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Economic Welfare Of Firefighting Service In Detroit

Matthias H. Jung
Wayne State University,

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MATTHIAS JUNG

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DEDICATION

To Detroit,

the people who call it home,

and Wahnabezee.

Speramus Meliora.

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CHAPTER 1 "PUBLIC FIRE SERVICE – THOUGHTS ON UTILITY, ECONOMIC WELFARE, AND EQUITY"

1.1 Introduction

This research is concerned with various welfare economic aspects of public service allocation, particularly with regard to public fire service. Although subject to substantial debate in the 1970s and 80s, this topic has not received much attention over the last two decades. However, not only has current research on fire risk determinants brought new insights with regard to socio-economic, housing, and spatial factors, but it is also worth revisiting the difficult question of "fair" distribution of public service in times of severe public budget constraints.

Section 1.2 develops a theoretical model to describe utility gained by individuals as a result of public fire service, expressed in terms of service quality. Using von Neumann-Morgenstern utility functions, I account for various fire risk groups, depending on socio-economic, housing, and spatial factors. In a second step, I build on existing literature to describe the functional difficulties accompanying the technology and cost structure of public fire service. Thereafter, I employ comparative statics to analyze the effect of a change in public budget on service quality, and thus, utility of various fire risk groups.

Section 1.3 links quality of fire service to two extreme theoretical social welfare frameworks – Utilitarianism and Rawlsianism. Based on that, I then review several aspects of equity and assess their applicability with regard to public fire service. Section 1.4 can be described as a case study, where I test various equity concepts empirically using Detroit incident micro data from 2012. I employ a GIS equity mapping strategy to analyze a change in Detroit's fire service budget, effective in the middle of 2012, with respect to its impact on intra-city service allocation and two dimensions of equity.

1.2 Utility and fire risk – a model

Based on previous literature, the following section develops a theoretical model to analyze various aspects of individual utility gained through the provision of fire service. First, I account for non-constant fire risk across different groups of individuals based on socio-economic, housing, and spatial factors, and describe how the quality of fire service can affect utility gained by these risk groups. Second, I discuss various issues regarding the output and cost structures of fire service, which will also include the comparison of standard production functions and scale economies. Thereafter, I carry out a constrained utility maximization to derive the effect of a change in budget on quality of fire service, and hence on individual utility.

1.2.1 Utility and quality of fire service

Duncombe (1991) drew on an expenditure model to describe individual local public service demand. Based on the work of Bowen (1943), he presented the preference structure of a median voter who gains utility from housing and other private goods. Following his line of reasoning, we can interpret equation (1) below as individual utility gained both through the consumption of public fire service (*F*), as well as all other public services (*Z*), including police protection, public education, refuse collection, and other non-specified locally financed public services. I will assume that the corresponding input factors are demanded and paid for by a public entity in order to provide fundamental services to individuals. For simplicity, and without loss of generality, (*Z*) is defined as a numéraire with a price of $p_Z = 1$. It is then convenient to divide public services into those affecting the value of a house (*H*), and others, not affecting the value of a house (*B*). Under the assumption that fire service *(F)* only affects the value of a house, we can describe utility gained through the value of a house as a function of fire service, $H = h(F)$. It is frankly acknowledged that the duties of the fire department embrace a myriad of tasks other than dealing with building fires. However, this simplification allows me to investigate the link between quality of fire service and individual utility more closely throughout this study. Public services not affecting the value of a house (*B*), on the other hand, can be represented as a function of (*Z*), so that $B = v(Z)$.

$$U = u\big(h(F), v(Z)\big) \tag{1}$$

Let us further suppose that fire service can be provided at different levels of quality which depend on a number of parameters. Ahlbrandt (1973) recognized four different groups of parameters – fire prevention, fire suppression, first aid, and training. Flynn (2009) described eight parameters in greater detail. The first one is known as *fire rate*, and is defined as the number of reported fires per 1,000 population, or the number of reported fires per 1,000 buildings (by occupancy). This variable can be used to measure fire prevention efforts by the fire department and other institutions. The second parameter is called *fire response and control times*. While there exists an extensive body of literature dealing with various issues of this indicator, it is widely used to describe the performance of fire service, due to its level of availability and simple calculation. Fire response time can be divided into *turnout time* and *travel time*. According to the National Fire Protection Agency (NFPA), turnout time is defined as: “The time interval that begins when the emergency response facilities’ (ERFs) and emergency response units’ (ERUs) notification process begins by either an audible alarm or visual annunciation, or both, and ends at the beginning point of travel time” (NFPA, 2010, p.1710-7). *Travel time* measures the time until an engine company gets on scene. The second part of the indicator, *time to control of fire*, measures the period between arrival of the fire engine or unit, and control of the fire. Parameter three is known as *fire spread*, defined as “[…] the extent of fire spread in terms of how far the flame damage extended. This includes areas that are actually burned or charred, but not areas receiving only heat, smoke or water damage” (Flynn, 2009, p.17). The fourth quality indicator is the *civilian fire death and injury rate*.

Common definitions use the number of civilian deaths (or injuries) per 100,000 population, or the number of civilian deaths (injuries) per 1,000 fires. Parameter five denotes the *firefighter death and injury rate*, which can be calculated similarly to the previous variable: number of firefighter fatalities (injuries) per 1,000 firefighters, or number of firefighter fatalities (injuries) per 1,000 fires. *Human saves and rescues* can be used as a sixth quality indicator. It captures the saves to be reported "[…] in terms of danger the fire posed to the person saved and the degree of assistance needed" (Flynn, 2009, p.22). Performance parameter number seven is known as *property saves*, which can be measured in several ways. It can either be done in total dollars saved in terms of structure and contents, average dollars saved per fire, or percentage of fires in which dollars saved was greater than "x" amount of dollars. Finally, Flynn (2009) listed *training and certification* as the eighth parameter, which measures the percentage of firefighters with completed, up-to-date training, or percentage of firefighters that are certified.

Formally, we can now define public fire service as a function of quality:

$$F = e(Q_F). \tag{2}$$

Based on these definitions, it is also possible to develop a loss function (L) which indicates the effect of a fire on individual utility, where (L) is expressed in terms of quality of fire service (Q_F). This can be most conveniently represented in terms of fire response time (t), the time it takes the fire service to get on scene, since "time is of the essence if losses are to be limited" (Rider, 1979, p.249). Barr and Caputo (2003) also stressed the importance of this statement, as, due to the exponential growth structure of a typical fire, response time is critical to minimize losses. Formally, this substitution can be written as follows:

$$L = e\big(t(Q_F)\big). \tag{3}$$

Rider (1976) offered a definition for average response time which has proven to be a good predictor while being used at the New York City Fire Department. According to his theory, response time (t) depends on the size of the area (A), the number of companies allocated to this area (n), as well as the average number of companies busy in the area (b), and travel coefficients (c), (α), determined by street configuration, company location, and other factors. Equation (4) formally describes Rider's approach:

$$t = c\left[\frac{A}{n-b}\right]^{\alpha}. \tag{4}$$

Let us now consider fire service in an expected utility framework. To accomplish this, I employ a von Neumann-Morgenstern expected utility function of the following general form:

$$EU = \sum_{j=1}^{n} \pi_j u(a_j), \tag{5}$$

where π_j is the probability of outcome a_j (von Neumann & Morgenstern, 2007). By employing this function in our framework, expected utility gained by consumers now depends on the probability that fire service is actually needed, or, in other words, how likely it is for a fire to occur. Therefore, we can add $\pi^f = [0,1]$, which signifies the probability of the occurrence of such event, and $(1-\pi^f)$, which is the complementary event. As a result, our utility function takes the following expected form:

$$EU^F = \pi^f u(aL) + (1-\pi^f)u(a), \tag{6}$$

where $L \in [0,1]$ indicates the severity of the loss in case of the event of a fire. By substituting equations (1) and (3) into equation (6), we arrive at the following:

$$EU^F(\pi^f, Q_F, H, Z) = \pi^f u\big[He\big(t(Q_F)\big)\big] + (1-\pi^f)u(H) + v(Z), \tag{7}$$

where $e(t)$ can be regarded as a function determining the fraction of housing value left if it takes fire service t minutes to get on scene, where $e(0) = 1$, $e'(t)$ is a decreasing function of t, $e(t)$ is a concave function of t, and $e(t) = 0$ for $t \geq T$ for some value of T.

Furthermore, we can account for a variety of different "fire-risk groups". This is based on the observation that fires are not distributed uniformly across any given urban space. In their work on optimal fire station distribution, Corman et al. (1976) have already emphasized that fire risk varies greatly across different regions of a city. Other researchers found that the occurrence of fires may depend on socio-economic, housing, and other spatial factors. Accordingly, many studies pointed out strong evidence for a positive relationship between poverty and fire risk (see, e.g., Gunther (1981), Fahy and Norton (1989), Chhetri et al. (2010)). Others noted that housing age, the level of vacancy, and the rate of abandoned structures in a particular area may be positively correlated to fire risk (see, e.g., Accordino (2000), Shai (2006)). Finally, some literature discussed spatial spillover effects, where the case seems to be that the closer in proximity a lower fire risk area (area A) is to an area experiencing a relatively higher fire risk (area B), there may also be an increase in the fire risk in area A (see, e.g., Corcoran et al. (2007), (2013)). Based on this evidence, it seems necessary to account for these various aspects of fire risk in our theoretical model. We can therefore account for different individuals, or groups of individuals $i = \{1,2, \dots, n\}$ who, based on socio-economic factors (X), housing factors (R), and spatial factors (S), vary in the fire risk they face. We can define $\pi_i^f(X_i, R_i, S_i)$, and substitute it into equation (7), leading to an expression which can be interpreted as individual expected utility dependent on fire risk and quality of fire service:

$$EU_i^F\left(\pi_i^f, Q_F, H_i, R_i, S_i, X_i, Z\right) = \pi_i^f(X_i, R_i, S_i)u\left[H_i e\left(t(Q_F)\right)\right] +$$

$$\left(1 - \pi_i^f(X_i, R_i, S_i)\right)u(H_i) + v(Z). \tag{8}$$

Let us now turn to what this result might imply for groups of individuals facing various risks of actually experiencing a fire. In the simplest, most extreme case, we can think of two groups, $i = \{1,2\}$. Group 1 faces a relatively high risk of fire, and group 2 faces a relatively low risk of fire. Therefore, $\pi_1^f > \pi_2^f$, and $(\pi_1^f, \pi_2^f) \in [0,1]$, where a probability of 1 indicates that fire service will be needed with certainty. Let us further assume that quality of fire service can be measured on a scale between 0 and 1, where the latter specifies the best possible service, $Q_F \in [0,1]$.

