness arrests and key theoretical variables was largely inconsistent. This suggests that even though different methods of operationalizing vigor may be significantly correlated and demonstrate similar spatial patterning there may still be reason to investigate vigor at different points of officer discretion.

Turning to the statistical models, all three dependent variables had different relationships with key theoretical predictors. Unfounded events, low seriousness arrests, and traffic stops had varying degrees of concurrence with theoretical expectations. Low seriousness arrests had less theoretically consistent relationships with key predictor variables than other outcome measures. Specifically, the two key theoretical variables, workload and officer staffing, were not significantly related to the number of low seriousness arrests made (in both the cross-sectional and longitudinal models). While being careful not to draw too many implications from non-significant results it is worth attempting to understand why these results patterned themselves the way they did.

Considering the unfounded events and traffic stops the pattern of results was clear: higher levels of workload or lower levels of officer staffing lead to less vigorous officer activity in high discretion situations. This relationship, however, did not manifest itself between low seriousness arrests and these variables. One explanation for this is perhaps the lack of conceptual clarity found in defining an event as being of "low seriousness". The types of events that constitute a low seriousness event span a wide range of offense types from firearm violations to sexual offenses. While it is conceptually simple to call all UCR part two crimes "low seriousness" offenses it requires a much larger stretch of the imagination to believe that officers treat all of these offenses in a similar manner.

For example, a substantial proportion of low seriousness arrests were comprised of arrests for drug offenses- including both simple possession and possession with intent to distribute. While many people may categorize a drug arrest as low seriousness, it is not obvious that the arresting officer would feel the same way. Extensive discussions with Philadelphia Police officers suggest the opposite may be true; officers seem to think that these arrests are an important facet to an overall crime reduction strategy. A null finding then, may better be interpreted as a call for further conceptualization of the notion of a low seriousness offense. It may be that patrol officers possess a unique perspective on what types of events constitute low or high seriousness. The results for the low seriousness arrest outcome can also be considered in light of alternative theories regarding the type and quantity of police action. Drawing from the dragnet theory (discussed in detail beginning on page 30) it is possible to postulate that officers may be using arrests for drug offenses as a spring board to search for more serious crimes. Under this theory, the drug crimes are not necessarily an end, but merely a means to an end. The ultimate goal may be to use drug crimes as justification to investigate more serious criminal activity. This is, of course, only speculation and additional research would be needed to tease out this relationship.

The low seriousness arrest outcome measure was also the only variable to have a significant relationship with officer assaults. Higher levels of officer assaults was significantly related to higher levels of low seriousness arrests. The relationship between this variable and the other outcome measures was non-significant. Recall that officer assaults were utilized to operationalize Klinger's conception of officer safety; officers always react vigorously when issues of officer safety are at stake regardless of workload or staffing issues. Once again the broad range of events that qualify as low seriousness events makes it difficult to clearly explicate the underlying processes. It may be that in areas of high officer danger, officers are more likely to strictly enforce clear violations of law where they may be able to remove someone from the streets through an arrest (a suggestion that would be closely tied to Herbert's territoriality thesis). This may not necessarily mean that officers would be more proactive, that is, they may not be more likely to found an event or conduct a traffic stop.

Several alterative explanations can be postulated. The first explanation may have to do with public backlash against the enforcement of low seriousness crimes. Officers in these areas may be enforcing laws against offenses that many people consider of low importance. It may be that the people in these areas do not hold the same value, or place the same emphasis, in enforcing laws which they feel are not relevant. This could lead to greater friction between officers and the public leading to more people resisting arrest and ultimately to more charges of officer assaults. A second explanation may be that officers working in high crime districts may simply have more contact with the public in general and more contact with high risk offenders specifically. If this were the case higher levels of officer assaults may result in areas with higher levels of arrests. This would suggest that future models need to account for this underlying difference in contact (another example of the denominator problem discussed earlier). This is, of course, only speculation but it does point out the importance in conceptually clarifying how vigor is quantified.

What the pattern of findings suggests is that the relationship between vigor and key theoretical predictors is strongest when the method of operationalizing vigor is the most conceptually clear. Unfounding events has the most conceptual clarity with vigor: unfounding events requires less vigor than conducting an investigation and filing a report. Traffic stops have a less clear relationship with vigor. In general officers busy with other crimes would not have time to engage in proactive traffic work. However, in high crime districts officers may be using traffic stops as an investigative tool to ultimately reduce violent crime. And, for reasons discussed above, low serious arrests have an even less clear relationship with vigor.

A reviewer of a previous draft of this manuscript pointed out that traffic stops may be measuring vigor at a different stage of processing compared to the other outcome measures. Consider that the other two variables, unfounded events and low seriousness arrests, represent the end decision to invoke, or not invoke, formal authority. Officers respond to a call and unfound an event or, officers respond to a call and make an arrest. Both of these could be thought of as decisions being made at the end stage of an officer's involvement with an event. Traffic stops are perhaps conceptually different because traffic stops can be thought of as the beginning of an interaction. This places the decision to issue a citation as the corollary to the other outcome measures. This understanding of the dynamics of traffic stops, however, ignores the rationale set out previously; the stop itself can be seen as an end stage of officer decision making. It is argued here that the decision to make a stop versus not making a stop is as valid a measure of vigor as the relationship between issuing a citation versus not issuing a citation. Furthermore, it would be possible to argue that the decision to make the traffic stop would be a larger commitment of an officer's time than the decision to make issue a citation. Once an officer has committed to making the stop the actual issuing of a citation is just another brief task for the officer. These arguments notwithstanding, measuring vigor at multiple stages of the same interaction is an interesting avenue for future research.

Chapter 2 discussed several possible relationships between serious crimes and low seriousness crimes. Under Klinger's ecological theory of policing, vigor towards low seriousness incidents should go down as high serious crimes increase. Several other possibilities for this relationship exist. Other authors have argued that as high serious crimes go up attention to low seriousness crimes will also increase (the dragnet hypothesis). This argument was based on the idea that officers will use investigations and arrests for low seriousness incidents to indirectly investigate more serious incidents. This may help to explain the pattern of results seen here when operationalizing vigor as the number of low seriousness arrests or the number of traffic stops.

The remainder of this chapter is devoted to discussing the pattern of results of the independent variables and implications that could be drawn from these findings. Although both cross-sectional and longitudinal models were conducted, the discussion section focuses on key concepts and draws from both analytic techniques concurrently.

Workload

Table 29 summarizes the results for workload and officer staffing from both the cross-sectional and longitudinal models. In this table a value of *'consistent'* would imply that the relationship found between the theoretical predictor and the measure of vigor was consistent with theoretical expectations from Klinger's ecological theory. A rating of *'inconsistent'* would suggest that the variables had a relationship inconsistent (either the opposite direction or non-significant) with theoretical predictions.

Table 29: Summary of the relationship between workload, staffing, and vigor

	Unfounded events		Low seriousness arrests		Traffic stops	
	Workload	Staffing	Workload	Staffing	Workload	Staffing
Longitudinal models	Consistent	Consistent	Inconsistent	Inconsistent	Consistent	Consistent
Cross-sectional models	Consistent	---	Inconsistent	---	Inconsistent	---

Consistent- Findings from the models were consistent with theoretical predictions
Inconsistent- Findings from the models were either in direction opposite to what was expected based on theoretical predictions or the relationship was non-significant

The relationship between workload and officer vigor (hypothesis 3; page 6) had a varied relationship that depended upon the analytic technique used and the method of operationalizing vigor. Vigor, as operationalized by the number of unfounded events, had the most consistent relationship with workload both as operationalized in the cross-sectional models as the number of homicides and as operationalized in the longitudinal models as the number of serious incidents. The relationship between vigor and unfounded events in both the cross-sectional and longitudinal models were consistently significant and in the direction predicted by the theoretical model (hypothesis 5a; page 8). Higher workload was associated with higher levels of unfounded events, net of other relevant characteristics.

Vigor, as operationalized by the count of traffic stops, did not have such a clear relationship with workload. The longitudinal model found a significant and theoretically correct relationship between these two variables: higher workload was related to lower levels of traffic stops. The cross-sectional models, however, found a significant relationship that was counter to theoretical predictions: higher levels of homicide were associated with higher counts of traffic stops.

Vigor, as operationalized by low seriousness arrests, produced results that were least consistent with theoretical predictions. Neither the longitudinal nor cross-sectional models found a relationship between low seriousness arrests and workload that could be considered consistent with theoretical predictions. The relationship between workload indicators was either non-significant or in the opposite direction to what would have been predicted based on theory. This is perhaps not surprising given the substantial range of law violations that were considered to be “low seriousness”.

Taken together these findings suggest that a relationship between workload and vigor exists in the theoretically expected direction but this relationship is sensitive to how vigor is operationalized (hypothesis 3 and hypothesis 5a; pages 6 and 8 respectively). The relationship between workload and vigor was strongest in the dependent variable that had the clearest association with vigor, unfounded events. This relationship was least clear when considering the outcome variable that had the least conceptual clarity with vigor, low seriousness arrests.

Resources

Officer staffing was explored only in the longitudinal models and followed a similar pattern to workload (hypothesis 5b; page 9). The relationship between officer staffing and vigor was most consistently related to the outcome measures with the clearest link to vigor. Consistent with theoretical predictions officer hours were negatively associated with unfounded events suggesting that greater resources reduces the number of events officers unfound.

Klinger's ecological theory of policing suggests a mediating model between resource constraint and the level of officer vigor. Resource constraints influence group norms towards vigor and it is ultimately these group norms that influence the actual vigor officers expend. A more simple explanation for this relationship can also be proposed. It would be reasonable to assume that officers experiencing greater resource constraint would take longer to respond to calls than officers experiencing less constraint. The longer an officer takes to respond to a call the more likely it is that whatever generated the call would have resolved itself. In other words, the longer an officer takes to respond to a call the more likely it is that a fight would have been broken up, or the loud music would have been turned down, or the crowd would have dispersed. In these cases the officer would be justified in unfounding the event. Unfortunately the data used in these analyses do not provide enough information to study this hypothesis directly. These competing theories do, however, provide an interesting avenue for future research.

Traffic stops also demonstrated a theoretically consistent relationship with officer staffing. Higher levels of officer staffing were related to a higher count of traffic stops. On average, every additional 100 officer hours assigned to patrol per day, per district was associated with a 3.8% increase in the number of traffic stops, net of other relevant variables. Placed in more conventional terms, for every four to five[29] additional patrol officers added to each shift, a district could expect to see a 4% increase in the count of traffic stops made per month. This relationship was robust to various model specifications.

When vigor was operationalized as the count of low seriousness arrests, no significant relationship was found with officer staffing. At least in this setting, the amount of patrol officer hours working in a district was not significantly related to the number of low seriousness arrests made. This could be due to a number of factors. First, as discussed previously, it is not at all clear that the crimes defined here as low seriousness are truly considered low seriousness by patrol officers. If officers feel that certain drug offenses are serious issues then the relationship seen here would not be surprising. Second, low seriousness arrests are made by officers other than those working in patrol. Officers working in the narcotics strike force or highway patrol, for example, may also be making arrests for low seriousness events. Again, if this is true it may be wiping out the effect of patrol officer hours on the low seriousness arrest outcome. Third, it may be that the specified temporal period adopted by this analysis was not appropriate to track the relationship between low seriousness arrests and resource constraint. The month long temporal periods were chosen because they represented a temporal unit of analysis small enough to build up reliable trend data within the confines of available data. These monthly periods, however, may have been too long to track the relationship between arrests and resources. These patterns may only manifest themselves at smaller temporal resolutions. Finally, it may be that the

[29] 100 officer hours divided among officers working 8 hours per person spread over 3 shifts per day. Placed in a different metric 100 officer hours per day per district is roughly an additional 288 officers (roughly 5% of the total PPD sworn personnel) working 8 hours shifts per day throughout the city.

ecological theory of policing is incorrectly specified on this measure. It may be that if an officer is going to make an arrest for an event she or he will make that arrest regardless of other resource constraints. In other words, once the threshold for an arrest has been met, the arrest will happen regardless of the ongoing resource constraints in the district.

Generally the relationship between overtime hours and officer vigor was non-significant. One possible explanation for this finding was that it was very difficult to accurately classify exactly why officers were getting overtime. For example, the ecological theory would suggest that overtime hours going to patrol should reduce the overall officer workload and allow for more proactive police work or allow officers to pursue events that may otherwise go unfounded. However, if overtime hours are used for different purposes, say to process an arrest made towards the end of an officer's shift, then they would not have an impact on the outcomes studied here. Officers working overtime to process an arrest would not have an impact on whether an officer currently out on the street feels the need to unfound an event, or their willingness to make an arrest, or their desire to conduct a traffic stop. A measure of overtime hours that only captured the quantity of officer hours worked on the street in a patrol capacity was not achievable with the available data. More succinctly, while the theoretical implications of overtime hours are clear the operationalization of the measure in this study using these data may not have been sensitive enough to capture this relationship.