In the first extreme scenario (α), I consider a situation where a given, non-further specified governmental budget is sufficient to provide fire service of excellent quality, $Q_F = 1$. We can think about it as Ahlbrandt's (1973) group one quality indicators, that is perfect fire prevention. As a result, losses can be eliminated altogether. In other words, preventative efforts preclude fires from causing any damage. Furthermore, I assume that, based on their fire risk factors defined earlier, the group 1 individuals will need the fire department with certainty, and that group 2 will certainly not need it. The expected utility equations for groups 1 and 2 take on the following forms, respectively:

$$EU_1^F\left(\pi_1^f, Q_F, H_1, Z\right) = u\left[H_1 e\left(t(Q_F)\right)\right] + (1-1)u(H_1) + v(Z)$$

$$= u\left[H_1 e\left(t(Q_F)\right)\right] + v(Z) \tag{9}$$

$$= u\left(H_1 e(0)\right) + v(Z), \qquad where\ e(0) = 1$$

$$= u(H_1) + v(Z) \tag{10}$$

$$EU_2^F\left(\pi_2^f, Q_F, H_2, Z\right) = 0u\left[H_2 e\left(t(Q_F)\right)\right] + (1-0)u(H_2) + v(Z)$$

$$= u(H_2) + v(Z). \tag{11}$$

This result suggests, regardless of the fire risk each group faces, and as long as the quality of fire service cannot be further improved, both of them can realize the maximum utility possible, given their individual endowments. Moreover, it is possible to show that the expected utility of both groups is the same, as long as $H_1 = H_2$, whereas both groups can still differ in fire risk based on $X_1 \neq X_2$, $R_1 \neq R_2$, and $S_1 \neq S_2$.

$$\Longrightarrow EU_1^F = EU_2^F. \tag{12}$$

In a second scenario (β), I consider another extreme situation where the governmental budget has significantly decreased, and, as a result, the quality of fire service is zero, $Q_F = 0$. In other words, one might argue that there is no fire protection at all. The probabilities of fire risk have not changed among the groups and are still determined by socio-economic, housing, and spatial factors. However, the potential loss caused through fire is now at its maximum, indicated by the complete destruction of the house:

$$EU_1^F\left(\pi_f^1, Q_F, H_1, Z\right) = 1u\left[H_1 e\left(t(Q_F)\right)\right] + (1-1)u(H_1) + v(Z)$$

$$= u\left[H_1 e\left(t(Q_F)\right)\right] + v(Z) \tag{13}$$

$$= u\left(H_1 e(T)\right) + v(Z), \qquad where\ e(T) = 0, and\ u(0) = 0$$

$$= v(Z) \tag{14}$$

$$EU_2^F\left(\pi_f^2, Q_F, H_2, Z\right) = 0u\left[H_2 e\left(t(Q_F)\right)\right] + (1-0)u(H_2) + v(Z)$$

$$= u(H_2) + v(Z) \tag{15}$$

$$\Rightarrow EU_1^F < EU_2^F. \tag{16}$$

Now, we can see that group 1 is worse off than group 2 by H_1. Both still get utility from public services not affecting the value of a house (Z), yet group 1 has to cope with the complete loss of H_1 through fire. Therefore, unlike in scenario (α), it is not possible for group 1 to be equally as well off as group 2.

Generalizing the two extreme cases, we can record that as long as $\pi_f^1 > \pi_f^2$, which is true by assumption, and as long as $H_1 \leq H_2$, group 1 will always be worse off than group 2, if the quality of fire service is not providing maximum protection.

1.2.2 Production and cost of fire service

Various authors have investigated the production and cost structure of fire service in the past, which I would like to review at this point, and add to in some respects. Following Duncombe (1992), I define a standard production function for fire service with two input factors, labor (L) and capital (K), generating intermediate output (y):

$$y = f(L, K), \tag{17}$$

where f is assumed to be monotonically increasing and continuous, and a cost function

$$C = c(y, p_F), \tag{18}$$

where (p_F) represents factor prices of labor and capital. Based on the work by Bradford et al. (1969), Duncombe (1992) then argued that this (first stage) output function is not capable of accounting for exogenous socio-economic factors. Only the inclusion of these factors, however, accurately reflects the output of two areas, varying in the "harshness of their fire-fighting environment" (Duncombe, 1992, p. 180). Hence, in a second stage, I augment final output (*F*), so that it can be described as:

$$Q_F = g(y, X, R, S), \tag{19}$$

where (*X*, *R*, *S*) indicate the already familiar socio-economic, housing, and spatial factors, respectively, introduced earlier. In other words, this equation describes the amount of (*y*) needed to generate (*F*), adjusted for exogenous factors. By solving equation (19) for (*y*), and by substituting it into equation (18), it is then possible to expand on previous literature even further, by adding a quality restriction; the idea being that final output (*F*) is provided at quality level (Q_F), which implies that first stage output (*y*) is also adjusted for quality, which means that cost depends on the desired level of quality, too. The resulting expressions for output and cost appear as follows:

$$y(Q_F) = g^{-1}(Q_F, X, R, S), \tag{20}$$

$$C(Q_F) = c[g^{-1}(Q_F, X, R, S), p_F(Q_F)]. \tag{21}$$

Using nonlinear, seemingly unrelated regression (SUR) analysis, Duncombe (1992) estimated both a modified translog cost function (originally developed by Christensen et al. (1973)) and a labor share function, and found evidence that exogenous socio-economic factors are positively correlated with costs in the public sector. He also found that "poor building conditions [...] add significantly to the cost of providing a given level of fire service" (Duncombe, 1992, p. 184).

The author also tested various types of production functions previously employed by other researchers who have also investigated issues regarding the supply and demand of public services. Finding a suitable functional form for public production is a trade-off between imposing restrictions to ensure ease of use and accurate representation of reality. Hirsch (1959), for instance, used a linear production function while investigating the effect of horizontal, vertical, and circular integration of local government services on per capita expenditures. Southwick and Butler (1985), on the other hand, used a Leontief technology in order to model the production of fire protection in 65 major US cities. In his work on the demand for and the production of educational outputs, Baum (1986) used a Cobb-Douglas production technology to model the total output of educational services using labor and capital as inputs. By analyzing data on 197 paid municipal fire departments in the state of New York between 1984 and 1986, Duncombe (1992) empirically investigated whether the use of these technologies was justified. By testing the cost function for homogeneity with respect to final output, the author argued that neither Cobb-Douglas nor CES production functions fit production technology for fire service. He also found that the use of Leontief technology seems inappropriate when socio-economic factors are controlled for in the output function, as is the case in equation (20), since "factor substitution falls between restrictions imposed by Leontief and Cobb-Douglas technology" (Duncombe, 1992, p.184).

Another stream of literature investigated scale economics in the provision of public services, and findings were not always concordant. Early research often focused on the correlation between population size and public expenditure in the context of optimal city size. For municipalities with a population between 10,000 and 150,000 people, for instance, Bergstrom and Goodman (1973) looked at determinants of public expenditures in general and police protection in particular. By estimating a crowding parameter $\gamma = \left(\alpha/(1+\delta)\right)$, where α, δ denote population and tax share elasticity, respectively, the authors predict its value to be close to unity. In other words, no economies of scale seem to be present in the provision of public services. However, it might be possible that this result holds true only after a certain critical size is reached, and that scale effects can be found for smaller municipalities. Brueckner (1981) estimated the correlation between congestion and fire protection. He found evidence for increasing returns to scale in consumption, while examining a sample of 100 communities with a size of at least 30,000 citizens. In other words, any level of fire protection can be provided at a lower cost in larger communities. He also found that fire protection increases with fire and water expenditure and decreases with hazard and population increase. However, his estimated congestion parameter $(\hat{\gamma})$ predicts a one percent decrease in fire protection for every four percent increase in population, holding fire risk and suppression capacity constant. Southwick et al. (1985) used 2SLS estimation to determine supply and demand for fire service in large cities, while employing various loss measures as dependent variables. They found mixed evidence for the existence of scale economies. With respect to fire deaths, for instance, no significant results could be obtained. However, the number of building fires seemed to be significantly negatively related to city size, where a one percent increase in size was estimated to lead to a decrease in per capita building fires of 0.5 percent, indicating a substantial scale effect.

Finally, Duncombe and Yinger (1993) looked into returns to scale in a more differentiated, multidimensional way. By using the earlier introduced two stage output framework and a translog cost function, the authors defined returns to population scale and returns to quality scale, where the latter is defined as:

$$\frac{\partial(C/F)}{\partial F} = \frac{MC_F - AC_F}{F}, \tag{22}$$

where (F) is the second stage output, and (MC_F), (AC_F) are marginal and average cost of producing (F). Furthermore, Duncombe and colleague tested for economies of scope, defined as a situation where marginal cost of one final output decreases as the level of another goes up. Using nonlinear 2SLS regression analysis, they found evidence for constant returns to population scale, which implied that combining smaller fire departments would not lead to cost savings. There were, however, economies of quality scale in the provision of fire protection. In combination with evident economies of scope, improving fire protection might lead to a decrease in average costs. Finally, the authors distinguished between fire prevention and fire suppression efforts. By defining output of fire service as the inverse of property losses, fire prevention was understood as a reduction of fires, while fire suppression was characterized by the loss per fire. Consequently, the presence of economies of scope suggested sharing of inputs of the two types of output.

1.2.3 Budget and quality of fire service

The goal of the following exercise is to carry out a theoretical analysis capable of describing the correlation between governmental budget and quality of public service. Numerous examples show that such theory is needed to evaluate empirical public policy decision making regarding the optimal supply of public service. To address the issue mathematically, I use comparative statics and the implicit function theorem as a tool in a constrained utility maximization framework, where the government, or a social planner, aims to maximize each individual's utility through the provision of public services. Furthermore, I assume that all individuals are risk averse.

We can start by using the expected utility function already developed earlier in this research. For that matter, let us recall equation (8):

$$EU_i^F\left(\pi_i^f, Q_F, H_i, R_i, S_i, X_i, Z\right) = \pi_i^f(X_i, R_i, S_i)u\left[H_i e\left(t(Q_F)\right)\right] +$$

$$\left(1 - \pi_i^f(X_i, R_i, S_i)\right)u(H_i) + v(Z).$$

The budget constraint is determined by the government spending variable (G), and uses the cost function already developed earlier in equation (21) to account for the cost of fire service provided at quality (Q_F). Secondly, the government has to pay for all other public goods and services (Z), which I also have defined earlier as a numéraire. Hence, our constraint can be written as

$$G = C(Q_F) + Z, \tag{23}$$

where we would like to maximize the individual expected utility:

$$max\ EU_i^F\left(\pi_i^f, Q_F, H_i, R_i, S_i, X_i, Z\right). \tag{24}$$

The corresponding Lagrangian equation appears as follows:

$$\mathcal{L} = \pi_i^f u\left[H_i e\left(t(Q_F)\right)\right] + \left(1 - \pi_i^f\right)u(H_i) + v(Z) + \lambda(G - C(Q_F) - Z). \tag{25}$$

Taking the first order partial derivative with respect to Q_F, Z, and the Lagrange multiplier λ, we see:

$$\frac{\partial \mathcal{L}}{\partial Q_F} = 0\colon \pi_i^f H_i t'(Q_F) e'\left(t(Q_F)\right) u'\left(H_i e\left(t(Q_F)\right)\right) - \lambda C'(Q_F) \tag{26}$$

$$\frac{\partial \mathcal{L}}{\partial Z} = 0\colon v'(Z) - \lambda \tag{27}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = 0\colon G - C(Q_F) - Z. \tag{28}$$

The second order derivative takes the following special matrix form (29), (30):

$$\begin{bmatrix} \frac{\partial^2 \mathcal{L}}{\partial Q_F^2} & \frac{\partial^2 \mathcal{L}}{\partial Q_F \partial Z} & \frac{\partial^2 \mathcal{L}}{\partial Q_F \partial \lambda} \\ \frac{\partial^2 \mathcal{L}}{\partial Z \partial Q_F} & \frac{\partial^2 \mathcal{L}}{\partial Z^2} & \frac{\partial^2 \mathcal{L}}{\partial Z \partial \lambda} \\ \frac{\partial^2 \mathcal{L}}{\partial \lambda \partial Q_F} & \frac{\partial^2 \mathcal{L}}{\partial \lambda \partial Z} & \frac{\partial^2 \mathcal{L}}{\partial \lambda^2} \end{bmatrix} \tag{29}$$

$$= \begin{bmatrix} \pi_i^f H_i \left(t''(Q_F) e'\left(t(Q_F)\right) u'\left(H_i e\left(t(Q_F)\right)\right) + t'(Q_F)^2 \left(e''\left(t(Q_F)\right) u'\left(H_i e\left(t(Q_F)\right)\right) + H_i e'\left(t(Q_F)\right)^2 u''\left(H_i e\left(t(Q_F)\right)\right)\right)\right) - \lambda C''(Q_F) & 0 & -C'(Q_F) \\ 0 & v''(Z) & -1 \\ -C'(Q_F) & -1 & 0 \end{bmatrix} \tag{30}$$

Employing the implicit function theorem, we know that Q_F, Z, and λ are also functions of p_F and G. Hence, we can rewrite equations (26), (27), and (28) as follows:

$$\frac{\partial \mathcal{L}}{\partial Q_F}(Q_F^*(p_F,G),Z^*(p_F,G),\lambda^*(p_F,G),G) = \tag{31}$$

$$\pi_i^f H_i t'(Q_F^*(p_F,G))e'\left(t(Q_F^*(p_F,G))\right)u'\left(H_i e\left(t(Q_F^*(p_F,G))\right)\right) - \lambda^*(p_F,G)C'(Q_F^*(p_F,G)) = 0$$

$$\frac{\partial \mathcal{L}}{\partial z}(Q_F^*(p_F,G),Z^*(p_F,G),\lambda^*(p_F,G),G) = v'(Z^*(p_F,G)) - \lambda^*(p_F,G) = 0 \tag{32}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda}(Q_F^*(p_F,G),Z^*(p_F,G),\lambda^*(p_F,G),G) = G - C(Q_F^*(p_F,G)) - Z^*(p_F,G) = 0 \tag{33}$$

By taking the second order derivative with respect to G, while taking into account the implicit functions of Q_F^*, Z^*, we can obtain an expression which tells us what happens to the optimal levels of Q_F^* and z^* when the budget changes:

$$\frac{\partial^2 \mathcal{L}}{\partial Q_F^2}\frac{\partial Q_F^*}{\partial G} + \frac{\partial^2 \mathcal{L}}{\partial Q_F \partial Z}\frac{\partial Z^*}{\partial G} + \frac{\partial^2 \mathcal{L}}{\partial Q_F \partial \lambda}\frac{\partial \lambda^*}{\partial G} + \frac{\partial^2 \mathcal{L}}{\partial Q_F \partial G} = 0 \tag{34}$$

$$\frac{\partial^2 \mathcal{L}}{\partial Z \partial Q_F}\frac{\partial Q_F^*}{\partial G} + \frac{\partial^2 \mathcal{L}}{\partial Z^2}\frac{\partial Z^*}{\partial G} + \frac{\partial^2 \mathcal{L}}{\partial Z \partial \lambda}\frac{\partial \lambda^*}{\partial G} + \frac{\partial^2 \mathcal{L}}{\partial Z \partial G} = 0 \tag{35}$$

$$\frac{\partial^2 \mathcal{L}}{\partial \lambda \partial Q_F}\frac{\partial Q_F^*}{\partial G} + \frac{\partial^2 \mathcal{L}}{\partial \lambda \partial Z}\frac{\partial Z^*}{\partial G} + \frac{\partial^2 \mathcal{L}}{\partial \lambda^2}\frac{\partial \lambda^*}{\partial G} + \frac{\partial^2 \mathcal{L}}{\partial \lambda \partial G} = 0 \tag{36}$$

Again, I use matrix form to simplify equations (31), (32), and (33) to arrive at:

$$\begin{bmatrix} \pi_i^f H_i\left(t''(Q_F)e'(t(Q_F))u'\left(H_i e(t(Q_F))\right) + t'(Q_F)^2\left(e''(t(Q_F))u'\left(H_i e(t(Q_F))\right) + H_i e'(t(Q_F))^2 u''\left(H_i e(t(Q_F))\right)\right)\right) - \lambda C''(Q_F) & 0 & -C'(Q_F) \\ 0 & v''(Z) & -1 \\ -C'(Q_F) & -1 & 0 \end{bmatrix} \begin{bmatrix} \frac{\partial Q_F^*}{\partial G} \\ \frac{\partial Z^*}{\partial G} \\ \frac{\partial \lambda^*}{\partial G} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ -1 \end{bmatrix} \tag{37}$$

Under the application of Cramer's rule, it is now possible to swap the first column with the right hand side of equation (37). This is feasible since we are primarily interested in the effect on Q_F^*. Next, we can divide everything using the bordered Hessian matrix, which, as we know, is greater than 0. Finally, equation (38) offers a clue to how quality of fire service changes as the budget changes.

$$\frac{\partial Q_F^*}{\partial G} = \frac{\begin{bmatrix} 0 & 0 & -C'(Q_F) \\ 0 & v''(Z) & -1 \\ -1 & -1 & 0 \end{bmatrix}}{|H| > 0} = (-1)\frac{\begin{bmatrix} 0 & -C'(Q_F) \\ v''(Z) & -1 \end{bmatrix}}{|H| > 0} =$$

$$(-1)\frac{[0 - [-C'(Q_F)v''(Z)]]}{|H| > 0} =$$

$$\frac{-C'(Q_F)v''(Z)}{|H| > 0} \tag{38}$$

As by assumption we know that we are dealing with risk averse individuals, and find that $v''(Z) < 0$. Therefore, the numerator becomes positive, and so does equation (38). It follows that governmental spending and quality of fire service are positively correlated. More specifically, as the size of the budget shrinks, quality of service suffers due to increased fire response times.

1.3 Social welfare and equity

1.3.1 Social welfare and fire service

Based on previous findings, I would like to address briefly the issue of "fair" public service distribution, exemplified through public fire service, especially in light of the described change in governmental budget. Rider (1976) acknowledged the difficulty of this task by enumerating various goal conflicts, for instance, whether the primary goal of fire service should be to minimize fire losses in a city, or to ensure that the risk of loss is spread evenly across a city. He also points out that a most equitable manner of resource allocation would imply defining a social welfare function first. Without question, there will be more than just one opinion on that matter. In a strictly utilitarian framework, for instance, one might argue that, regardless of who benefits from fire service, social welfare (W_U^F) is maximized as long as it is provided efficiently, for example, as long as output is maximized, given a certain level of inputs. As described by equation (39), total welfare would then be the sum of individual expected utility:

$$W_U^F = \sum_{i=1}^{n} EU_i^F. \tag{39}$$

Lucy (1981), who investigated aspects of equity with regard to local public planning efforts, emphasizes that output of fire departments is often measured in terms of potential fire losses, or potential insurance claims. Therefore, it makes sense to locate fire stations close to heavily insured structures, such as schools, industrial plants, or department stores, as overall fire losses can potentially be minimized, implying the maximization of social welfare in a utilitarian sense. The author then followed with "[the] proximity of fire stations to residences may be more a consequence of the fortuitous distribution of nonresidential structures […]" (Lucy, 1981, p.453).

On the other end of the spectrum, we can think of a social welfare function in a Rawlsian sense, which might be more suitable to approach the question of fair or equitable distribution of fire risk (Rawls, 1971). In the crudest, one-dimensional sense, social welfare can be expressed in terms of individual income (Y_i), so that, in a Rawlsian sense, it is determined by the poorest individual. In the previous section, I provide evidence that fire risk in residential areas, among other things, is determined by socio-economic factors, one of them being income. According to earlier conducted research, relative fire risk is strongly correlated with the degree of poverty, and thus, social welfare (W_R^F) is equal to the individual facing the highest fire risk. Adapted to our framework, where expected utility is gained exclusively through public services, it can be formally described as follows:

$$W_R^F = \min(EU_1^F, EU_2^F, \dots, EU_n^F), \tag{40}$$

where W_R^F, the overall welfare in society generated through fire service, is measured according to the expected utility gained by the least well-off individual. Section 2 also develops a theoretical model to describe who benefits from fire service, and in which way, based on quality of service. We have seen that high fire risk areas can possibly gain the same amount of expected utility as low fire risk areas, as long as the maximum quality of service is achieved. On the other hand, a situation of reduced quality of fire service leaves individuals living in high fire risk areas potentially worse off than individuals living in low fire risk areas. We have seen that the lower quality of service, the higher the discrepancy between the expected utility gained by groups 1 and 2, EU_1^F and EU_2^F, respectively. Therefore, it follows that in scenario (β), where $EU_1^F < EU_2^F$, social welfare $\mathrm{W}_{R\beta}^F = EU_1^F$, whereas in scenario (α), where $EU_1^F = EU_2^F$ (assuming that $H_1 = H_2$), social welfare $\mathrm{W}_{R\alpha}^F = EU_1^F = EU_2^F$. In other words, the overall social welfare in scenario (α), in a Rawlsian sense, is greater than in scenario (β):

$$W^F_{R\alpha} > W^F_{R\beta} \tag{41}$$

Scenario (α) could therefore be described as a situation where individual expected utility is maximized, even though fire risk is not necessarily minimized. With regard to the previous analysis, it seems that a decrease in budget, although likely to cause an increase in response time, may not jeopardize an efficient outcome in a utilitarian sense, as long as output is still maximized, given the new diminished inputs. However, in a Rawlsian sense, the level of equity may have decreased. Therefore, under certain assumptions, fire service can directly affect social welfare in a Rawlsian framework, and, correspondingly, higher quality of fire service can lead to a more equal outcome.

1.3.2 Equity and fire service

Lucy (1981) also approached the issue of distributional fairness, or equity of public service distribution, by dividing it into five different concepts – equality, need, demand, preferences, and willingness to pay. He argues that although any one of these concepts can be applied separately, a planner should incorporate two or more, if possible, especially when deciding on marginal addition to, or deletion from, a certain public service. In the case of fire protection, the empirical application of Lucy's logic is harder than one would expect, not only because of conflicting goals among dimensions, but also because of the nature of fire protection, which in some respects is quite different from other public services (e.g., parks, schools, or libraries). The concept of equality might be interpreted as a state of nature, where all individuals receive equal service. Although this is intuitively easy to understand, it might be difficult, or nearly impossible, to implement in practice. Equal service might be translated into equal fire response time, and therefore into equal distance from fire station to fire incident, assuming all engine companies follow the same procedures, use identical trucks, and face similar spatial circumstances. Clearly, this goal will remain largely unattainable for any planner, which is why Lucy advocated having at least certain defined threshold levels. To add some more complexity, one might also distinguish equality regarding input indicators, such as response time, and output indicators, such as fire loss, where equality in the former may not necessarily lead to equality in the latter.