Demographics

Local demographic characteristics had a varied relationship with officer vigor. Table 30 provides a brief summary of the relationship between demographics and the three outcome measures from the cross-sectional models. A rating of *'consistent'* suggests that the broad pattern of findings between the predictor and the outcome was consistent with theoretical predictions. A rating of *'inconsistent'* suggests that the outcome and predictor were related in a way that was counter-theoretical. A rating of *'non-significant'* suggests that there was no significant association between the vigor measure and the land use factor. Finally, a rating of varied was given if the relationship between the land use measure and the vigor measure varied over time.

Table 30: Summary of the relationship between demographics and vigor

Outcome	Demographic			
	SES	Stability	Ethnicity	% Af. Am.
Unfounded events	Consistent	NS	NS	Consistent
Low seriousness arrests	Consistent	Inconsistent	Inconsistent	Inconsistent
Traffic stops	Varied	NS	NS	NS

Consistent - Findings from the models were generally consistent with theoretical predictions (across most years and specifications)
Inconsistent - Findings from the models were either in direction opposite to what was expected based on theoretical predictions (across most years and specifications)
NS - The relationship between the demographic characteristic and the outcome was non-significant.
Varied - Findings may have been consistent or inconsistent with theoretical predictions depending upon year under consideration

Demographic variables were selected to represent the three socio-demographic structures frequently associated with crime and disorder: status, race/ethnicity, and stability/familism. A number of significant relationships between these variables and vigor were found. The socioeconomic scale was the most consistent predictor of vigor. This relationship, however, was not always in the direction specified by the theory (hypothesis 2; page 5). When operationalized as unfounded events, the relationship between vigor and socioeconomics was in the expected direction: higher socioeconomic status was related to lower levels of unfounded events, an indicator of higher levels of vigor. Higher socioeconomic status was also negatively related to low seriousness arrests and traffic stops, a relationship opposite to what was predicted by theory. With one exception these relationships were consistent across the different years of analysis. The ecological theory suggests that officers working in higher socioeconomic regions of the city should be engaging in more vigorous enforcement of law by arresting for more low seriousness events or by conducting more traffic related activity.

The question then becomes, what is the process that can explain the relationship between socioeconomic status and the vigor of police action? It may be that socioeconomic status is simply reducing the amount of residential and non-residential population or vehicle traffic. In other words, less activity occurs in high socioeconomic areas and, therefore, less policing is necessary in these areas. Additionally, socioeconomic status may have the potential to drive officer perceptions of where they work. For example, socioeconomic status may be standing in for other related factors such as home ownership. Home ownership has been linked to properties that are better maintained (the physical structure as well as surrounding lawns and gardens) than their rental counterparts (Taylor, 1988). This maintenance, this greater residential territorial functioning, may reduce an officer's perception of deviance and thereby influence the vigor of their actions. Put simply, socioeconomic status may be standing in as a proxy for the deviance, or perceived deviance, of an area. The exact mechanism whereby socioeconomic status influences the vigor of an officer's actions is an important avenue for future research.

The relationship between socioeconomic status and vigor may also be consistent with Black's theory of law. Socioeconomic status was associated with lower levels of unfounded events. This could be interpreted as wealthier people having access to a greater quantity of law (i.e. wealthy people have issues that are more likely to be taken seriously by responding officers). Lower counts of arrests and traffic stops comes about because there are generally less people in wealthy neighborhoods (possibly because of lower population density or because of lower pedestrian activity) or officers do not want to harass wealthy residents. Taken together these findings align well with Blacks theory of law: more law is available to wealthy people (in the form of filing reports) while simultaneously being less likely to be used against them (in the form of arrests and traffic stops). This, of course, is purely speculation and while the results are suggestive they are in no way conclusive of this interpretation.

The results of the low seriousness arrest and traffic stop outcomes must be considered in light of some limitations of the current analysis. Mirroring a larger discussion undertaken earlier, it was not entirely clear that the population of interest was adequately controlled for in this study (see page 71 for a complete discussion on exposure variables). For instance, it may be that vehicle traffic in high socioeconomic areas is generally lower than it is in low socioeconomic areas. If so the lower levels of traffic stops may be representing lower levels of population at risk rather than lower levels of vigor. With this outcome it may be that the control variables were not adequately specified. Another explanation may be that officers use traffic stops as a method of investigation for more serious crimes. If this is the case, officers may be conducting less traffic stops in high socioeconomic areas because offenders are less likely to be in those areas. Alternatively traffic stops and arrests are activities frequently undertaken by the narcotics strike force and highway patrol. The activity of these officers may have altered the relationship between vigor and socioeconomics. This process may have been responsible for the pattern found here.

Other demographic variables were not as consistently related to vigor. Percent African American was significantly related to two outcome variables, unfounded events and low seriousness arrests. Hypothesis 1 (page 5) would have predicted that higher levels of African

American population would be related to lower levels of officer vigor. This prediction was consistent with the results of unfounded events but inconsistent with the results of the low seriousness arrests and traffic stops. Stability and the ethnicity scales were only significantly related to one outcome measure, low seriousness arrests, in a direction that was opposite to theoretical predictions. Placed within the context of the ecological theory of policing these results appear to be largely counter theoretical. Theory suggests that certain demographic characteristics become associated with crime and disorder and drive the development of group norms that ultimately reduce officer vigor. These findings suggest that, at least at the sub-district level, local demographics frequently linked to differences in officer vigor, a relationship that was contingent upon how vigor was operationalized.

Land Use

The relationship between local land use and vigor was found to be both consistent and inconsistent with theoretical predictions, non-significant, temporally varied, and highly dependent upon the method of operationalizing vigor. Table 31 provides a summary of the relationships between land use and vigor and uses the same terminology as those found in the demographic variable summary table (page 194).

Table 31: Summary of the relationship between land uses and vigor

Outcome	Land Use											
	Com	St. Liq.	Liq.	Club	Pawn	Check	Homeless	Drug	Halfway	Rail	Sub	Bus
Unfounded events	Con.	NS	Varied	NS	Con.	NS	NS	NS	NS	NS	Con.	NS
Low seriousness arrests	Incon.	Incon.	Incon.	NS	Varied	NS	NS	Incon.	NS	NS	Incon.	Varied
Traffic stops	Incon.	NS	NS	NS	Incon.	NS	Varied	NS	NS	NS	Incon.	Varied

Con. - Findings from the models were generally consistent with theoretical predictions (across most years and specifications)
Incon. - Findings from the models were either in direction opposite to what was expected based on theoretical predictions (across most years and specifications)
NS - The relationship between the demographic characteristic and the outcome was non-significant.
Varied - Findings may have been consistent or inconsistent with theoretical predictions depending upon year under consideration

The relationship between land use and vigor, at a sub-district level, displayed a complicated relationship that varied both by the type of land use under consideration and the method of operationalizing the construct of vigor (hypothesis 4; page 7). Commercial land use had the most consistent relationship with vigor. Commercial land use was consistently related to unfounded events, low seriousness arrests, and traffic stops but not always in the predicted direction. Commercial land use was associated with higher counts of low seriousness arrests and higher counts of traffic stops. This effect, however, seemed to be sensitive to the method of controlling officer workload. Controlling for the number of serious events as opposed to the number of homicides turned commercial land use non-significant for all outcome measures. This suggests that the method of quantifying workload, much like the method of quantifying vigor, is a critical research decision that has substantial implications for the research results.

The only individual land use to be consistently related to vigor was subway stops. Again this relationship was positive for all dependent variables suggesting that the relationship was counter theoretical for both low seriousness arrests and traffic stops. Other land use variables had significant relationships with only one or two measures of vigor. Occasionally the relationship between a land use and vigor would be significant in the five year averaged models but not in the individual year models. More commonly land use indicators would be significantly associated with a vigor measure for only one or two years of data.

The relationship between land use, demographics, and traffic stops was particularly complex. Demographics, when entered in a model without land use, were not significant predictors of the count of traffic stops in a block group. When land use was considered in the models, however, socio-economic status attained significance. This may have been reflecting the importance of land use in structuring the spatial patterning of vehicular traffic. It was only after taking account of this underlying spatial structure that the impact of socio-economic status could be seen.

These findings make it more difficult to specify the exact relationship between vigor and land use. Given the varying and often counter theoretical relationship between land use and vigor the conclusions drawn from these findings must be tentative. It would appear that land use, under some circumstances links to differences in measured vigor. These results clearly suggest, however, that greater conceptual clarity is needed to accurately specify the relationship between these land uses and their impact on vigor. It remains unknown if these relationships would have been substantively different if facility data corresponding to the outcome year could have been sourced. Once again the temporal mismatch between key datasets presents questions that cannot be answered here.

Spatial effects

The spatial lag terms in the longitudinal models were significant regardless of model specification or dependent variable under consideration. Higher levels of unfounded events, low seriousness arrests, or traffic stops in the three nearest neighboring police districts were significantly associated with higher levels of the outcome in the target district. This finding was unexpected for a number of reasons. First, the theory argues that the district is the key ecological unit of analysis. Norms regarding work load develop at the district level which leads to the development of districts that are largely independent of the influence of other districts. The spatial lag variable would suggest that the districts are not as independent as postulated and perhaps some spatial process was crossing district boundaries. Second, the analytic choices made regarding the decision to group mean center the spatial lag variable (subtracting the 60 month district mean from each monthly observation - see pages 106, 120, 159 and for a discussion on the implications of group mean centering in the cross-sectional and longitudinal models) means that the spatial lag variable was measuring the influence of other districts on the target districts change over time. In other words, because the spatial lag variable was group mean centered its impact can be thought of as the unique effect of nearby districts on the time varying outcome. This implies that there was a time varying dynamic at work that crosses district boundaries. Finally, given the size of police districts, a strong spatial effect would not necessarily have been expected. Police districts are large, especially when compared to block groups or census tracts. While it would be reasonable to expect that social or environmental processes would cross smaller geographic boundaries it would be less expected for very large ecological units such as police districts.

It would appear that internal district dynamics are sensitive to not only crime levels within their own district but also crime levels in the surrounding districts. This finding may indicate that organizational dynamics do indeed cross district boundaries in a way that is counter to theoretical explanations. Alternatively, the spatial lag variable may be picking up the additional patrol related activity generated by special operation units such as narcotics strike force or highway patrol. These officers may be generating unfounded events, low seriousness arrests, or traffic stops or they may be a supplementary resource that allows standard patrol officers the additional time necessary to undertake these activities.

The spatial lag variables in the cross-sectional models were also generally significant. This suggests that the level of vigor found within a block group is influenced by the level of vigor in nearby block groups. The one exception to this general trend was the spatial lag variable in the yearly unfounded event cross-sectional models. These models suggested a significant spatial effect in 2004 that degraded monotonically to non-significance by 2008. This finding is interesting given that a unique spatial lag variable was created for each outcome year. This suggests that the spatial process driving the patterning of unfounded events may have been changing over time- another temporally dynamic spatial pattern consistent with what was seen in the longitudinal models. The temporally dependent spatial clustering suggests there were increasing levels of spatial differentiation over time. Lower levels of spatial clustering could be interpreted as an increasing level of equality in the spatial distribution of officer vigor. This line of reasoning is one, but not the only, possible explanation for the declining impact of the spatial lag term in explaining the count of unfounded events. These findings also suggest that it would be inappropriate to assume that different measures of vigor will have the same type of static spatial dependency.

Determining the exact meaning behind a significant spatial lag term is difficult given that its expressed purpose is to capture unexplained spatial variations that would otherwise go unmeasured and bias parameter estimates. Some researchers have suggested that spatial lag terms can be of actual substantive interest (cf. Taniguchi, Rengert, & McCord, 2009) under certain conditions. Nevertheless, even the most logically sound theoretical explanation for a significant spatial lag must remain exactly that – a theoretical explanation for something that is unknown. Under ideal circumstances a researcher would continue adding variables to the statistical model to the point where the spatial lag was no longer significant suggesting that the previous unknown spatial process was being captured in the model. Ideal circumstances rarely materialize into actual research and, as such, it is necessary to accept that the exact meaning behind the spatial lag term must remain a target for future research.