Planning according to the second concept of equity: need, by definition, already creates a goal conflict with the first concept. Here, a situation where someone must have something, yet someone else does not, leads to unequal treatment of the two. This situation was most concisely defined more than two thousand years ago by Aristotle. According to his view of fairness, equals must be treated equally, and unequals must be treated unequally (Ostwald, 1962). In the case of fire protection, the implementation of this dimension seems viable, as need might be determined by individual fire risk, which appears to be determined by socio-economic, housing, and spatial factors. Planning based on need might then justify why, for instance, low income regions, or areas with a high poverty rate, should receive more attention by fire service than others, or why the grid of stations should be denser in these areas than in lower fire risk areas.

Demand, being the third dimension, basically dictates that “active interest in a service should be rewarded” (Lucy, 1981, p.449). Demand can be understood in a purely microeconomic sense as well as a political sense. Immediately, one can see that the mere application of this concept can lead to a very different distribution of services compared to the previous one. Here, influence of interest groups may be the driving force, or, in other words, “the squeaky wheel gets the grease”. Moreover, it seems that, even though personal interest and taking action is honorable, this concept aims more at what people want, as in “a public park makes our neighborhood more beautiful”, and not what they actually need, in the sense of lacking essential services to protect life and property. The latter seems to be especially applicable for fire and police protection.

Preference, as the fourth concept of equity, can be understood as a more general form of demand, where unexpressed opinions of less publicly active individuals are also taken into account by the planner, as opposed to demand, which may only represent the opinion of a small, outspoken group. Various types of surveys may be a means to overcome the shortcomings of the demand concept; however, this dimension does not seem to be any more pertinent in the case of fire service than concept three, as most people would simply choose more protection over less, regardless of their individual fire risk.

Finally, Lucy (1981) advocated willingness to pay as a dimension of equity. The idea is straightforward, and certainly a concept every undergraduate economics student is familiar with. Closely related to the concept of demand, it simply states that whoever would like to consume a good or service has to pay for it. Again, with regard to certain public services, this concept might work well if, for instance, planners are to decide whether to build a new park, where in theory, tax money is used to finance the park and only people who have paid their taxes are eligible to enter the park. Practically, this concept might be very difficult to implement, since the very definition of a public good or service is non-rivalry and non-excludability, leading to problems such as free-riding, all of which have been discussed extensively in the past. With regard to fire service, the application of this concept seems to be especially challenging. Going back to section 1.2, we have seen that fire risk varies across individuals and that poverty plays a significant role. Therefore, it seems counterintuitive to ask for more from individuals who have less in order to meet the increased need of fire protection.

In summary, it seems that need is the most promising concept, useful both in theory and practice, when it comes to analyzing equity and fairness in fire service. Using GIS mapping, Talen

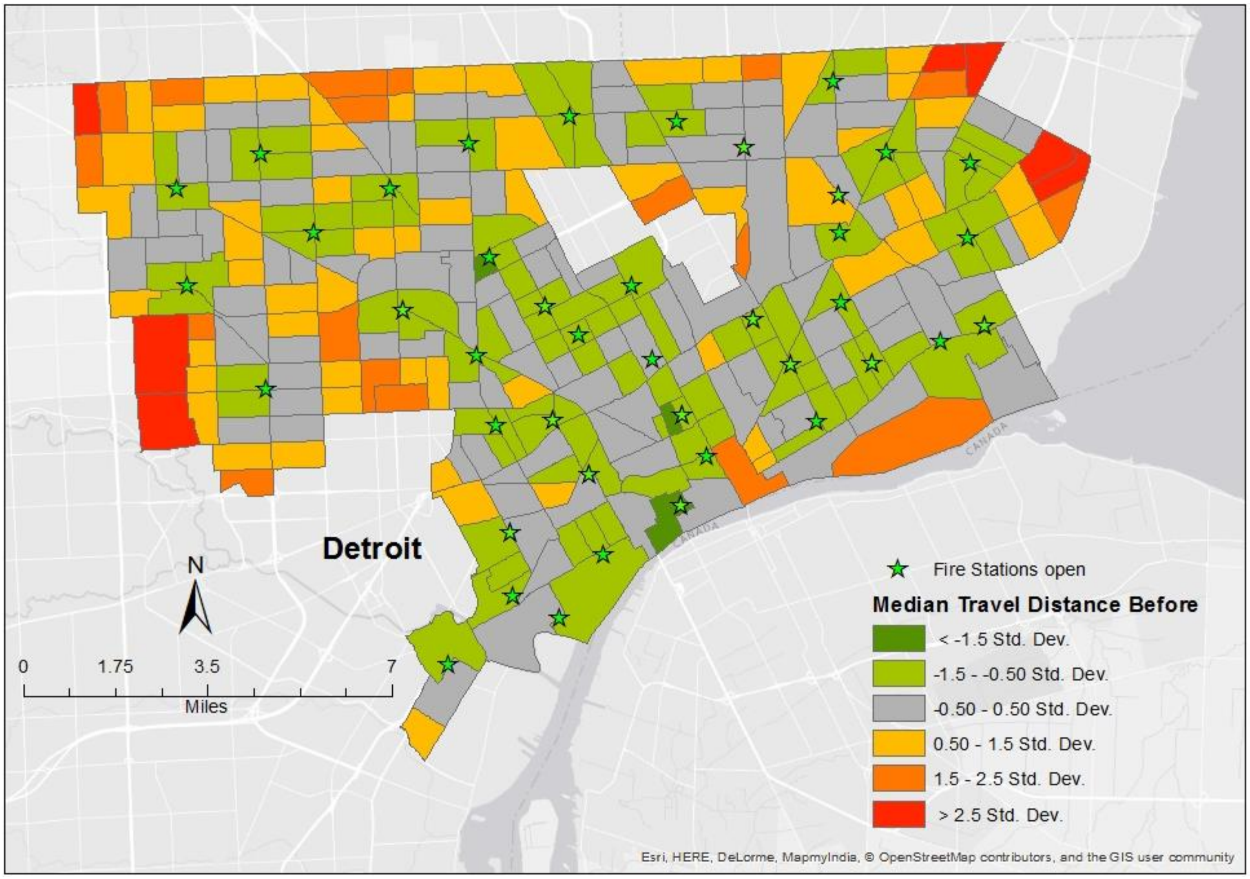
(1998) employed this concept to analyze equity empirically. Her research investigated spatial equity with respect to public parks for the city of Pueblo, California. Although not without its problems, equity mapping provides a simple alternative to a more sophisticated, quantitative spatial analysis, or it can at least enable the researcher to give a first assessment on the basis of which further inquiry regarding any public distributional subject matter can be pursued. In the final section of this chapter, I will apply Talen's framework to address the issue of "fair" fire service, using Detroit, Michigan, fire incident data.

1.4 Case Study – Equity of fire service in Detroit

In Detroit, the fire department had to cope with a significant budget cut at the beginning of fiscal year 2013 (July 1st, 2012). As a result, the number of firefighters on duty per day decreased by about 30 percent and numerous fire stations had to be closed. On the one hand, the total cost of providing fire service could be reduced, and hence, so could overall public spending. However, it seems logical that benefits of fire protection, expressed as utility gained by Detroit's citizens, might also have suffered. The reason is that, after the budget change, we can still assume a certain exogenous level of individual fire risk and spatial distribution, as developed in section 1.2, as well as a certain exogenous number of fire incidents. Given that, we would expect an increase in workload for the remaining engine companies (e.g., fires per shift), and also an overall increase in their travel distance, as the density of the fire station grid has decreased, which will likely lead to an increase in response time (Rider, 1979). The theoretical analysis of section 1.2 has shown that, as a result, the overall quality of fire service decreases, potentially increasing hazard to life and property, thus causing a lower utility level for Detroit citizens. It is the goal of this exercise to find out whether the change in budget also had an effect on distributional equity across Detroit.

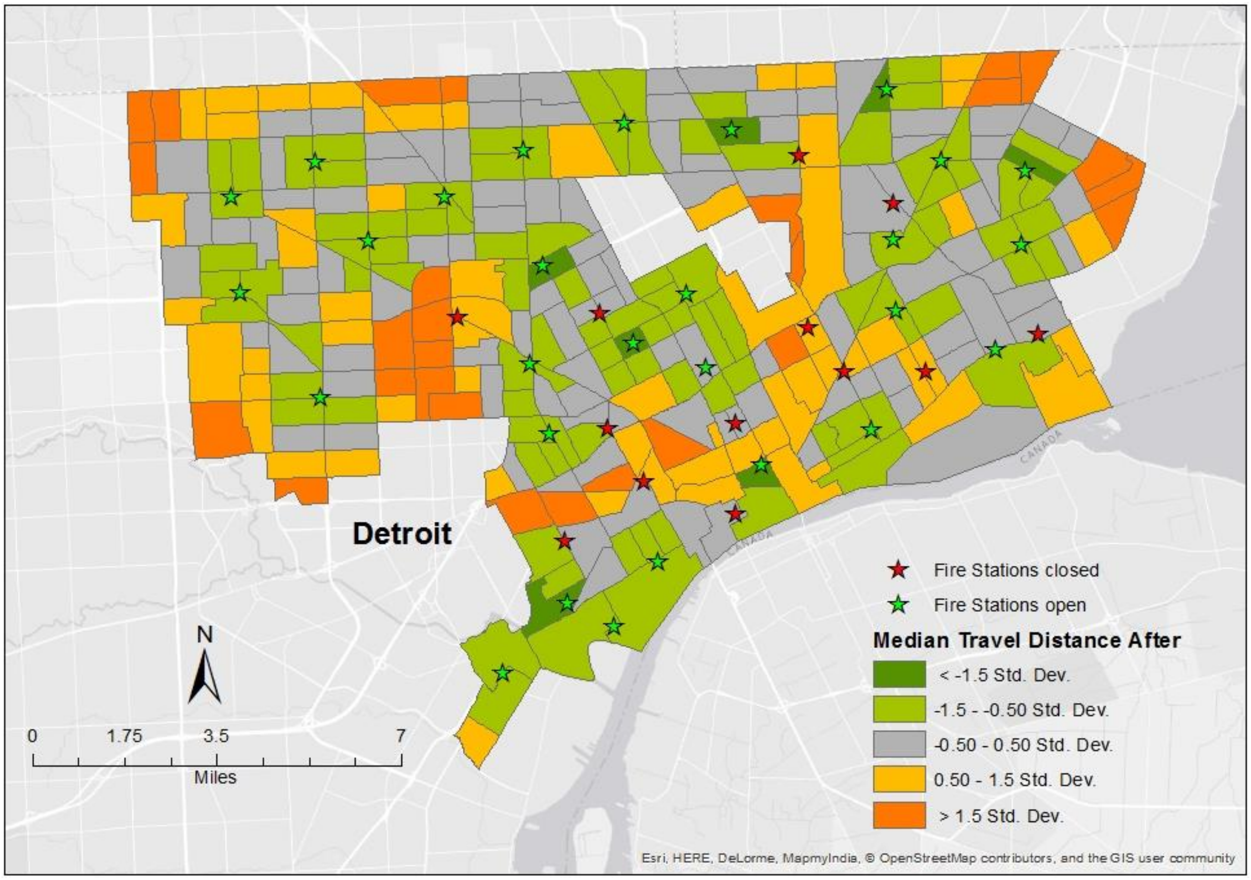
Following Lucy (1981), in the first step, I analyze Detroit fire service with respect to equality of service. To do this, I geocode every incident of the year 2012 according to 297 Detroit census tracts and map them with respect to the indicator variable "distance traveled" by fire company between fire station and incident. The 2012 data set consists of 14,988 incidents before, and 9147 incidents after, the closing of 13 fire stations. Map 1 shows the standard deviations of the median distance traveled per tract before the budget cut.

Map 1: Median travel distance per census tract before budget cut 2012



With a value of 0.450, it comes as no surprise that the distribution is far from perfect equality (gray color). With an overall median distance of 0.89 miles, it appears that the closer a fire station is located to a tract, or is even located within a certain tract, the shorter the distance traveled by the fire company. Almost all of these areas show a negative deviation from the mean (green color). Areas located on the fringe of the city, on the other hand, are generally further away from fire stations, and therefore those census tracts deviate positively from the mean (orange and red color). This result comes as no surprise and makes sense intuitively. Map 2 displays the distribution after stations were closed (red stars). With a standard deviation of 0.460, the change is minimal; however, the median travel distance has increased by 16 percent to 1.03 miles. We can record that close proximity to open fire stations leads to a stronger negative deviation from the mean, whereas close proximity to closed fire stations mostly leads to strong positive deviation. This point manifests itself in the mid-western area of the city, as well as the area south and east of Hamtramck.

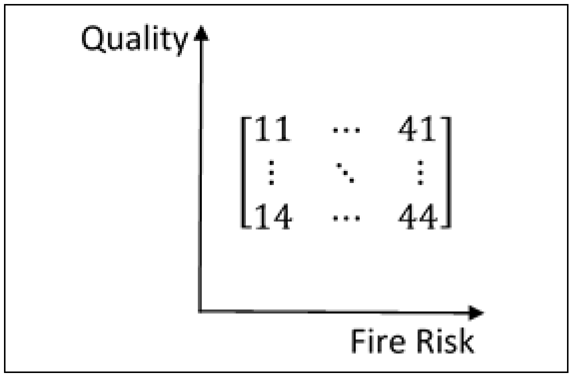
Map 2: Median travel distance per census tract after budget cut 2012



Even though a final judgment is not possible, it seems that, if anything, equality in terms of travel distance has decreased after the change in budget.

In a second step, I analyze Detroit fire service with respect to need for service, the second dimension of equity proposed by Lucy (1981) and favored by Talen (1998), and link it to quality of fire service. The idea, how to determine need for fire service, is straightforward. I interpret need as individual fire risk. To approximate fire risk, I use 5-year estimates of the percentage of households living in poverty per census tract according to the 2012 American Community Survey (ACS). Moreover, I use the quality variable "response time", in line with the theoretical model developed earlier. Thereafter, I calculate a 4x4 matrix to determine the correlation between fire risk and quality.

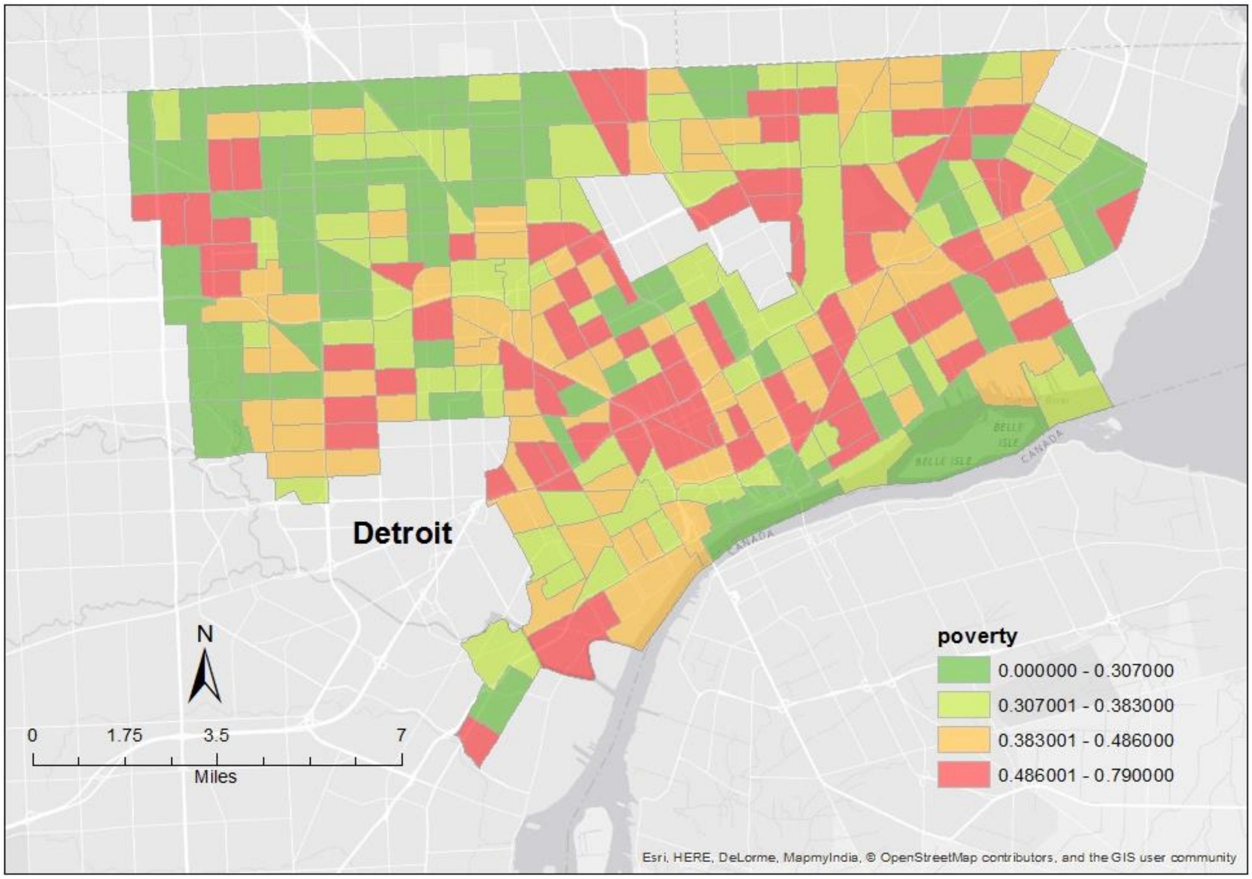
Figure 1: Equity and need of fire service, concept



I divide fire risk into four poverty categories, where (1) is the lowest and (4) indicates the highest poverty quartile. I also divide quality into four response time categories, where (1) is the lowest and (4) indicates the highest response time quartile. Note that the matrix takes an inverted form, as quality, expressed as response time, is inversely related to the latter. In order to stay as close as possible to the theoretical model of section 1.2, I only look at building fires for the year 2012, potentially affecting housing value (*H*). As a result, the sample size decreases to 5914 observations - 3707 before, and 2207 after - the change in budget. I calculate the median response time per census tract, which leaves 176 observations. For the remaining census tracts, not enough building fires occurred in 2012 to obtain reliable results.

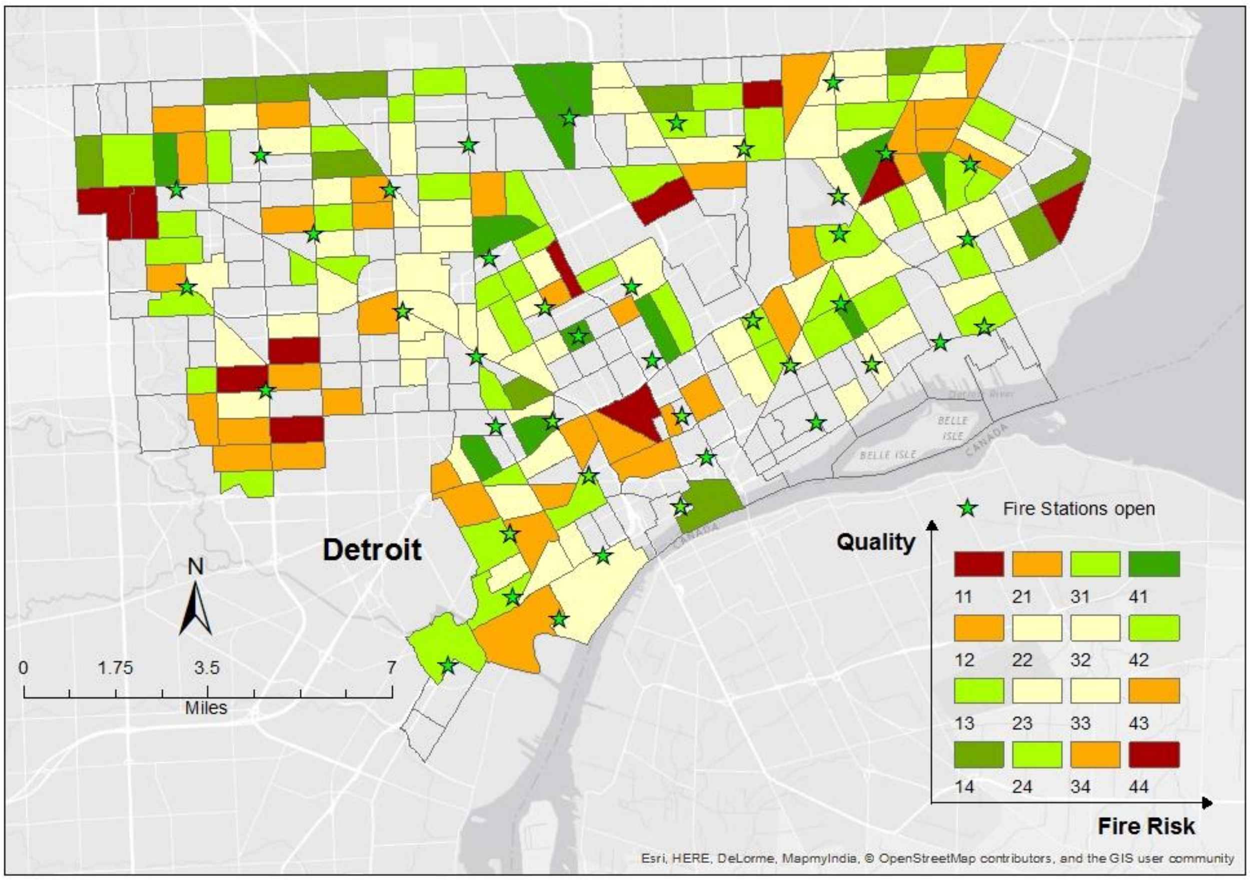
Map 3 portrays the poverty distribution across Detroit. With a mean of 42 percent of all households living in poverty, Detroit takes on one of the highest ranks in a national comparison among cities, and one could argue that individual fire risk in Detroit is generally higher than in almost all other cities. Therefore, one could argue that the overall quality of fire service should be exceptionally high in order to counteract the level of overall poverty. However, if one were to compare tracts within the city, poverty seems to be highest in the east, the south-west, and south of Highland Park, closer to the geographical center of the city.

Map 3: Percentage of households living in poverty (ACS 5-year estimates)



Based on these observations, and with respect to equity interpreted as need, one could argue that a fair distribution of fire service justifies a higher service quality the higher the fire risk is. In other words, relatively speaking, a fair distribution would justify a higher response time in areas with relatively lower poverty. Based on the concept described in Figure 1, that means that a combination of poverty quartile (1) and response time quartile (4) (scenario (14)), as well as poverty quartile (4) and response time quartile (1) (scenario (41)) would be considered as fair (green areas). On the other hand, poverty quartile (1) and response time quartile (1) (scenario (11)), as well as poverty quartile (4) and response time quartile (4) (scenario (44)) would be considered as unfair (red and orange areas). Map 4 illustrates this type of equity map with regard to observations before the change in budget. In a perfectly fair distribution, we would expect exclusively green areas. However, for the 176 census tracts under investigation, no such observation can be made. Especially in the lower western and south-western regions, high fire risk seems to be accompanied by low service quality.