Cynicism

The ecological theory argues that higher levels of officer cynicism should be associated with lower levels of officer vigor. The results presented in the proceeding chapter did not directly address the issue of officer cynicism. Cynicism was not investigated in these models because of its level of spatial and temporal resolution. Recall that cynicism was measured at one time point and was available only as an aggregate district measure. This would mean that in both the cross-sectional and the longitudinal models the cynicism measure would have been included at level-2. These models, however, were constructed to investigate vigor at the sub-district level (cross-sectional; level-1) and over time (longitudinal; level-1). In short, because of the centering techniques adopted these models were not attempting to predict differences between districts, they were only attempting to predict differences at the sub-district level and differences within districts over time.

Subsequent models (results omitted) found that the relationship between cynicism and vigor varied depending upon how vigor was operationalized and the analytic technique. Across all longitudinal models and all three dependent variables the relationship between vigor and cynicism was non-significant. The cross-sectional models, however, demonstrated a more varied relationship between vigor and cynicism. These models suggested a significant relationship between cynicism and low seriousness arrests and cynicism and traffic stops. In both cases the results were counter theoretical with higher levels of cynicism being associated with higher levels of arrests and higher levels of traffic stops (both indicative of greater vigor).

The substantive conclusions, however, that can be drawn from these finding must be approached with caution. Cynicism data were collected in 2000, several years before the crime data used in these analyses. This makes it necessary to assume that the level of officer cynicism in a district is stable over time, an assumption that is concurrent with theoretical predictions but not necessarily supported by existing research which suggests that an individual officer's cynicism may vary over time with their tenure in the department (Niederhoffer, 1967). Researchers have yet to address the issue of aggregate district level cynicism so it remains unknown if cynicism – measured as an aggregate district level characteristic – changes over time. What can be said is that district level cynicism appears to explain some of the differences between districts depending upon how vigor is operationalized. Whether this relationship persists at a sub-district resolution or whether this relationship persist over time remains a future avenue of research requiring cynicism data that are far more nuanced and comprehensive than what was available here.

Implications for Theory, Policy, and Practice

This dissertation contributes significant knowledge to both criminal justice theory and theories and practices of police management. The Philadelphia Police Department is responsible for a wide range of communities that vary greatly on socio-demographic, economic, and environmental characteristics. A number of important contributions from both the longitudinal and the cross-sectional models can be derived.

The cross-sectional models investigated the effects of demographic variables at the sub-district level; a level of analysis outside the original scope of the ecological theory of policing. These findings suggested that vigor was at least partially driven by demographic and environmental characteristics that vary both between districts and, more importantly, within the district. Recall that the ecological theory argues that the effect of demographic characteristics on vigor is mediated by group norms. This suggests that vigor should be uniformly applied to all sub-district units. These findings, however, suggest that vigor does indeed vary at a sub-district level of analysis. These sub-district variations were driven by both demographic characteristics of the block group as well as characteristics of the built environment.

These models furthermore suggest that the dynamics influencing vigor may have been operating at multiple levels of spatial aggregation. Recall that the cross-sectional models suggested that there were differences in vigor both across districts (as suggested by significant level-2 variance) and within districts (as suggested by the significant spatial lag term). It's possible that the process driving vigor at the police district level was different than the process driving vigor at the sub-district level. Exploring how vigor, and subsequently discretion, varies at different levels of spatial aggregation will be an important avenue of future research.

The cross-sectional models also demonstrated the importance of considering multiple years of data when conducting studies investigating the impact of environmental characteristics. Recall that numerous land use and demographic variables had relationships with vigor that varied depending upon the year under consideration. Had only a single year of these data been used to conduct these analyses a substantively different understanding about the relationship between land use and vigor may have been reached. The differences seen both between years and between measures of vigor underscored the hazard in attempting to make strong inferences based upon a single cross-sectional snapshot of the relationships.

The cross-sectional models have implications for studies attempting to assess police behavior at units of aggregation smaller than a police district or in areal units that transverse multiple police districts. Studying crime that has been aggregated to any spatial unit should be sensitive to both community level and police organizational level dynamics. A number of approaches to deal with this problem have been suggested. Skogan and colleagues (1999), suggested that the police beat (a rather small geographic unit) was the most appropriate method of matching community dynamics with police activity. This approach has the ability to capture police district level dynamics (beats generally nest within districts) but may ignore larger neighborhood effects that may not be captured by the police beat. Addressing this potential shortcoming, Taylor (2001) proposed a neighborhood centric approach. Under this model police activity is matched to existing neighborhood structures. This approach locates community dynamics as the key factor in understanding police-community dynamics. Note that the approaches suggested by Skogan et al (1999) and Taylor (2001) differ not necessarily on the size of the spatial unit but on the underlying dynamics driving the selection of the unit of aggregation. Beats are a distinct police organizational unit of analysis while neighborhoods are a community driven dynamic.

The findings of the current study suggest an alternative approach: neighborhood level dynamics should be understood in terms of police district level dynamics. Police activity must be understood in the context of both the community and the organizational structure in which it takes place. Recall that vigor varied by district and failing to account for these differences when considering neighborhood context could result in misspecified models and may incorrectly allocate police organization dynamics to neighborhoods or individuals (an example of the ecological fallacy). Analyzing community level dynamics must occur while considering the organizational dynamics occurring at the police district.

The longitudinal models demonstrated that varying levels of officer workload have an impact upon an officer’s vigor towards proactive police work (in the form of traffic enforcement) and general willingness to investigate potential criminal activity (in the form of unfounding events). The longitudinal model also demonstrated that an officer’s vigor level was at least partially dependent upon the level of resources available within a district. These models also suggest that relatively modest changes in officer staffing (a few dozen officers spread throughout the city) could have measurable changes on the vigor of officer activity. This finding links to broader research investigating the relationship between the number of officers in a police department and the crime level in the jurisdiction (see Levitt, 1997 for a summary of this research). While historically researchers have failed to find an association between police and crime levels (Cameron, 1988), recent improvements in data measurement and analytic techniques have generated a resurgence in research suggesting police can indeed reduce crime (Klick & Tararrok, 2005; Levitt, 2002).

The current research approaches the issue from a different angle and asks if it is possible to measure the relationship between officer staffing and the quantity of “work” produced. These longitudinal models suggest that there is a significant relationship between officer staffing and officer vigor. This is useful information for police departments that frequently need to argue for adequate officer staffing levels or for departments looking to evaluate issues revolving around staffing levels. This research suggests that realistic changes to the level of officer staffing can have measurable and significant impacts upon the work output of patrol officers. This finding also suggests important avenues for future research. It would be informative to know if this relationship exists for other types of police activity. What, for example, is the relationship between officer staffing and crime clearance rates? Or, what is the relationship between aggregate officer staffing levels and officer call response time? It may also be worth inquiring how officer staffing levels impact case disposition for situations other than unfounded events. In other words, what is the relationship between officer staffing and other case dispositions such as forwarding the case to detectives, writing reports, or issuing citations?

There are also a number of police related outputs that are much more difficult to measure with administrative records which, nonetheless, may be of interest to practitioners and researchers. How does officer staffing effect officer cynicism? Existing literature (cited earlier) suggested that higher levels of officer workload would be associated with higher levels of cynicism. This is a hypothesis that would best be assessed with longitudinal models and require sensitive measures of both cynicism and officer staffing. These questions take a different approach to the traditional rational for increasing police patrol presence.

Finding that patrol officer work output is sensitive to both officer resources and officer workload has larger implications for the criminal justice system as a whole. Taken together as a system, this suggests that patrol officers with greater resources or less workload are likely to engage in more proactive work. This increased work output has the potential to drive unintended consequences for the rest of the criminal justice system. Goldkamp and Vîlcică (2008: 374) refer to these as "system side effects" and caution that intensive police operations may result in negative consequences for courts and corrections. If this is true then it may be wise to spend this additional capacity on crime prevention initiatives, such as problem oriented policing, rather than more enforcement focused zero-tolerance type programs. Crime prevention initiatives have the potential to reduce crime without the often dramatic impact on later stages of the criminal justice system.

Considered together, the two analytic techniques provide extensive insight into the ecological theory of policing. Perhaps not surprisingly, under certain conditions the cross-sectional models produced substantively different results than the longitudinal models. Had this analysis been conducted using a purely cross-sectional methodology support for key theoretical propositions would have gone largely unsupported. Recall that officer workload was frequently related to vigor in a direction opposite to what was expected based on theory. The longitudinal models, however, suggested there was support for these key ideas. It appears that when vigor is operationalized in a cross-sectional analysis the measure of vigor responds very much like other measures of criminality. In a cross-sectional analysis, and dependent upon how vigor is operationalized, it appears to be difficult to separate the vigor of police actions from criminal activity more generally. These differences underlie the importance of studying research questions both longitudinally and cross-sectionally.

These findings can be placed within the framework of alternative spatially oriented theories of policing, namely Herbert's territoriality thesis. Recall that Herbert argues that policing is largely about the control of micro-space (e.g. specific locations or intersections). The results of the cross-sectional model, namely that officers conduct more traffic stops and more arrests in areas with high levels of serious crimes, may be taken as support for Herbert's thesis. The census block group (the level-1 unit of analysis in the cross-sectional models) can be seen as a corollary to the micro-space approach employed by Herbert. Both low seriousness arrests and traffic stops may be actions that officers undertake to gain control and maintain jurisdictional mandate over discrete spatial locations: arrests remove people from locations and traffic stops may restrict spatial mobility. Again this may be indicative of different dynamics operating at different levels of spatial aggregation.

These findings suggest that districts may respond differently to citywide crime prevention initiatives. Implementation of certain crime public safety initiatives (for example, mandating a focus on traffic stops and citations) will have differential impacts upon some districts. Some districts may be more capable of dealing with requirements to focus attention on traffic work because they have characteristics necessary to pursue these additional responsibilities. These results suggested that both the workload and officer staffing of a district had the potential to impact the vigor with which officers pursue traffic related offenses. Take, for example, two districts with similar officer workload but substantially different levels of officer staffing, both of which were given a directive to increase the number of traffic stops or citations. The district with lower levels of officer staffing may not be able to accomplish the same magnitude of gains as the district with higher levels of officer staffing. Of course this should not be seen as a failure of the district or the officers working within the district. Instead this thought exercise suggests that a number of factors may impact on the perceived success or failure of a district in response to broad mandates to alter patrol officer activity. Failure to account for this “starting point” of a district has the potential to seriously undermine the effectiveness of city-wide crime prevention efforts.

Furthermore, differences between districts may have a rather substantial impact on the ability to evaluate the success of certain crime prevention strategies. One strategic policy that has risen to prominence in the last few years is the idea of targeted policing at crime hotspots (see, for example, Mastrofski, Weisburd, & Braga, 2010). Suppose that a hot spot derived place based crime prevention initiative was located in a few dozen locations scattered across four or five districts. These results suggest that the impact of these programs must be measured while accounting for variations of the districts in which the operation was located. Failing to do so could lead to the allocation of district level differences to each treatment site biasing findings in a direction that could not be specified a priori. Controlling district level effect through randomized design or through appropriate statistical procedures in quasi-experimental designs would be necessary to minimize the impact of the differences found between districts.

Underlying this is the understanding that districts differ and may, therefore, require different approaches to solving the crime problems existing in each area. This is further complicated by the finding that vigor varies at a sub-district level. This suggests that the most appropriate question may not be “how are districts policed?” but instead may be “how are certain parts of districts policed?” This may be a manifestation of unwritten understanding, or organizational knowledge in more formal management theory, that officers working in a district develop over time (Nonaka, 1994).

Looking more broadly, this dissertation makes substantial contributions to criminal justice theory. The ecological theory of policing represents an important step in integrating police organizational and environmental factors into a cohesive framework. The fact that this theory had existed for over a decade with limited empirical assessment represented a serious gap in understanding how these two important features relate. The current study takes a first pass at attempting to further clarify Klinger’s (1997) conceptual model while also examining the underlying dynamics in a longitudinal framework. While it is clear that some conceptual parts could use further clarification it is also clear that the dynamics underlying the ecological theory of policing exist in a measureable and quantifiable way. Perhaps most importantly, officers vary vigor in response to both the level of workload as well as in response to the level of resource constraint. Officers having to deal with more serious incidents and more time demanding incidents shed workload by unfounding in a greater number of events and reducing discretionary activities such as traffic stops. Resource constraint (the number of patrol officer hours available) also played a critical role in determining officer vigor. When there were more officers working, fewer events were unfounded and more traffic stops were conducted. In economic terms we would say that the relationship between vigor, officer staffing, and workload is elastic. Consistent with Klinger’s theory, officers respond to external pressures by managing how they allocate their time and efforts.