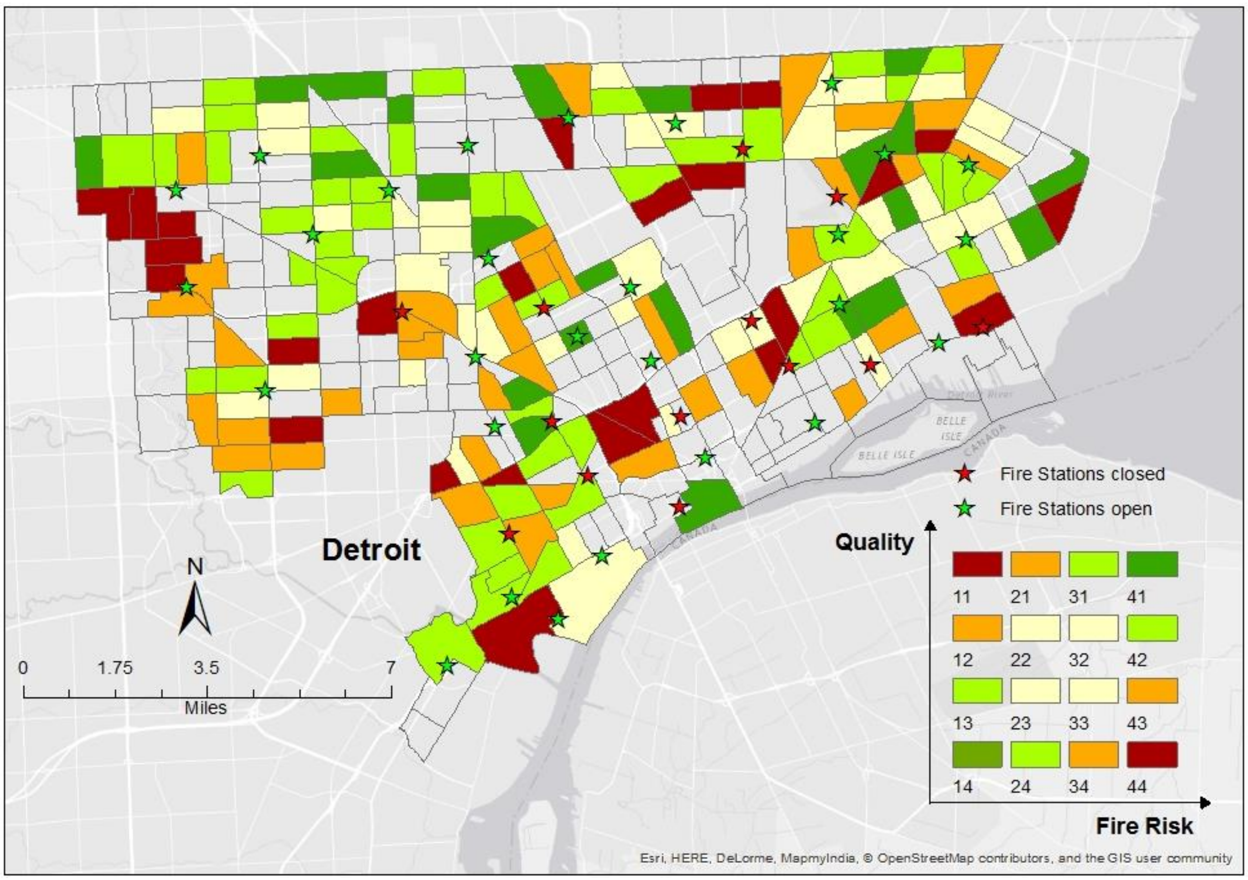
Map 4: Equity and need - fire risk and quality before change in budget



After the cut in budget and the closing of fire stations, it appears that equity in terms of need has decreased, as the number of areas with both high fire risk and low quality of fire service and vice versa (marked in red) have increased. Map 5 shows that these tracts can be found throughout the city, mostly, however, in the proximity of a recently closed fire station. Nevertheless, this evaluation does not hold true for the far western area of the city. The increased number of areas marked

(11) and (44), especially the latter, can likely be explained by the change in response time after the change in budget. While the poverty estimate has not changed, mean response time for building fires increased by nine percent, or from 4 minutes and 11 seconds, to 4 minutes and 36 seconds. The maximum response time per tract increased by 13 percent, from 6 minutes and 33 seconds to 7 minutes and 13 seconds.

Map 5: Equity and need - fire risk and quality after change in budget



Concluding this case study, we can see that equity mapping is a valuable technique to visualize various dimensions of equity in an urban area. Furthermore, it seems that even though the equality dimension is easy to implement and easy to understand, at least for Detroit fire service, its informational value outside of merely theoretical considerations is limited. Although controversial, the need dimension seems to be more suited for equity mapping and provides valuable insight into fair distribution of public services such as fire protection. There is no doubt that the equity mapping approach can be refined almost indefinitely, and provides researchers and planners with a simple tool to approach the difficult question of equity. However, Talen was right when she made it clear that "the purpose of equity mapping is to stimulate further inquiry" (Talen, 1998, p.29).

1.5 Conclusion

This research aims to add to the existing body of literature by addressing various aspects of individual utility, social welfare, and equity through the provision of public fire service. A microeconomic model was developed to describe expected individual utility as a result of various levels of service quality. A theoretical connection was established between socio-economic, housing and spatial factors, and individual fire risk. According to the model, it seems plausible that a change in public budget affects expected utility of individuals differently, depending on the level of fire risk they face. Unsurprisingly, it could be shown that quality of fire service, for instance, expressed in fire response time, is positively correlated with public budget. It was shown that in a Rawlsian framework, fire service can directly affect social welfare, and that higher service quality can lead to higher overall social welfare.

In a Detroit fire service specific case study, the effect of a change in budget on the equitable allocation of fire service was investigated. GIS equity mapping was found to be a valuable tool for this job; however, more in-depth, quantitative analysis is needed to reach compelling results. It seems that only two proposed dimensions of equity are applicable in the case of fire service – equality and need. Even though the concept of equality appears to be mostly justified in a theoretical context, it can be concluded that the allocation of Detroit fire service represents far from perfect equality, and that, if anything, the intra-city inequality has increased since the budget cut in 2012. The concept of equity as need seems to have higher empirical relevance and was found to be met in some areas of Detroit, whereas, for other areas, no such conclusion could be drawn. Finally, there is evidence that after the new, smaller budget was implemented and numerous fire stations had to be closed, fewer areas achieved a fair correlation between fire risk and service quality than before, at least when fairness is interpreted as need for service.

CHAPTER 2 “FIRE RISK ACROSS DETROIT – SOCIO-ECONOMIC, HOUSING, AND SPATIAL FACTORS”

2.1 Introduction

The relationship between socio-economic factors such as income, race, household composition, and fire risk in an urban environment has long been of interest to researchers across disciplines such as urban planning, geography, engineering, and sociology. Previous literature finds that individuals living in poverty face a greater risk of experiencing a fire than others. Additional studies find mixed evidence regarding the correlation between the number of vacant structures and fire.

How to tackle poverty, as well as the problem of vacant and abandoned structures, is a top priority on the agenda of Detroit residents and policy makers. A relatively high volume of fires, especially proven and suspected arson fires, contributes to the complexity of this endeavor. By using Detroit-specific micro data, this research examines whether socio-economic factors, various aspects of housing, and spatial features can explain differences in fire risk across Detroit neighborhoods.

This paper expands on existing literature by investigating not only building fires in general but also by distinguishing between unintentional and intentional building fires. Various fire incident maps illustrate the differences in distribution, especially between unintentional and intentional fires. By using classical regression models, as well as more advanced spatial techniques, I’m able to account for spatial autocorrelation effects across the city.

2.2 Literature Review

The relationship between various socio-economic determinants, especially low income and the risk of fire, has been well established over the last few decades. In this literature review, I will summarize briefly some of the important articles.[1] Karter and Donner (1978) investigated the relationship between fire rates and census characteristics of five communities in the United States. For Newark, New Jersey, Phoenix, Arizona, and Toledo, Ohio, their findings confirmed a strongly positive relationship between fire rates and poverty, measured as the percentage of persons below the poverty level. In Newark, the mean fire rate per 1,000 people was almost double (3.32 to 6.44) when comparing a low level poverty group among tracts (5 percent to 31 percent) with a high level poverty group (31.1 percent to 51.3 percent). In Phoenix, the mean fire rate changed from 3.07 in the low level poverty group (1.1 percent – 14.2 percent) to 8.31 in the high level poverty group (14.2 percent – 50.3 percent). Finally, in Toledo, the mean fire rate was more than twice as high when comparing the low poverty group (0.6 percent – 15.7 percent) with the high level poverty group (15.8 percent – 52 percent).

Gunther (1981) also looked at census tract data for Toledo in conjunction with National Fire Incident Reporting System (NFIRS) data to investigate the relationship between family income and race on fire risk. Based on a five-group city clustering method and linear regression analysis, the author found a strong negative relationship between income and overall fire rates. He found little indication that race affects fire rates, after controlling for income. If the fire rates of Toledo's low income areas, which account for almost half of the population, were reduced to the level encountered by middle income areas, Gunther estimated the overall number of fires would decrease by as much as 35 percent.

[1] Jennings (1999, 2013) provides a comprehensive review of relevant literature.

Based on National Fire Protection Agency (NFPA) data, Fahy and Norton (1989) expanded on prior work by examining 50 US cities with a population greater than 250,000 residents for the years 1986 and 1987. The authors analyzed the relationship between fire death rates and the percentage of families living below the poverty level. They found that cities with higher levels of poverty tended to experience higher occurrence of residential fires and were more likely to suffer fire deaths.

Other authors employed multiple OLS regression analysis to explore the social and demographic correlates of fire deaths for large metropolitan areas. Using census data along with statistics on fire death rates collected by the US Centers for Disease Control and Prevention (CDC), Hannon and Shai (2003) focused on counties with a population greater than 250,000 and investigated the correlation between variables such as median family income, race, age of housing stock, as well as vacancy rate and fire deaths. Except for vacancy rate, these variables turned out to be statistically significant at a 95 percent confidence interval, confirming results of previous literature. More specifically, the authors found that median family income and fire deaths were negatively related, while higher age of housing stock and areas with a higher African-American population seemed to be positively linked to fire death rates. However, by including an interaction term (African-American x Income), the authors found that fire death rates seemed to be highest in areas characterized by a high ratio of African-Americans and a low median level of income, whereas racial composition did not seem to be important in high income areas.

Crawford (2005) analyzed the risk of fire for residents living below the poverty level in Shreveport, Louisiana. The author found that in census tracts where fire deaths were recorded between 1999 and 2004, on average, 50.7 percent of the households lived below the poverty threshold. Crawford stated further that in Louisiana, where about one-fourth of the population lived below the poverty line, the chance of a fire-caused death was 1:40,000, whereas in New Hampshire, where about one-thirteenth lived below the poverty line, the ratio was 1:143,000.

Another stream of literature embraces the effect of vacant and abandoned structures on building fire risk in urban surroundings. In Newark, New Jersey, Sternlieb and Burchell (1973) first documented this phenomenon at the beginning of the 1970s. Their findings suggested that, primarily, fire leads to abandonment, but also that abandonment may lead to an increase in the frequency of building fires. Among 1,600 of Newark's buildings which were or became abandoned in 1970/71, 20 percent experienced a fire, with about 81.5 percent before the abandonment and the remaining fraction after it. Moreover, the analysis suggested that almost 50 percent of all abandoned buildings were prone to see at least two fires, and that arson was suspected in 90 percent of all cases.

In 1977, Schaenman et al. used census tracts of Charlotte, North Carolina, St. Petersburg, Florida, San Diego, California, Seattle, Washington, and Fairfax County, Virginia, to assess the relationship between various socio-economic variables and fire risk. As inter-city comparisons did not provide meaningful results, the authors analyzed intra-city variations in fire rates. Three of their variables, parental presence, poverty, and the percentage of over 25-year-old individuals who had less than eight years of schooling, best explained variations in fire rates. Nonetheless, housing vacancy also turned out to be a moderately strong predictor of fire rates in some of the analyses. Skarbek (1989) also described abandoned buildings as potential fire hazards, particularly in regard to firefighters and their occupational safety.

Greenberg et al. (1990) investigated the “temporarily obsolete abandoned derelict sites” (TOADS) phenomenon and the problems that came with it. Based on interviews with urban planning and health departments of 14 of the largest cities in the US, Greenberg and his colleagues found that TOADS were a greater problem for cities in the northeast and the Midwest than for cities in the south and the west. One reason was that housing stock in the former areas was older, and that structural economic changes led citizens to leave their homes in order to look for employment in other regions of the country. Interviewees reported fire safety as the number one problem with regard to TOADS, as these buildings can catch on fire quickly due to old wiring, illegally dumped debris, and various other factors. Moreover, they can attract arsonists. Particularly in dense neighborhoods, that makes them dangerous, as they impose a risk on surrounding structures which might fall prey to the flames as well.

Accordino and Johnson (2000) found that ten years later, vacant and abandoned properties were a problem more than ever before and ranked high on city officials’ to-do lists, as they were perceived as neighborhood-destabilizing and crime-fostering nuisances. The authors documented this in a survey of the 200 most populated cities in the US. According to their investigation, vacant and abandoned structures had “moderate” negative effects on fire prevention efforts.

Shai (2006) used Philadelphia, Pennsylvania, census tract data for the years 1993 - 2001 in order to investigate the relationship between income, housing, and 1,563 non-fatal fire injuries. As already established above, it comes as no surprise that the author found a highly significant correlation between low income households, defined as household with income smaller than $15,000 in 1989, and fire injuries. She also found vacant housing to be a highly significant predictor variable. As vacant structures may generally be regarded as a “contributor to decline as well as an indicator of it” (Shai, 2006, p.151), injuries can be caused in two different ways. Unintentional injuries can be the consequence of fires ignited by people seeking shelter and warmth. Yet, it is also known that abandoned buildings frequently attract crime, as demonstrated by Spelman (1993). In that case, intentional arsonists might be responsible for an increased risk of fire injury in and around vacant structures.

Summarizing the reviewed literature, we find that there is very strong evidence for a positive correlation between poverty and fire risk. For vacancy and abandonment, on the other hand, the link is less obvious, as there is mixed evidence regarding the level of significance.

2.3 Empirical Analysis

Building on the reviewed literature, the following analysis tests whether similar results can be obtained for Detroit, using city-specific micro data. In a first step, I check whether there is a significant correlation between the risk of fire and the level of income and various other control variables. In a second step, I perform robustness checks in the form of kernel density analyses and spatial regression techniques.

2.3.1 Estimation

2.3.1.1 Data

The empirical estimation is based on fire incident micro data provided by the Detroit Fire Department. The raw data set includes every incident from the years 2008 - 2012 and is collected electronically as a combination of Computer Aided Dispatch (CAD) data and NFIRS data. Records of the time period from December 11th, 2012 to December 16th, 2012 are not provided in the data set due to systemic malfunction. All incidents in the data set are consistently marked "priority 1", and handled by the fire department. No exclusive emergency medical services (EMS) records are included. For this particular study, I focus on incidents indicated as "building fires", code "111", which leaves 26,488 observations over the five-year period. About 78 percent of all building fires are recorded as "1 or 2 dwelling" fires, an additional 6 percent are recorded as "multifamily dwelling/ apartment" fires. "Other residential" fires amount to 3 percent, "non-residential" fires to 7 percent, and the remaining 6 percent of recorded building fires are either "undetermined", or no further specification is provided in the data. As the data are recorded in GPS format, using latitude and longitude, I convert the information of each incident to census tract format. Additional data are collected from the American Community Survey (ACS) 5-year estimates, produced and published by the US Census Bureau for the same period, 2008 – 2012. Detroit consists of 297 census tracts, for 14 of which no data on either the number for median housing income or employment status could be obtained.[2] Therefore, these census tracts are not part of this analysis.

2.3.1.2 Model specification

Three different empirical models are employed to test whether the level of poverty, and, more generally speaking, the level of household income, can explain fire risk across Detroit. Model F1 uses the number of all building fires per 1000 housing units as the dependent variable. This approach is in line with previous literature and provides a general understanding of the correlation. I then expand on existing literature by examining only incidents marked as unintentional building fires per 1000 housing units, model F2. In so doing, I test whether the level of income plays a significant role, or if unintentional fires are much rather explained by random, incident-specific reasons and circumstances. Thereafter, I look at the number of intentional fires per 1000 housing units, model F3.[3] This analysis allows me to investigate whether the risk of arson-related building fires changes as a result of increased poverty. All three models are then tested in the form of base-line models (a), including various socio-economic control variables, and augmented models (b), which include additional, housing-specific explanatory variables.

For each analysis, a simple OLS framework is used to estimate the baseline model. It takes the following classic form:

$$y = f(\boldsymbol{X}) + \epsilon, \tag{42}$$

where y is the dependent variable, $\boldsymbol{X}$ is a vector of all independent variables, and ϵ is the random error term. Various standard tests are carried out to ensure that the Gauss-Markov assumptions for

[2] Census tracts 5167, 5169, 5171, 5172, 5175, 5189, 5208, 5218, 9850, 9851, 9852, 9853, 9855, 9859 are excluded, which reduces the number of observed fires by 261.
[3] Due to lack of observations, census tracts 5157, 5156, 5180, 5323, 5386, 5428, 5429, and 5464 had to be dropped from the analysis for model F3.

unbiased model specification are met. A maximum variance inflation factor-test score of 1.71 indicates that multi-collinearity does not pose a severe problem to the model. A Breusch-Pagan-test for homoskedasticity finds no significant evidence for the presence of heteroskedasticity (F1, 1a: $chi2 = 0.06, where\ Prob > chi2 = 0.8110$; 1b: $chi2 = 0.96, where\ Prob > chi2, = 0.3262$) while the White-test suggests that homoskedasticity cannot be assumed for the model(F1, 1a: $chi2 = 81.80, where\ Prob > chi2 = 0.0086$; 1b: $chi2 = 148.23, where\ Prob > chi2 = 0.0029$).[4] Based on these ambiguous observations, I also use the feasible generalized least squares (FGLS) estimator to test the validity of the results obtained previously.

Thereafter, I employ spatial lag and spatial error models to control for potential spatial autocorrelation. The spatial lag model takes the following standard form (Ward and Skrede Gleditsch, 2008):

$$y = \rho W y + X\beta + \varepsilon, \tag{43}$$

where y is the dependent variable, ρ is the spatial lag parameter, W is the calculated weight matrix, X are the independent variables, and ϵ is the error term. This model directs the focus of the regression analysis on the dependent variable. In other words, we are controlling for the effect of the number of building fires in one census tract on the number of building fires in another tract.

Secondly, I estimate a spatial error model of the following form (Ward and Skrede Gleditsch, 2008):

$$y = X\beta + \varepsilon + \lambda W \xi, \tag{44}$$

[4] Similar results are obtained for models 2a, 2b, and F2, F3.

where the error term is now decomposed into two separate terms. Again, ε represents the spatially uncorrelated error, while ξ is the spatial factor of the error term, and λ denotes the spatial dependence parameter. In using this model, no feedback effect between the number of fires in one area and any other neighboring area is assumed. The predominant purpose of this estimation is to account for spatially correlated errors (much like other temporal serial correlation measures), due to unobservable features associated with location.

2.3.1.3 Variable definition

Table 2 of the appendix summarizes the variables determining the econometric model as well as their definitions. All variables are census-tract-specific, and calculated averages for the time period between 2008 and 2012. The outcome variables are *fires*, *unintentional fires*, and *intentional fires*. They are constructed as the corresponding log-number of building fires per 1000 housing units. These variables indicate the risk of fire in a certain geographical area relative to all other Detroit areas. *Fires* is composed of unintentional and intentional fires, but also of all other building fires, where no such indication is provided in the data set. Whereas Corcoran et al. (2007) propose the use of a negative binomial distribution estimation in case of fire incidents analyses, Figures 1-3 of the appendix show that the standardization as well as the log-normalization of the dependent variables do not make such a step necessary.

As far as independent variables are concerned, the model considers various socio-economic indicators, and various other housing-related control variables. The main focus of this research lies on *poverty*, which is the percentage of households living below the poverty line (model 1). The numbers are based on the ACS "poverty status in the last 12 months" estimates. Depending on household size, household composition, and other parameters, dollar value thresholds are calculated, below which the interviewees are considered to have lived in poverty over the last 12 months.

Individual answers are then aggregated for the five-year time period in question. In addition, I use the *median household income* (model 2) to verify previously obtained results. If findings of prior research can be confirmed, we would expect a positive correlation between the level of individuals living in poverty and the regressand, as well as a negative correlation under the application of the median household income variable.

Secondly, I look at the general *unemployment rate*, the unemployment rate for the population *between 16 and 19* years of age, as well as for the population *between 20 and 24 years* of age. Following prior research by Chhetri et al. (2010) , who analyzed socio-economic determinants of building fires in Southeast Queensland, I expect to find a positive coefficient for these variables. However, Shai (2006) could not find a significant correlation, which makes the outcome less predictable. Thereafter, I control for the percentage of households living with at least one *child* under 18 years of age. This indicator variable has also been used by Chhetri and his colleagues and found to be positively correlated with fire risk. Next, I account for the fraction of households with children under 18 years of age that are *single-parent* families. As I would suspect more children experiencing insufficient supervision, this variable might be positively correlated with fire risk. I also control for single *teenage males* between 15 and 17 years old, and *young adult single males* between 20 and 24 years old, as a fraction of all males older than 15. These variables may carry relevant information, especially when it comes to intentional fires, as there exists an extensive literature on the gender gap in crime, some of it suggesting young males to be more likely to commit crimes than young females (see, e.g., Steffensmeier and Allan (1996), Kruttschnitt (2013)). Finally, I control for the percentage of householders equal to or *over the age of 65* living in a household by themselves. In general, there seems to be evidence indicating increased risk of injury and death for the elderly being exposed to a fire. The federal emergency management agency

(FEMA, 2013) estimates the risk for people 65 and over dying in a fire to be 2.7 times higher compared to the general public. However, for the purpose of this study, it is also interesting to explore whether people over the age of 65 are more prone to experience a fire than others.