Nevertheless, these findings have also demonstrated that the operationalization of key theoretical constructs is a critical decision that must be undertaken with great care. It was found that, at least at this level of spatial and temporal aggregation, outcomes with the clearest conceptual link to vigor produced the most consistent and expected results. Taken as a whole, these results suggest that conceptions of “low seriousness” events need further elaboration and clarification. Recall that the use of UCR classification to determine serious versus less serious events was originally adopted to avoid arbitrary, subjective, and potentially unreliable estimates as to what constitutes serious versus non-serious events. This classification method produced an outcome variable that placed an arrest for drug possession with intent to distribute on equal footing with an arrest for disorderly conduct; a grouping that many may find suspect. It would appear that the desire to avoid the ambiguity surrounding the serious versus low seriousness distinction is not tenable. Future development of the ecological theory of policing may first require better methods of classifying the seriousness of an event. This may entail surveying police officers to determine their views on the seriousness of crime events. Such a study would need to account for numerous potential threats to internal validity and assure that officers from all districts, with various ranks, and with a range of tenures are surveyed. A more comprehensive survey would be longitudinal and investigate how officer views towards the seriousness of crimes change over time.

Operationalizing other key constructs presented additional issues. Officer workload, for example, was operationalized using two variables, the count of homicides and the count of serious incidents. Both workload measures were explored in the cross-sectional models. The results of using these different measures of officer workload had dramatic impacts upon some land use and demographics variables also included in the model. More generally, the use of crime data as a measure of officer workload may be problematic. While theory argues that officers are unlikely to unfound serious incidents, this assumption is by no means definitive. Exploring other methods of quantifying workload remains an important avenue for future research. Measuring officer response times to calls, the length of time an officer spends at calls or the number of calls an officer responds to may be alternative indicators of officer workload.

CHAPTER 6:

CONCLUSION

Taken as a whole, these research findings suggest that vigor is an ongoing dynamic process that is sensitive to both officer workload and officer resources. Furthermore, vigor displays both spatial and temporal patterning that, if ignored, have the potential to dramatically alter how these relationships are assessed.

Strengths, Limitations, & Avenues for Future Research

Like much research, the findings of this dissertation raise as many questions as they answers. One important avenue for future research will be to investigate how the temporal mismatch between key datasets impacts the findings. Most obviously, the use of facility data from a time outside the main study period or data that were collected at only one time point represents a limitation of the current study. This is especially true for the facility data used in the repeated cross-sectional models. Recall that facility data were only collected in one year, 2005. These data however were used in the yearly cross-sectional models through 2008. It is unknown how this temporal mismatch affected results. If facility locations changed significantly from year to year this could have a potentially large impact on the findings. If we assume, however, that facility locations were relatively stable during the study period, the failure to account for the minor changes may not have had any significant impact. Clarifying how local environmental dynamics change over time and how these changes impact officer vigor is an important avenue for future research.

The longitudinal model found that there were significant ongoing temporal trends in the dependent variables. These models also found that the spatial lag term was consistently significantly related to the outcome measures. The significance of both spatial and temporal terms indicates that there may be significant spatio-temporal patterns underlying the data. While the methodology used provided adequate control over these patterns, it was not the only possible solution. Programs such as WinBUGS have the capability of modeling spatio-temporal interactions through the use of Bayesian statistical methods. This approach traditionally models spatio-temporal interactions as a conditional autoregressive function with significance testing being accomplished through Markov Chain Monte Carlo simulations. Alternatives to the maximum likelihood estimation techniques used here presents an important methodology for clarifying the spatio-temporal aspect of officer vigor.

One of the key findings was that the method of operationalizing vigor mattered a great deal. The outcome with the clearest conceptual link to vigor, unfounded events, was also the outcome measure that was most consistent with the predictions made by the ecological theory. The outcome with the most tenuous link to vigor, low seriousness arrests, was the least consistent with theoretical predictions. It was suggested earlier that patrol officers may view certain drug arrests as an important tool to an overall crime reduction strategy. If this is so, then including drug arrests in the low seriousness category would be inappropriate. This suggests that future studies would do well to more fully explore the definition of low seriousness, especially in the context of decisionmaking made by police patrol officers. This may require rather extensive survey data collection of patrol officers on their attitudes towards the seriousness of crimes. Conducting such research would shed a great deal of light on how police officers perceive events and would allow for a more refined approach to the definition of “low seriousness”.

This dissertation made a significant contribution to the ecological theory by longitudinalizing key concepts and studying relationships over time. The results from the longitudinal model suggested that these dynamics change over time and that further study in this area would be wise to consider these temporal patterns. This study, however, used a fixed temporal period of one month as the level-1 unit. It is possible, however, that the dynamics under study play out in temporal periods that are much shorter than months. For example, it would be reasonable to postulate that an officer feels high workload or excessive resource constraint on a shift-by-shift or even hour-by-hour basis (see for example Klick & Tararrok, 2005 who use daily crime counts to measure police effectiveness). If so, then further refining the temporal resolution of the analysis may be in order. A more definitive link between vigor and workload or vigor and resources may be found at smaller units of temporal aggregation.

Final Remarks

The findings of this dissertation, in general, support the key propositions first laid out by Klinger more than a decade ago. As discussed earlier, Klinger's ecological theory of policing, as originally conceived, is nearly impossible to test directly. No department is going to keep enough time sensitive indicators to reliably model the underlying dynamic processes. This problem, a lack of relevant indicators, is not insurmountable, but would require extensive large scale data collection. A more difficult problem to solve revolves around the relatively small number of districts found in each department. Even the largest police department in the country has less than 100 districts. This issue, again, is not insurmountable. It is possible, for example, to imagine data collection at numerous police departments thereby ameliorating issues relating to the small number of districts in each individual police department. Taken together, however, these two points may suggest that evaluating Klinger's ecological theory using quantitative methodologies may be practically implausible, if not necessarily impossible. While directly testing the totality of Klinger's theory may be beyond reach, the current study suggests several ways of expanding and clarifying Klinger's theory in a direction that makes it a more willing subject for empirical assessment.

More specifically, this dissertation tested and extended Klinger's ecological theory in the following way. First, the current research provides the first rigorous assessment of Klinger's conceptual model using administrative data and strong quantitative methodology. Second, the current research extends the scope and relevance of demographics and land use in explaining how vigor is spatially patterned within a district. Support for the notion that demographics and land use can drive variations in vigor was found. Finally, this dissertation contributes to the utility and strength of Klinger's conceptual model by placing key theoretical constructs into a longitudinal framework. On the whole, these longitudinal models showed greater concurrence with key theoretical postulates than their cross-sectional counterparts.

Perhaps the critical finding from this dissertation was that vigor varies as a result of officer workload and resource constraint. Greater workload or lower levels of officer resources linked to the quantity of vigor expended; a relationship that was at least partially dependent upon how vigor was operationalized. Of course not all relationships were consistent with Klinger's theory and some results linked more strongly to other ecological theories of policing. For example, the finding that vigor varied at a sub-district level links more closely to Herbert's territoriality thesis than to Klinger's conceptual model. Furthermore the relationship between the level of serious incidents and arrests for low seriousness crimes (higher levels of serious incidents linked to higher levels of low seriousness arrests) was more consistent with the dragnet thesis.

Other findings suggest that further conceptual development is still required. The relationship between vigor and key theoretical variables was frequently sensitive to how both vigor and workload were operationalized. More problematically, variations in vigor were expected to be greatest in events of low seriousness. Yet, defining an event as low or high seriousness is a difficult task that requires researchers to either rely upon arbitrary distinctions or make value judgments about the seriousness of a crime. Furthermore, these findings suggested that the spatial and temporal resolution through which a researcher investigates vigor will have potentially dramatic impacts upon their conclusions. These findings, taken as a whole, suggest that the ecological theory of policing has strength and utility in explaining patterns of police activity but also that a number of issues could use further conceptual clarity.

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APPENDICES

A. EXCLUDED CRIME TYPES

The following crime types were excluded from analysis because they were unlikely to be handled by police patrol officers or they did not have clear conceptual links to officer vigor. Table 32 presents the crimes excluded from these analyses.

Table 32: Crime types excluded from analysis

UCR Code	Description
1000 Series	Counterfeiting
1100 Series	Fraud
1200 Series	Embezzlement
1300 Series	Stolen property
2000 Series	Offenses against the family and children
2603-2613, 2615, 2617, 2622, 2623, 2630-2635, 2636-2639, 2641, 2645-2648, 2655-2660, 2663, 2665-2670, 2675, 2677, 2678, 2688, 2703-2710	Selling fireworks, fortune telling, violation of city ordinance, cigarette tax violation, scavenger, Sunday law violations, taxicab law violations, false report for police service / false alarm of fire other emergency, blackmail bribery, extortion, harassment by communication, child labor laws, causing a catastrophe, failure to prevent a catastrophe, abduction, concealing the death of a child, conspiracy, contempt of court, desertion- US services (AWOL), election law violations, escaped prisoner (adult), immigration law violation, impersonating a public servant, escaped prisoner (juvenile), kidnapping, parole violations, perjury, postal law violations, probation law violations, inciting to riot, dangerous dog, offenses other than specified, storage of explosives, ammunition (city ordinance), security measure- firearms, incendiary device, sale / illegal use of certain solvents, hindering apprehension or prosecution, interference custody of committed persons, criminal coercion, aiding or soliciting suicide, improper use of police uniform, tenant- landlord violation, failure to register (Megan's law), bomb-explosive facsimile, bomb- explosive device bomb or release of biological element, complaint against police- physical or verbal, complaint against police- other than physical or verbal, prison complaints, narcotics investigation, tow truck investigation, police vehicle pursuit, assist officer call- founded, assist officer call- unfounded
3000 Series	Hospital cases
3100 Series (except 3101, 3107, 3113, 3129, & 3140)	Other investigations
3200 Series	Lost and found property
3400 Series	Miscellaneous incidents
3500 Series	Missing persons
3600 Series	Reports affecting other city agencies
3700 Series	Motor vehicle accidents
3800 Series	Third party investigations

B. CENSUS ESTIMATION METHODOLOGY

This analysis used postcensal estimated demographic data. While these estimates are not perfect (cf. Land & Hough, 1986) they offer perhaps the only practical source of demographic data at the block group level for times between standard census years. These data were obtained from GeoLytics, an industry leading provider of demographic data used in both social science research and business marketing. The methodology used to produce demographic estimates can be found below. This methodological description was taken verbatim from the GeoLytics website (available at http://www.geolytics.com/).

Population

In building population estimates there are several pieces needed to begin. The changes that occur in an area will be the addition of births, subtraction of deaths and the addition/subtraction of those who moved. The starting point is the 2000 Short Form (SF1) BLOCK level data set. This has the most detailed and comprehensive numbers about where the entire population of the US lives, their age and their race. To progress from the 2000 data to current year estimates, we use the US Census Bureau's (USCB) County and State level annual estimates to roll the numbers forward to the current year. But the USCB data is only available at the County and State level, so the next challenge is distributing the data down to the smaller geographies.

The next step is to work with actuarial tables for births and deaths by age and race, and use them to create a model of "likelihood" of dying or likelihood of having a child. This then is what creates the engine driving the increase and decrease in population growth.

The third step is to look at immigration and emigration. Where are people moving "to" and where are they moving "from". The US Postal Service keeps track of all moves as a "to" and "from" location.

Now the more detailed explanation:

1. Working with the Census Bureau "estimation base" county level numbers. This data is processed to obtain "race distribution" coefficients. However, the Census Bureau estimation base data do not include "other" race category. Also, "two or more races" category is much smaller than it is in SF1/SF3 Census data. By comparing the estimation base to SF1 county level data, it is possible to obtain some numeric ratios as to how "other race" and "two or more races" populations were distributed among the remaining races in the USCB's

estimation base. These coefficients allow us to re-map the SF1 block level data and redistribute the "other race" and part of the "two or more races" population among the 6 remaining mutually exclusive races.

2. The SF1 block level data are processed with these new racial distribution coefficients. The resulting dataset is our estimation base. It includes 8 race/origin groups:

WA White alone
BA Black alone
NA Native American alone
AA Asian alone
PA Pacific alone
R2 Two or more races
HS Hispanic
WN White, not Hispanic

A few words on Census analogs: The Total Population count corresponds to the Census table P001, count P0010001. The rest correspond to Census age-race-sex tables from P012A to P012I, with the P012F (Other Race table) dropped. We do not have the "Other Race" category in the estimates even though Census 2000 does, because the USCB dropped the "Other Race" data from its estimates. They switched to 8 races in 2001 and we had to follow. It is worth mentioning that the USCB redistributed the racial counts of Other Race completely and the counts for "2 or more Races" were partially redistributed between the rest of the races in their estimates. We did the same and therefore the racial breakdown differs from the Census 2000 but fits the 2001 USCB estimates. We believe that the USCB made these changes because there are no actuarial tables for "other" or "2 or more" races so they needed to redistribute those people into one of the race categories by which they could create estimates

3. Having dealt with Race we then turn to Age. The USCB groups the population into 18 age groups. These range from age 0 (under 1) to age 108. The age groups are each 5 year intervals (0-4, 5-9, etc) except the ages 85 and up (85-108) are treated as a single group.

4. Now that we have the entire population broken down into age and race categories we begin building the death-birth model. With the use of Actuarial tables we calculate the statistical likelihood for any given age/race group to die or to give birth. We then apply these coefficients to the 2000 data to create an estimation base for 2001, the coefficients are reapplied to create 2002, and so on until we get to the current year.

The model includes:

- Transformation of age group distribution to "exact age" distribution. The resulting data set has population groups for each single year of age from 0 to 108.

- Application of death probabilities for a specific age, sex and race group.
- Application of birth rates for a specific age, sex and race group. The white population is treated as a mix of white not Hispanic and Hispanic population. The mix ratio is determined from the block data.
- 1 year shift.
- Collecting the annual data into 5-year buckets.
- Comparison of the results with Census Bureau estimates for this year.
- The results of comparison are used to tweak birth rates and death probabilities to make the numbers of both newborn and deceased in the model to be exactly equal to Census Bureau numbers for each county. The racial distribution is also tweaked to reflect that of Census Bureau data. It puts the annual estimates in sync with USCB data as much as possible.

5. The same model is applied to the results for 2008-2013. This time, however, the "tweaking coefficients" are predicted (as we do not have any materials for comparison) from the tweaking coefficients for 2002 to 2007. The prediction algorithm is based on a linear regression approach (they actually fit the linear plot very nicely).

Housing Estimates

The only way that the number of housing units (HU) changes is if new buildings are built or old ones torn down. Some houses can be built on empty lots, but if a lot of houses are built usually a whole new development gets put in. So the first thing that we did was to look at the TIGER/Line files. This is the USCB file that shows each and every street in the US and has the numbers of each housing unit. By looking at this dataset we can determine if new streets have been put in and by looking at the numbering we can determine about how many units are being built. We can also see if new numbers have been added to an existing street.

1. The TIGER/Lines records for the years 2000 and 2007 were analyzed. For each block, the sum of associated address ranges was calculated. As a result, each block was assigned a Change Coefficient (CC), a number representing the changes in the aggregate number of addresses within this block. The number is a fraction between -1 and +1. The number 0 represents a block that has not been changed within this time interval. The number +1 represents a block that did not have any addresses in 2000 and has some in 2007, and the number -1 is a block with no addresses in 2007 and has some addresses in 2000. The block changes were later summarized to BG level.

2. The Census Bureau Housing Units Estimates (at the county) for the years 2000 to 2007 were used to assess the number of HU per county for the year 2008 via a linear regression algorithm.

3. For each county, the Census Bureau HU growth/decline was distributed among BGs of this county so that:

BGs with CC = 0 did not change any HU counts

BGs with CC not equal to 0 received some parts of the county growth on proportional basis so that BGs with CC > 0 received some HUs and BGs with CC < 0 lose some HUs. The results vary from small changes (mostly, a few percent is a typical change) to some pretty dramatic changes of 3-5 times (rarely). These obviously are where large housing complexes went in and dramatically changed the number of housing units in the block group.

Once we had the change in the number of Housing Units we can then look at the other housing variables such as of number of rooms, vacancy status, tenure (own vs. rent) status, etc. People all live in either a household or a group quarter (military barracks, college dorms, nursing homes, prisons, mental institutions, half-way homes, etc). The group quarters were left stable so the changes in population were then accounted for in the changes in Housing Units that had now been calculated. So for example, if the housing units stayed the same but the population numbers dropped than the vacancy status would go up.

The sum of all changes for all BGs in a county is equal to the Census Bureau HU county growth estimates.

Income Estimates

When calculating Income Estimates there are several components. First we needed to calculate the changes in income from 1990 to 2000 so that we would have a basis for estimating forward. This again required some racial break-out changes because in 1990 the Race grouping was "Asian and Pacific Islanders" whereas in 2000 they are two separate races. Additionally the age changes had to be accounted for (everyone has aged since April 2000 so all of the age categories needed to shift up).

1. The first step was to create an Income Growth by Race number for each Block Group. Luckily, we were able to use both the GeoLytics Census CD 2000 Long Form (SF3) and the CensusCD 1990 in 2000 boundaries Long Form data product for the 1990 data. By using this normalized data set it means that we already have dealt with the geographic boundary changes from 1990 to 2000 and can then look at just the differences in incomes.

2. The BG-level racial growth data were applied to 2000 Census data to obtain 2008 racial income growth coefficients for each BG area. First, the growth data for 1990-2000 were processed using a compound interest model. Second, the calculated "interest rates" were applied to 2000 racial income data to get the 2008 growth data.

The Income Growth data by Race were not available for many BG for some races because if there are very few households of a given race in a block group than numbers were suppressed by the USCB in 1990. For these cases, we used the USCB Median Income Estimates for years 2000-2006 to get 2008 state median income growth data using a linear regression algorithm, and then used these state growth data for Block Groups and races.

3. The racial aggregate income data were processed in the same manner as racial median income data.

4. The Householder age distributions were estimated by using estimated Householder totals from our dataset and an age shift model. Namely, for each age group, a calculated number of householders was moved to the next age group. The first and last age groups were processed in a special way to take into account both new and dead householders. The sum of all householder age brackets is equal to our estimated HH total for 2008.

5. The area income range data were estimated using a distribution shift model. First, we assumed that the Census 2000 income brackets represent the "best fit curve" frequency distribution, and then applied a linear stretch transformation to the income scale. Finally, I calculated the new income bracket values produced by this linear stretching of the frequency distribution. The stretch coefficient was equal to the median income growth ratio for this area. What it all means is that the income increase moves some households from its income bracket in 2000 to the next income bracket in 2008. The number of such households can be estimated mathematically if we know the exact number of households for each income value. This exact number can be estimated using the "best fit curve" model.

6. Finally, the BG data (both medians and aggregates) were tuned so that summary state median values were exactly equal to the state median data for 2008, as estimated from Census Bureau publications for 2000-2006 (see item 2). It was done by using a two-section linear mapping scheme. The scheme

1. Moves the actual state median so it becomes equal to the target value;
2. leaves state minimum and maximum median values for state BGs intact;
3. is a*x + b - linear a) between state minimum median value for all state BGs and state median, and b) between state median and state maximum median value for all state BGs (with different a and b within these two segments).

While estimated data on small geographic areas such as census block groups are not perfect they represent the only realistic avenue for obtaining the demographic data needed for this analysis (Raymondo, 1992).

C. METHOD FOR AREALLY WEIGHTED CENSUS DATA

The longitudinal models required that demographic variables be available at the police district level. This was done by disaggregating the census block groups and re-aggregating the resulting units back into the shape of the police districts. First, a union (an operation within a geographic information system) was performed. This creates a set of new geographical units (NGU) wherever the boundaries of the block group overlap the boundaries of the police district. The area of these NGUs was then calculated and used for two calculations: (1) to calculate the percent of area of the census block group occupied by the NGU and (2) to calculate the percent of area of the police district occupied by the NGU.

The first area calculation (percent of census block group occupied by NGU) was used to determine the value of the demographic characteristic within the NGU. For example, one key variable that was necessary is the residential population. If a NGU comprises 20% of the total area of the original census block group from which it was drawn it would receive 20% of the population within the original census geography. This process works for all variables that are presented in the form of raw numbers (such as total population) but does not work for variables that are presented as rates (such as median home value). For rate variables, instead of multiplying by the percentage of area within the census geography it was necessary to multiply by the percentage of the police district polygon that is occupied by the NGU. Figure 12 illustrates the method used to allocate census data to police districts.

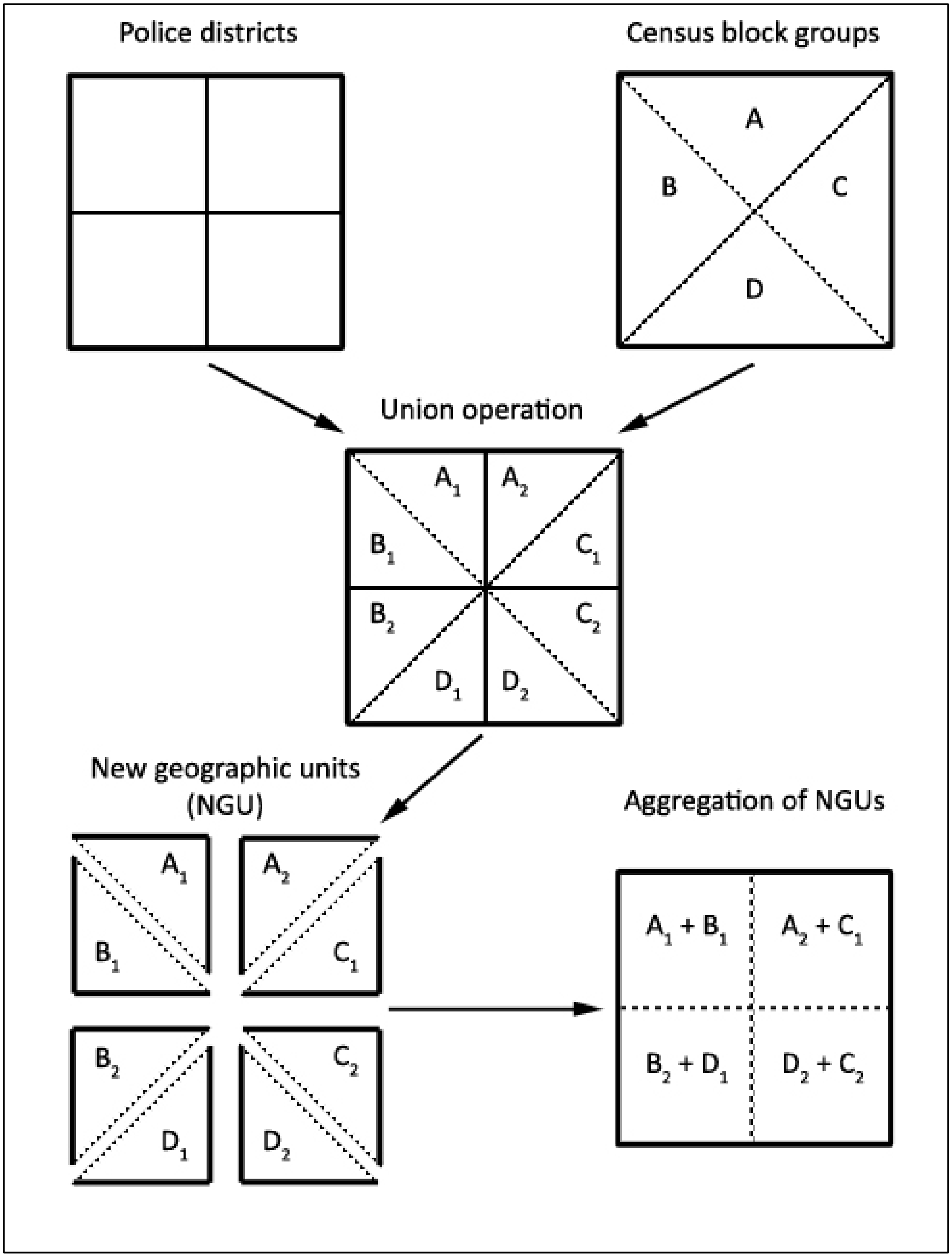

Figure 12: Allocating census data to police districts

After allocating census data to the NGUs it was necessary to aggregate these spatial units into the shape of the police districts. The values of variables of the NGUs can be summarized based on the police district identifier (an attribute given to the NGU during the union operation). This results in every NGU containing the final characteristics of the police district. Redundant NGUs were then identified and deleted from the file leaving 23 police districts with areally weighted census data.

D. CONSTRUCTION OF THE SPATIAL LAG TERM

Spatial autocorrelation in the cross-sectional models was corrected through a two-stage least squares (2SLS) spatial lag variable (Land & Deane, 1992). Land and Deane (1992: 230) argue that “direct OLS [ordinary least squares] estimation of the spatial-effects model will result in biased and inconsistent parameter estimates because of an unknown level of correlation of the generalized potential variable and the error term of the model”. To correct for the simultaneity between the spatial diffusion process and the dependent variable a two-stage least squares method was used. This process can be summarized as follows: (1) create an inverse weighted crime intensity value for each geographic unit, (2) predict the weighted crime intensity in a regression model, and (3) save the standardized predicted value from the regression. The standardized regression value becomes the spatial lag variable entered into final regression models. The first stage was to assign each geographic unit a crime intensity value weighted for crime in nearby geographies. This was done through a computer program written by Dr. Jerry Ratcliffe. The program uses an inverse distance weights matrix to calculate the effect of the crime count in the surrounding polygons. The inverse distance weighting indicates that polygons further away have less affect than nearby geographies. The output from this stage was a value for each polygon representing the “generalized population-potential” of crime in the surrounding polygons.

The second stage in the 2SLS method was to perform a regression analysis utilizing the generalized population-potential as the dependent variable. The predictors in this regression model (known as the instrumental variables or generalized clean instrument) must be more highly correlated with the population-potential than with the actual dependent variable in the final analysis. The standardized predicted values from the regression analysis were then saved and become the instrumented lag variable entered into the final regression model. Because these values are uncorrelated with the error term they are ideal for use as the spatial lag variable in the final analysis model.

A unique spatial lag variable for each dependent variable (unfounded events, low seriousness arrests, and traffic stops) for each year (2004-2008) was created. The first step was to create an inverse distance weighted crime value for each outcome in each year. These inverse distance weighted values were then predicted in a regression equation using variables referred to as the generalized clean instrument. These variables should adequately predict the inverse distance weighted crime values but be theoretically unrelated to the actual outcome measures. The generalized clean instrument was comprised of the following variables: the percent of people working from home; the percent of people that commute to work alone; the percent of people living in one or two person households; the percent of housing units with 3 or fewer rooms; the percent of single family detached, single family attached or double family housing units; the percent of housing units built after 1990; the percent of housing units heated by gas; the percent of housing units with two bedrooms or less; the median rent; the percent of owner occupied housing units with current mortgages; the distance to a home healthcare facility[30]; the distance to an interstate on/off ramp; the distance to a facility that emits potentially harmful exhaust gas[31]; the distance to a brownfield (abandoned or unused industrial sites)[29]; the distance to a hazardous waste facility[29]; the distance to a facility that emits radiation[29]; the X

[30] Facility locations identified by the Pennsylvania Department of Health's quality assurance database.
[31] Facility locations identified by the Pennsylvania Department of Environmental Protection.

centroid of the census block group; and the Y centroid of the census block group. Table 33 presents the adjusted R-squared values calculated from the first stage regression analysis.

Table 33: R-squared values for regression models used in creation of 2SLS spatial lag

Dependent variable	Adj. R^2 values
Unfounded 2004	0.704
Unfounded 2005	0.726
Unfounded 2006	0.724
Unfounded 2007	0.741
Unfounded 2008	0.727
Unfounded 2004-2008 Average	0.728
Traffic Stops 2004	0.765
Traffic Stops 2005	0.755
Traffic Stops 2006	0.770
Traffic Stops 2007	0.747
Traffic Stops 2008	0.724
Traffic Stops 2004-2008 Average	0.757
Low Seriousness Arrests 2004	0.679
Low Seriousness Arrests 2005	0.685
Low Seriousness Arrests 2006	0.689
Low Seriousness Arrests 2007	0.679
Low Seriousness Arrests 2008	0.681
Low Seriousness Arrests 2004-2008 Average	0.684

R-square values from OLS regression models conducted using instrumental variables not included in the final multilevel model specifications.

E: CONTROLLING ALPHA INFLATION

Conducting analyses on multiple correlated dependent variables raises the risk of committing a Type I error. That is, multiple tests on these dependent variables were likely to find a significant relationship between some or all of the independent variables simply by chance. The probability of Type I error can be calculated as follows:

$$Probability\ of\ Type\ I\ error = 1 - (1 - \alpha)^n$$

Take, for example, 10 analyses conducted each with an acceptable comparisonwise alpha level set to $p < .05$. The probability of finding a false positive in this situation would be $1-(1-.05)^{10}$ or 40% (Wilkinson, 1951). There would be a 40% chance of findings a significant relationship by chance alone. The Bonferroni correction has become the most common form of correcting this issue (Moran, 2003). The sequential Bonferroni adjusts global Type I error by dividing α by the number of statistical tests (n):

$$\alpha_\beta = \alpha / n$$

Where α_β is the Bonferroni adjusted alpha level, α is the original alpha level (traditionally $p < .05$), and n is the number of statistical tests conducted (Darlington, 1990). For example, an adjusted alpha value for two tests with an original alpha value of $p < .05$ would be $p < .025$. Referring back to the example discussed above, with 10 tests and a desired overall alpha level of $p < .05$ the Bonferroni adjusted alpha level would need to be set to $p < .005$. Many scholars have expressed concern over the use of the Bonferroni correction arguing that it is overly conservative and inhibits detailed analysis (Garcia, 2004; Moran, 2003). Other authors have been even more critical and argued that "…contrary to what some researchers believe, Bonferroni adjustments do not guarantee a 'prudent' interpretation of results" (Perneger, 1998: 1236).

Reducing the probability of Type I error corresponds to an increased probability of Type II error. In other words, reducing the chance of a false positive reciprocally increases the chance of a false negative. In response to these criticisms more sensitive and less strict procedures, such the false discovery rate (FDR), have been developed (Benjamini & Hochberg, 1995; Dudoit, Shaffer, & Boldrick, 2002). Other procedures consider the correlation between dependent variables in order to reduce the chance of type I error while not constraining alpha levels as dramatically as a simple Bonferroni correction (Sankoh & Dubey, 1997). These procedures reduce acceptable alpha less than the Bonferroni adjustment at the cost of slightly higher probability of Type I error.

The optimal solution to this problem should balance issues of statistical power with issues of statistical sensitivity to finding results. In the current study these two competing issues must be considered in light of a number of factors. Three points make this study unique. First, the relationship between vigor, workload, and officer staffing was conceptualized as a longitudinal relationship. This was not proposed in the original formulation of the theory and re-conceptualizes vigor and the norms driving vigor as a dynamic process. Second, officer workload was measured as the number of serious crime happening in a block group or in a district. This method of measuring patrol officer workload had not been done before. Finally, this study measured officer staffing as the number of officer hours worked. This measure was also new and has not been subjected to extensive empirical assessment. Given the unstudied nature of this topic, beginning with the theory and following all the way through to its operationalization, careful balance between Type I error and Type II error must be achieved.

Recall, that for the cross-sectional models power was found to be adequate (greater than 0.80) when effect sizes were medium or large and alpha was set to $p < .05$. Power was not adequate (less than 0.80) when effect size was small. Adjusting the acceptable alpha level[32] to $p < 0.0167$ results in a noteworthy loss of power under some circumstances. Namely when variance was large, a medium effect size is no longer above the 0.80 acceptable power level. Similar patterns were found for the longitudinal models. When variance was medium and effect size was medium power fell below acceptable levels. This pattern suggests that reducing the acceptable alpha level would impact upon the power of the analysis and ultimately upon the ability to find statistically significant results.

Notwithstanding these arguments, there will almost certainly be some readers that feel strict control over experimentwise error rate is of paramount concern even at the cost of excess Type II error. With three outcomes this would require reducing the alpha level to $p < .0167$. The overall impact of adopting this alpha level would have been minor. First, consider the cross-sectional models. Interpreting the impact of population, spatial effects, or key workload variables would not have changed as these variables were all significant at $p < .001$. Interpretation of some of the demographic variables may have differed. Socioeconomic status would have not changed for any of the outcomes; it was either significant at a $p < .001$ or it was non-significant. Stability was only marginally significant ($p < .05$) with low seriousness arrests. Under a Bonferroni corrected alpha level this variable would have been called non-significant. However, given the variability in this variables relationship to the various methods of operationalizing vigor, caution was already undertaken in interpreting the coefficients.

[32] .05 / 3 = 0.0167

Considering land use, the commercial land use indicator would not have changed dramatically. Under the adjusted alpha level one year on one outcome measure would have been non-significant. Changes to the significance of other land uses would have been a bit more noteworthy. Some land use variables were already on the edge of significance at $p < .05$ and would have been considered non-significant under an adjusted alpha level. However, the broader pattern regarding land use and vigor would not have had much impact when considering the relationship across the different means of operationalizing vigor. The overall pattern of findings in the cross-sectional models would not have been substantially altered if an adjusted p value had been adopted.

Similar consistency was found in the longitudinal models. Key officer workload variables would not have changed. These variables were either significant at $p < .001$ or were not significant at $p < .05$. In other words, the relationship between workload and vigor was either significant at a level less than the Bonferroni corrected alpha or were non-significant to begin with. Officer hours followed the same pattern. This variable was associated with unfounded events and traffic stops at $p < .001$ and was non-significantly associated to low seriousness arrests. Changes to the acceptable alpha level would not have altered these relationships. Other control variables in the longitudinal models may have moved from significance to non-significance with the adjusted alpha level but given their role as controls and not as variables of substantive interest these changes would have been largely irrelevant.

Considering these facts together suggests that adjusting the alpha level was largely unnecessary. This study was exploratory in the sense that both the conceptual model and the method of operationalizing vigor, workload, and staffing had never been subjected to rigorous empirical testing. This argues in favor of accepting slightly greater Type II error in order to take advantage of the additional power provided by a higher alpha level. Furthermore, the substantive interpretation of the relationship between the outcome and key predictors would have remained largely unchanged. Workload and officer staffing, two critical pieces to the conceptual model, would still be significant even under an adjusted p value. The only noteworthy change would have been to the land use variables. Given the already complicated relationship between these variables and the outcome, a relationship that varied by method of operationalization and by year under consideration, great care was already undertaken in interpreting the statistical as well as substantive impact. Had a slightly lower alpha level been adopted the relationship would have been no more or less clear than it had been under an alpha level of $p < .05$. The totality of these circumstances suggested that adjusting the alpha level by even the most conservative method would not have made a noteworthy impact on the key contributions of these models.

F. ASSESSING MODEL FIT

Model fit and model performance was assessed through two methods. First, multilevel modeling assumes that the errors in the level-1 model have equal variance over level-2 units. If variance varies as a function of level-1 or level-2 predictors (either those included in the model or those that were not included) than bias in standard errors and parameter estimates can arise (Raudenbush & Bryk, 2002). To assess this model assumption the residual values of level-1 units were aggregated by their level-2 grouping. The level-2 (police districts) standard deviation of the level-1 (block groups in the cross-sectional models, time in the longitudinal models) residual values was then entered into a probability plot to assess their normality. Second, a scatter plot of actual values versus predicted values from the models were created to assess how well the model was predicting values. This was done for the three dependent variables in both the cross-sectional and the longitudinal models. Model reliability in the cross-sectional models was assessed using the five year averaged outcome variables. All tests were done using the full model specification (model 5 in the cross-sectional and longitudinal models).

Cross-Sectional Models

Evaluation of the outcomes in the cross-sectional models is presented first, followed by the evaluation of the outcomes in the longitudinal models. Assessment begins with unfounded events.

Unfounded Events

Figure 13 presents the log of the standard deviation of the residuals for the full cross-sectional model predicting unfounded events at the census block group level. The values approximated normality to an acceptable degree with no obvious areas of discontinuity. This suggested that the level-1 residuals were normally distributed among level-2 units.

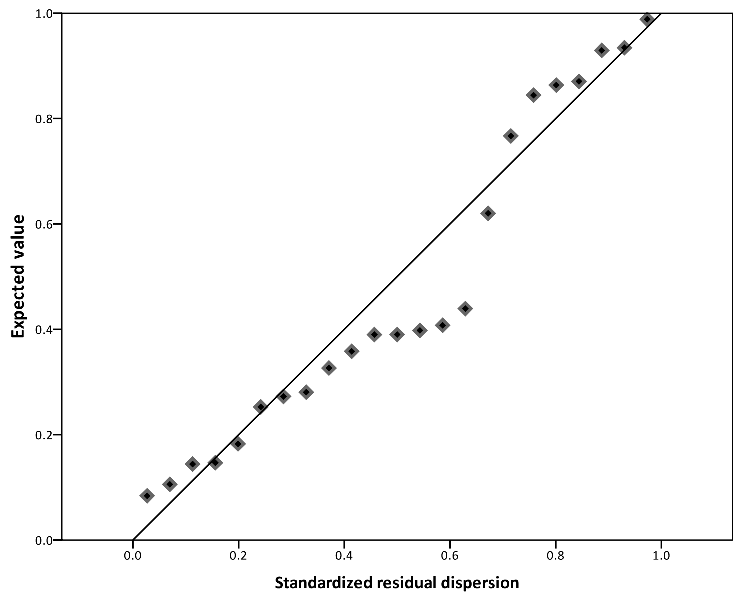

Figure 13: Probability plot of residual dispersions for unfounded events (cross-sectional)

Figure 14 presents the scatter plots of actual versus predicted values. There were a few cases of unusually high predicted values compared to their actual counts. Overall, however, the predicted values mirror the actual counts adequately.

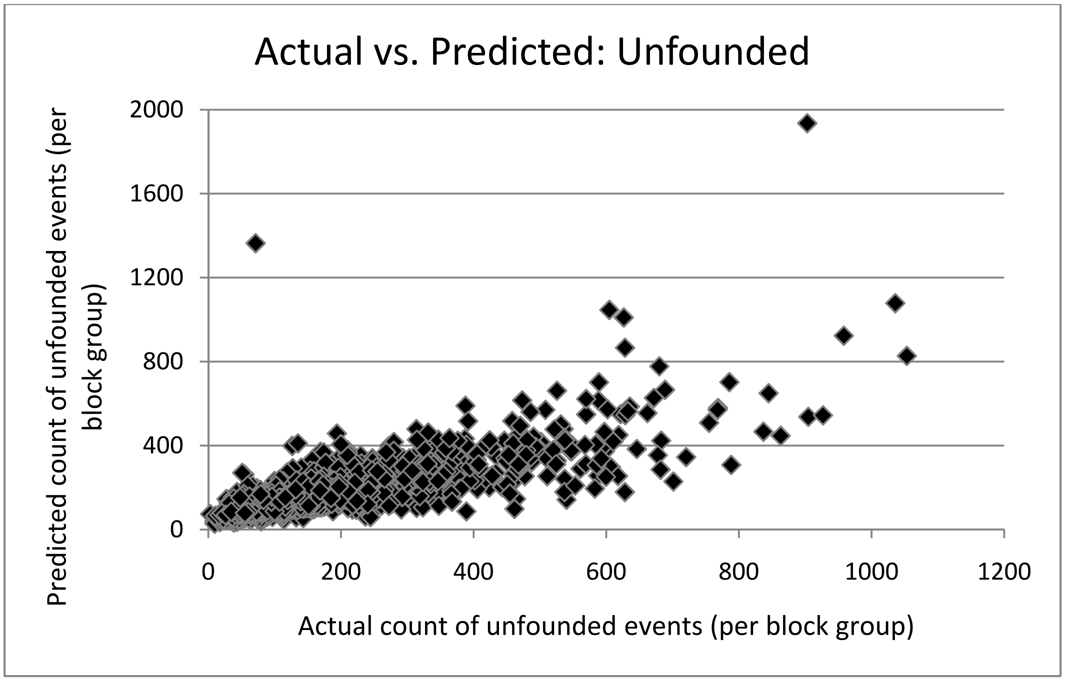

Figure 14: Actual vs. predicted counts of unfounded events (cross-sectional model)

Low Seriousness Arrests

Figure 15 presents the log of the standard deviation of the residuals for the full cross-sectional model predicting low seriousness arrests at the census block group level. The values appeared to be normally distributed to an acceptable degree with no obvious areas of discontinuity. This suggested that the level-1 residuals were normally distributed among level-2 units.

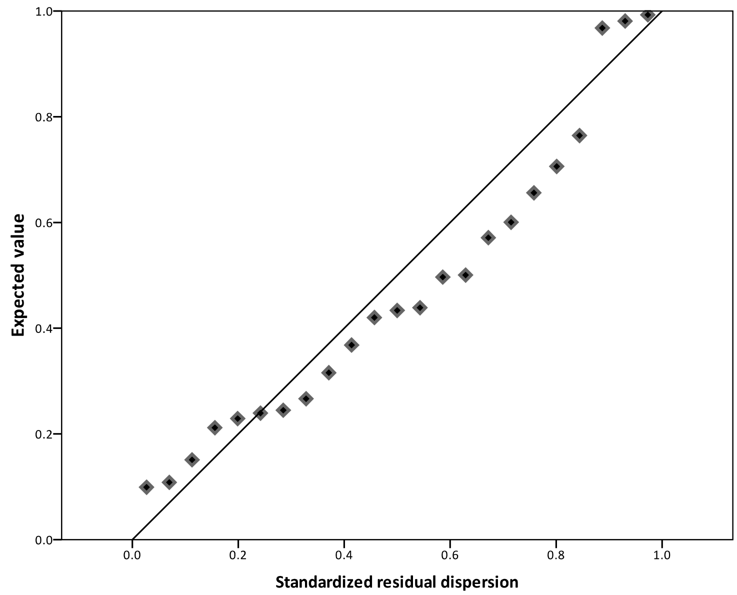

Figure 15: Probability plot of residual dispersions for low seriousness arrests (cross-sectional)

Figure 16 presents a graph of the actual versus predicted counts for low seriousness arrests generated by the cross-sectional model. For the most part the predicted values generally followed the actual values. The model appeared to underpredict in cases of extremely high counts of arrests.

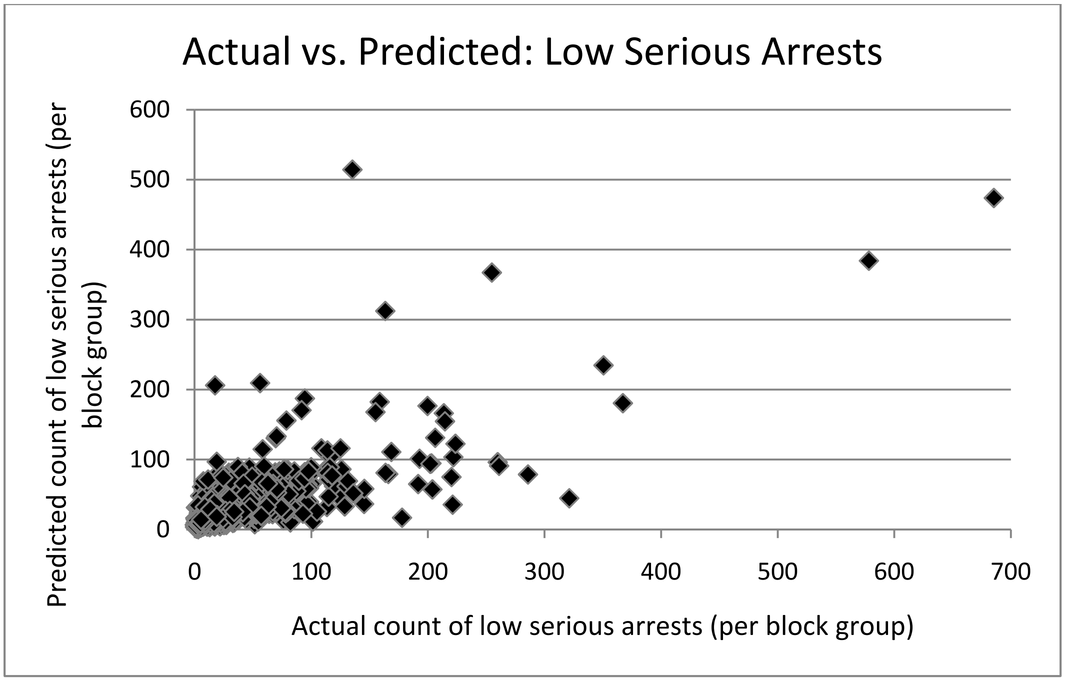

Figure 16: Actual vs. predicted counts of low seriousness arrests (cross-sectional model)

Traffic Stops

Figure 17 presents the log of the standard deviation of the residuals for the full cross-sectional model predicting traffic stops at the census block group level. The values appeared to be normally distributed to an acceptable degree with no obvious areas of discontinuity. This suggested that the level-1 residuals were normally distributed among level-2 units.

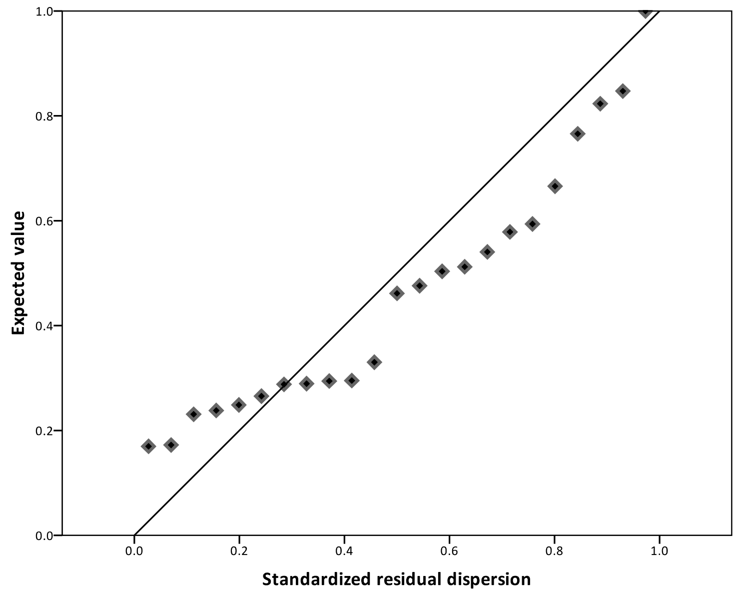

Figure 17: Probability plot of residual dispersions for traffic stops (cross-sectional)

Figure 18 presents a graph of the actual versus predicted counts for traffic stops generated by the cross-sectional model. For the most part the predicted values generally followed the actual values. A few outliers of high actual counts were noted. These cases of high counts were predicted with fair accuracy.

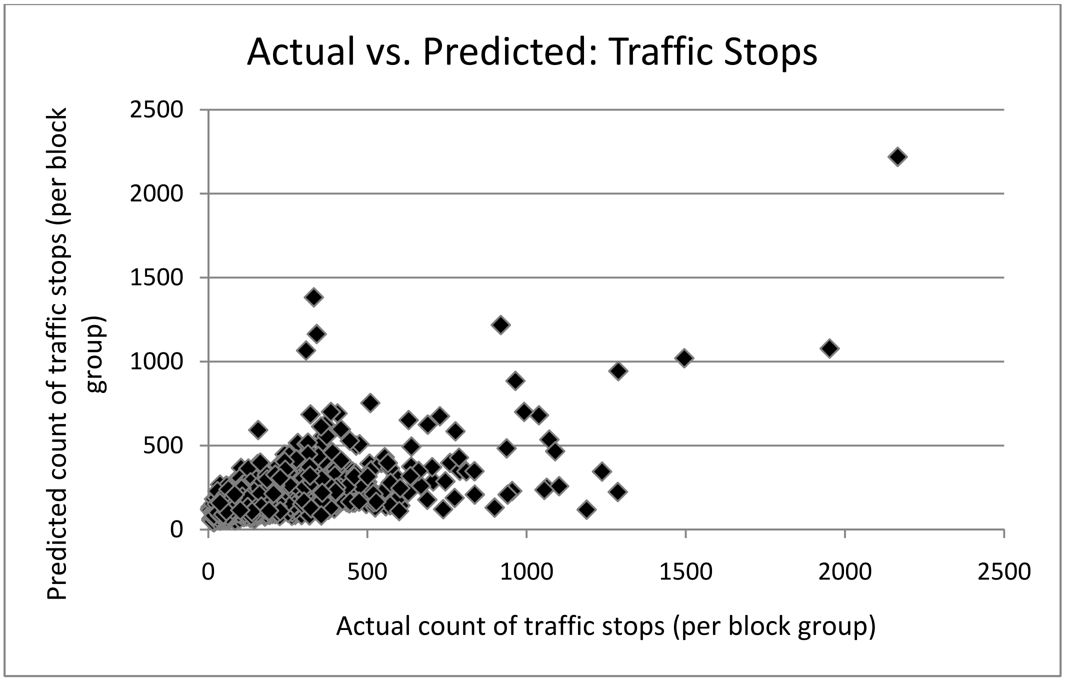

Figure 18: Actual vs. predicted counts of traffic stops (cross-sectional model)

The following section is devoted to assessing model fit in the longitudinal models. All model assessments were conducted on full model (model 5) for each dependent variable.

Unfounded Events

Figure 19 displays the log of the standard deviation of the residuals for the full longitudinal model predicting the number of unfounded events per month, per district. The values appeared to be normally distributed to an acceptable degree with no obvious areas of discontinuity. This suggested that the level-1 residuals were normally distributed among level-2 units.

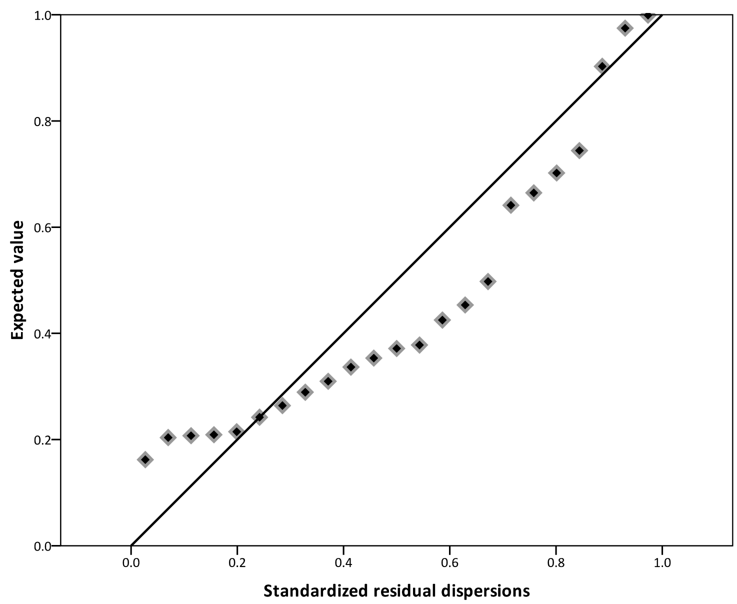

Figure 19: Probability plot of residual dispersions for unfounded events (longitudinal model)

Figure 20 displays a graph of the actual versus predicted counts for unfounded events in the longitudinal model (model 5). Predicted values appeared to accurately mirror actual values suggesting that the model was correctly specified.

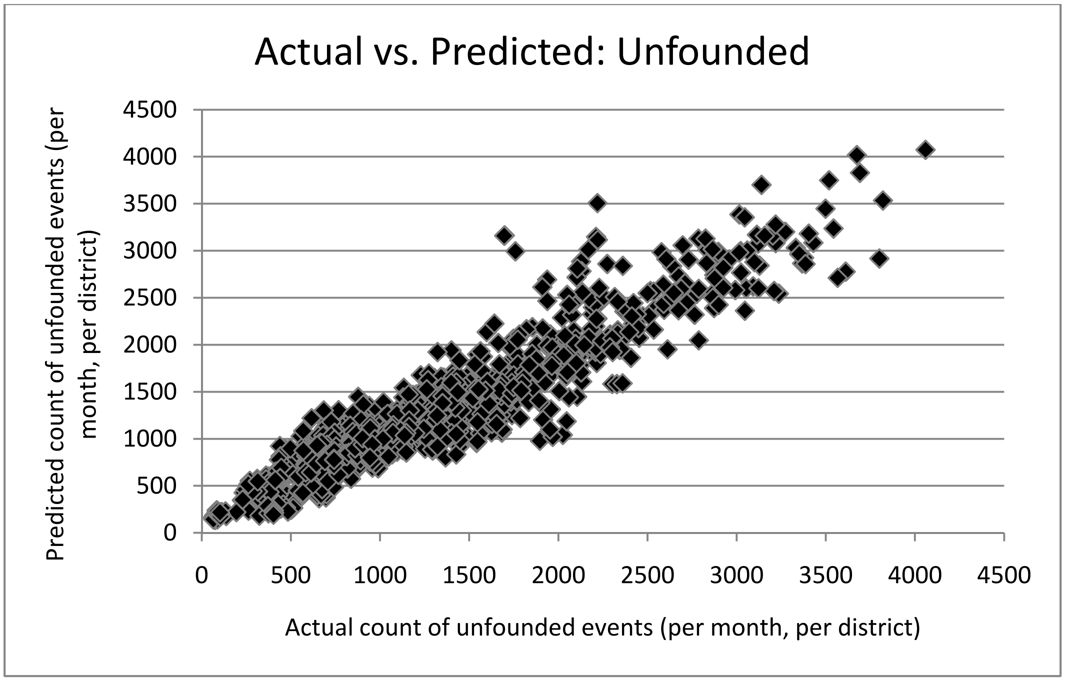

Figure 20: Actual vs. predicted counts of unfounded events (longitudinal model)

Low Seriousness Arrests

Figure 21 presents the log of the standard deviation of the residuals for the full longitudinal model predicting the number of low seriousness arrests per month, per district. The values appeared to be normally distributed to an acceptable degree with no obvious areas of discontinuity suggesting that the level-1 residuals were normally distributed among level-2 units.

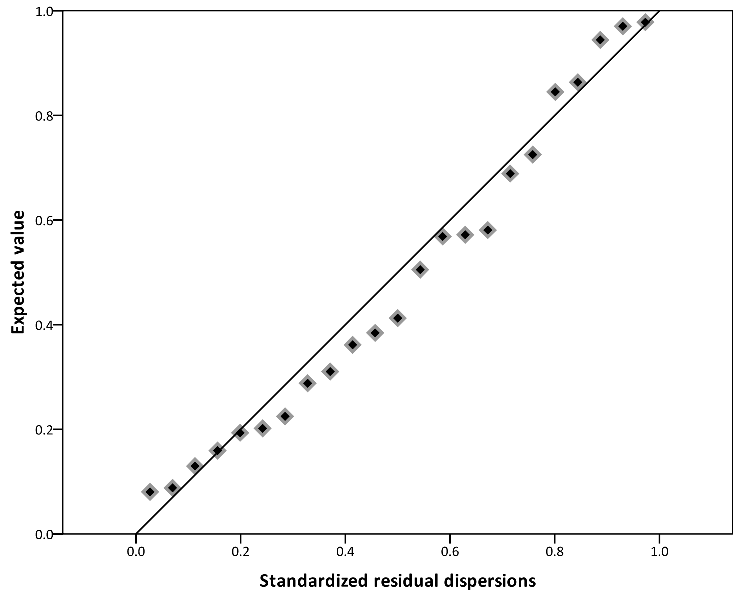

Figure 21: Probability plot of residual dispersions for low seriousness arrests (longitudinal model)

Figure 22 displays a graph of the actual versus predicted counts for low seriousness arrests in the fully specified longitudinal model. Generally the predicted values followed the actual values to an acceptable level. The model appeared to have slightly under predicted very high scores.

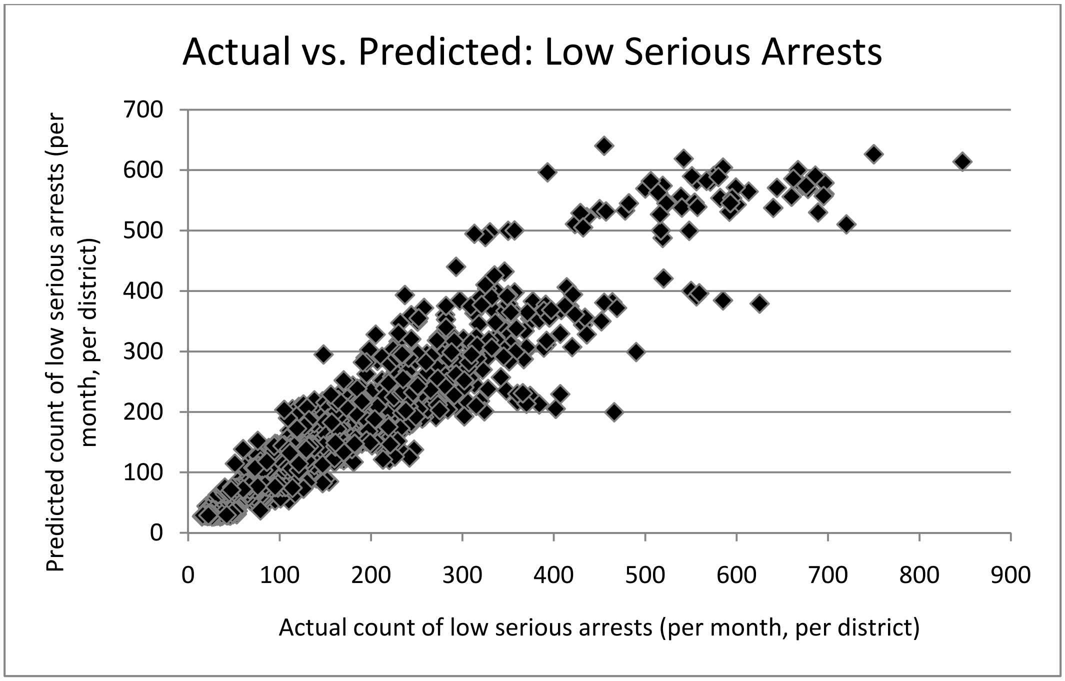

Figure 22: Actual vs. predicted counts of low seriousness arrests (longitudinal model)

Traffic Stops

Figure 23 presents the log of the standard deviation of the residuals for the full longitudinal model predicting the number of traffic stops per month, per district. The values appeared to be normally distributed to an acceptable degree with no obvious areas of discontinuity suggesting that the level-1 residuals were normally distributed among level-2 units.

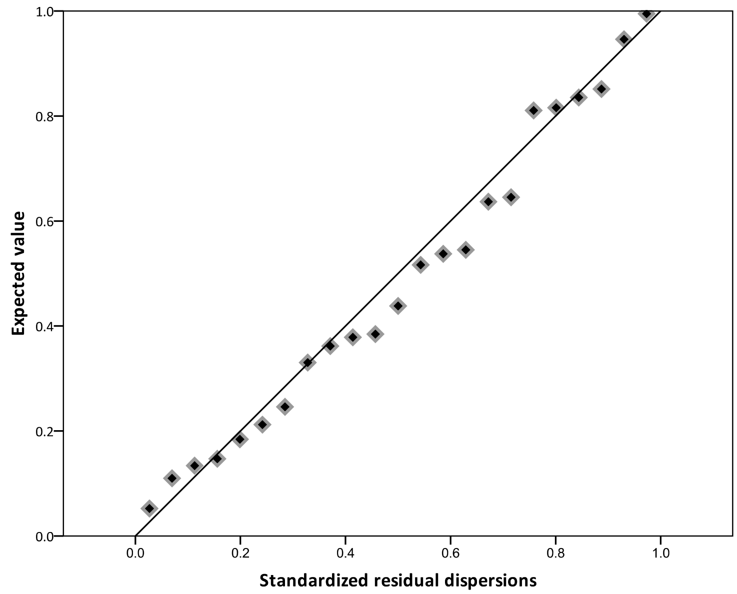

Figure 23: Probability plot of residual dispersions for traffic stops (longitudinal model)

Figure 24 displays a graph of the actual versus predicted counts for traffic stops in the fully specified longitudinal model. Generally the predicted values followed the actual values to an acceptable level.

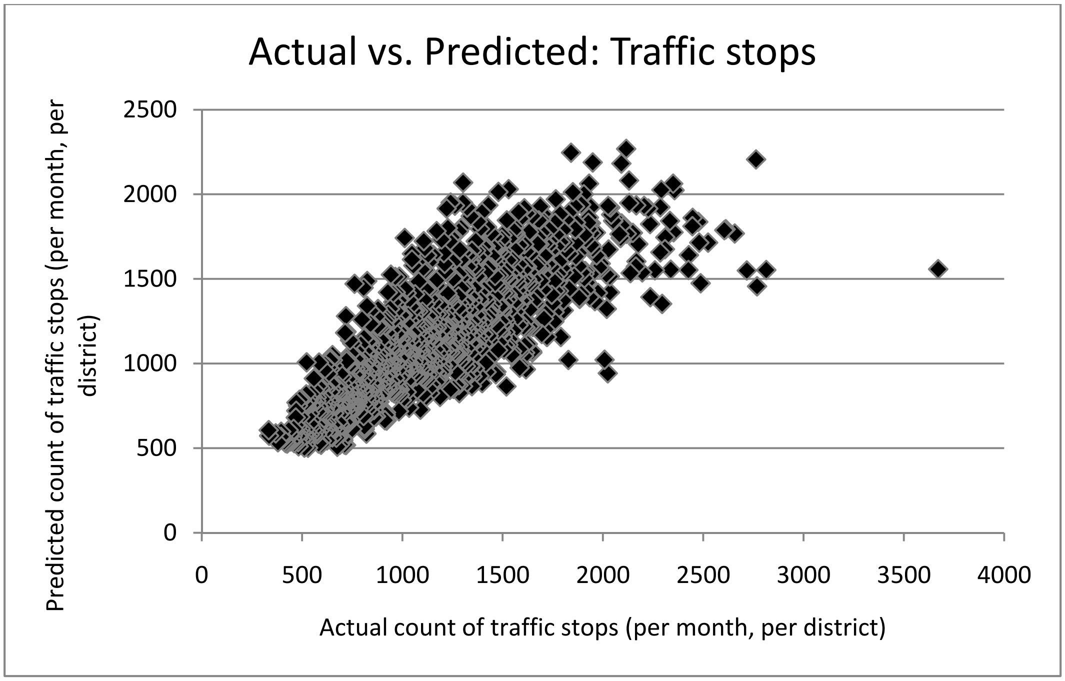

Figure 24: Actual vs. predicted counts of traffic stops (longitudinal model)

Overall, it appeared that by most measures the longitudinal models outperformed their cross-sectional counterparts. It would also appear that unfounded events performed best, followed by traffic stops, and then low seriousness arrests.