The augmented regression models (b) include an additional four housing-related control variables. The first is the *median housing unit value*, denoted in ten thousands of dollars. I expect this variable to be negatively correlated with fire risk. Similarly, I employ the percentage of housing units built before the year 1939 (*housing age*). As older housing stock is more likely to exhibit dated wiring, and other ailing building materials, I expect a positive coefficient, which Shai (2006) also found in her work. Next, I define the percentage of *vacant structures* out of all housing units. Based on prior research, it is not possible to predict the sign of the estimated coefficient. Furthermore, it has to be noted that there is a difference between vacant and abandoned housing, where, in the latter case, no owner can be determined. It seems that the transition from vacancy to abandoned housing may attract and also be caused by scrappers, squatters, and potentially even arsonists. Consequently, fire risk might increase in areas with high levels of vacant structures, but especially in areas with high levels of abandoned structures. The latter indicator, however, is not explicitly reported in the ACH data. Nevertheless, Goodman (2013) has successfully used the provided category "vacant other" as an indicator for the level of abandoned structures in any given census tract. Following his interpretation, I use this category to control for *abandoned structures*. It is defined as a percentage of all vacant structures.

Additional summary statistics for key explanatory variables can be found in the appendix of this paper, Table 3. Worth mentioning is the wide spread in poverty and median income between census tracts. The estimates for poverty range between 6.2 percent and 79 percent, while the estimates for median household income range between 10,360 dollars and 82,430 dollars.

2.3.2 Findings

2.3.2.1 All building fires (F1)

Standard OLS regression is employed as a reference (Table 1), to test which variables are able to predict the number of all building fires in any given Detroit census tract between 2008 and 2012. Model (1) uses poverty as the indicator for fire risk, while model (2) uses the median income as a more general approach to assess the relationship between income and fire risk. The estimated values of the baseline model (a), without housing-specific control variables, are reported in parentheses. I find mixed evidence for the level of significance of individual variables. Furthermore, not all results are in line with previous literature. The R^2-value suggests that the model is capable of explaining between 34 and 53.3 percent of the variance, while the use of poverty as an indicator variable returns slightly higher values than median income. Overall, the R^2-value seems acceptable, given the fact that we are dealing with noisy micro data.

As previous literature predicts, I find that being poor influences fire risk. The estimated coefficient suggests that a one percentage point increase in the rate of families living below the poverty line increases the number of fires in any given census tract by 0.66 (1.64) percent. The result is statistically significant at least at a 95 percent confidence interval. A similar conclusion can be drawn employing the level of median income. In this instance, OLS estimates the number of fires to increase by 1.9 percent for every $1,000 drop in median income. This estimate is significant at a 99 percent confidence interval. Adjusted for housing-specific variables, the estimate drops to 1.0 percent for every $1,000 drop in median income.

The rate of unemployment appears to be strongly positively connected to fire risk, where a one percentage point increase in unemployment causes a one percent increase in fire risk. This result is in line with previous literature (Chhetri et al., 2010). However, the effect disappears after introducing housing-specific variables to the model. A similar conclusion can be drawn from the estimation regarding the rate of teenage unemployment, except that the estimate is still marginally significant in model (b). Model (2) finds teenage unemployment to be significant at least at a 95 percent interval. Conversely, unemployment among 20- to 24-year-olds does not seem to have a measurable effect on fire risk. Families with children under the age of 18 years face a higher fire risk than their "childless" counterparts. A one percentage point increase in the rate of families with children is predicted to increase the number of fires anywhere between 0.89 (1.02) and 1.60 (1.24) percent. This result is in line with previous literature. The fraction of single parents among families with children doesn't seem significantly to influence fire risk. Census tracts with a higher ratio of single male teens appear to be more prone to experience a building fire than others. This effect disappears once the model is adjusted for aspects of housing. Areas with a higher number of single householders above the age of 65 years face a much lower fire risk than others. According to every estimation, an increase of one percentage point in the population of single householders above the age of 65 years is translated to a 2.36 (2.24) - 2.43 (2.65) percent lower occurrence of building fires.

There is strong evidence that quality of housing units indicated by housing value and age of housing stock significantly influences fire risk. As already suspected and estimated in prior studies, I find a negative correlation between the value of the housing unit and the number of fires. The opposite holds true for the correlation between housing age and the number of fires. Furthermore, I find a significantly positive relationship between the rate of vacant buildings and the risk of fire. The same can be recorded with regard to the rate of abandoned structures in a census tract. Although the estimated coefficient is smaller than in the case of vacant structures (0.86 – 1.19), the positive coefficient suggests that fire risk increases as the share of abandoned structures among vacant structures rises. Abandoned structures may still be "used" in one risky way or another, although not officially or legally, which would explain the positive coefficient.

I then employ a FGLS strategy to account for potential heteroskedasticity in the model (Table 1). As a result, the R^2-value improves slightly to 0.38 – 0.58. With the exception of unemployment among 20- to 24-year-olds, the signs of the estimated coefficients stay the same, while their magnitude changes slightly. Most importantly for the purposes of this study, census tracts are now estimated to face a 0.60 (1.51) percent increase in fires for every percentage point increase in households living below the poverty line. A slightly higher standard error of 0.27 corresponds to a 99 percent confidence interval. Similarly, I find that a $1,000 increase in median income reduces the number of fires by 2 percent, a marginal change of 0.1 percentage points compared to the OLS estimator. The estimation is highly significant both for the base line and augmented model. The level of unemployment is now at least marginally significant; however, the prediction power of teenage unemployment is slightly lower compared to OLS. The estimations for families with children, single parents, single householders above the age of 65 years, housing value, housing age, and the vacancy rate are all still significant at least at a 95 percent interval. In this setup, the level of abandonment does not carry statistically important information regarding the level of fire risk.

Table 1: F1 All building fires; OLS and FGLS

VARIABLES	(1a) OLS	(1b) OLS	(2a) OLS	(2b) OLS	(1a) FGLS	(1b) FGLS	(2a) FGLS	(2b) FGLS
poverty	1.642***	0.656**			1.509***	0.595**		
	(0.284)	(0.266)			(0.297)	(0.270)		
median income			-0.0185***	-0.0103***			-0.0200***	-0.0158***
			(0.00342)	(0.00348)			(0.00257)	(0.00265)
unemployment	1.090***	0.576	1.149***	0.822**	1.351***	0.625*	1.086***	0.769**
	(0.406)	(0.353)	(0.408)	(0.385)	(0.398)	(0.336)	(0.372)	(0.350)
unempl 16-19	0.289***	0.161*	0.291***	0.229**	0.220**	0.167*	0.229**	0.221**
	(0.104)	(0.0912)	(0.105)	(0.0997)	(0.102)	(0.0861)	(0.0961)	(0.0866)
unempl 20-24	-0.00661	-0.00642	0.0539	0.0984	-0.0555	0.0775	-0.0792	0.111
	(0.136)	(0.117)	(0.137)	(0.128)	(0.133)	(0.111)	(0.131)	(0.114)
child	1.019***	0.884**	1.244***	1.595***	0.994**	1.025***	0.865**	1.028***
	(0.383)	(0.348)	(0.382)	(0.366)	(0.394)	(0.357)	(0.353)	(0.353)
single parents	0.0723	0.0340	-0.0377	0.160	0.0288	0.0592	-0.168	0.0289
	(0.175)	(0.162)	(0.179)	(0.179)	(0.191)	(0.165)	(0.178)	(0.189)
single m 15-17	2.543*	1.500	2.023	1.538	1.868	0.589	0.945	0.438
	(1.477)	(1.283)	(1.483)	(1.403)	(1.449)	(1.333)	(1.416)	(1.400)
single m 18-24	0.531	0.674	0.340	-0.285	1.257	0.982	1.044	0.650
	(1.194)	(1.033)	(1.205)	(1.130)	(1.212)	(1.117)	(1.291)	(1.256)
age 65	-2.243***	-2.360***	-2.648***	-2.427***	-2.449***	-2.564***	-2.897***	-2.890***
	(0.647)	(0.556)	(0.663)	(0.623)	(0.626)	(0.547)	(0.671)	(0.636)
housing value		-0.0774***				-0.0766***		
		(0.0105)				(0.0124)		
housing age		0.505***		0.499***		0.594***		0.535***
		(0.154)		(0.169)		(0.160)		(0.166)
vacancy		0.862***		1.186***		0.951***		1.263***
		(0.315)		(0.349)		(0.292)		(0.316)
abandonment		0.254*		0.301**		0.0960		0.149
		(0.138)		(0.152)		(0.129)		(0.127)
Constant	2.838***	3.443***	4.036***	2.996***	2.920***	3.428***	4.421***	3.540***
	(0.205)	(0.242)	(0.272)	(0.298)	(0.206)	(0.240)	(0.276)	(0.298)
Observations	283	283	283	283	283	283	283	283
R-squared	0.349	0.533	0.340	0.434	0.381	0.532	0.472	0.584

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Based on these findings, I visually inspect the data for possible spatial autocorrelation, a phenomenon that has attracted increasing attention over the last several years (see, e.g., Asgary et al. (2010), Chhetri et al. (2010), Corcoran et al. (2007, 2011), Higgins et al. (2013)). The idea is that fires may not be distributed uniformly across any given space, in this example, Detroit. It might rather be the case that certain "hotspots" exist which may likely not be limited to the boundary of a census tract. Consequently, we may experience spatial spillover effects which have to be accounted for. Map 6 shows a kernel density methodology regarding the distribution of all building fires across Detroit. The visualization reveals that, indeed, hotspots exist. Predominantly, clustering of high fire risk areas can be found in the southwest, northeast, north, and, to some extent, in the northwest of the city. There is also evidence that high fire density areas cause spillover effects in surrounding areas, where spillovers seem to die out slowly, the greater the distance from the center of a hotspot area becomes.

On the basis of these first observations, it seems necessary to account for spatial correlation using spatial regression techniques. In order to do so, I use geocoded internal points, or centroids, of census tracts, collected from the 2010 Census Gazetteer Files. This information allows me to calculate a row-standardized spatial weight matrix, $W,$ based on distance d_{ij} for observations i, j. This matrix attributes lower weights the further observations $i \text{ and } j$ are spatially apart from each other. In order to choose the maximum bandwidth for d_{ij}, meaning that no spatial effects are assumed to be present for a distance greater than D, I refer back to Map 6. It seems that with a diameter of about five miles, the largest cluster prevails in the northeastern part of the city. Various values of d_{ij}, anywhere between two miles, the minimum value allowing every tract to have a neighbor, and 18.6 miles, the maximum recorded distance, have been tested. While the estimated z-values, as well as the coefficients, decrease in absolute terms the smaller the distance band becomes, the level of significance of the individual independent variables does not change. Based on the maximum bandwidth of 5 miles, the weight matrix is calculated and the fitted OLS regression is tested for spatial dependence. With a Moran's I of at least 9.833 ($p - value = 0.000$), and a Lagrange multiplier of at least 56.944 ($p - value = 0.000$) (Model (2): 10.195 ($p - value = 0.000$), and a Lagrange multiplier of 61.003 (p-value=0.000)), the initial suspicion is confirmed, and there is strong evidence justifying the use of a spatial regression model.

Map 6: Spatial distribution of building fires in Detroit 2008 - 2012

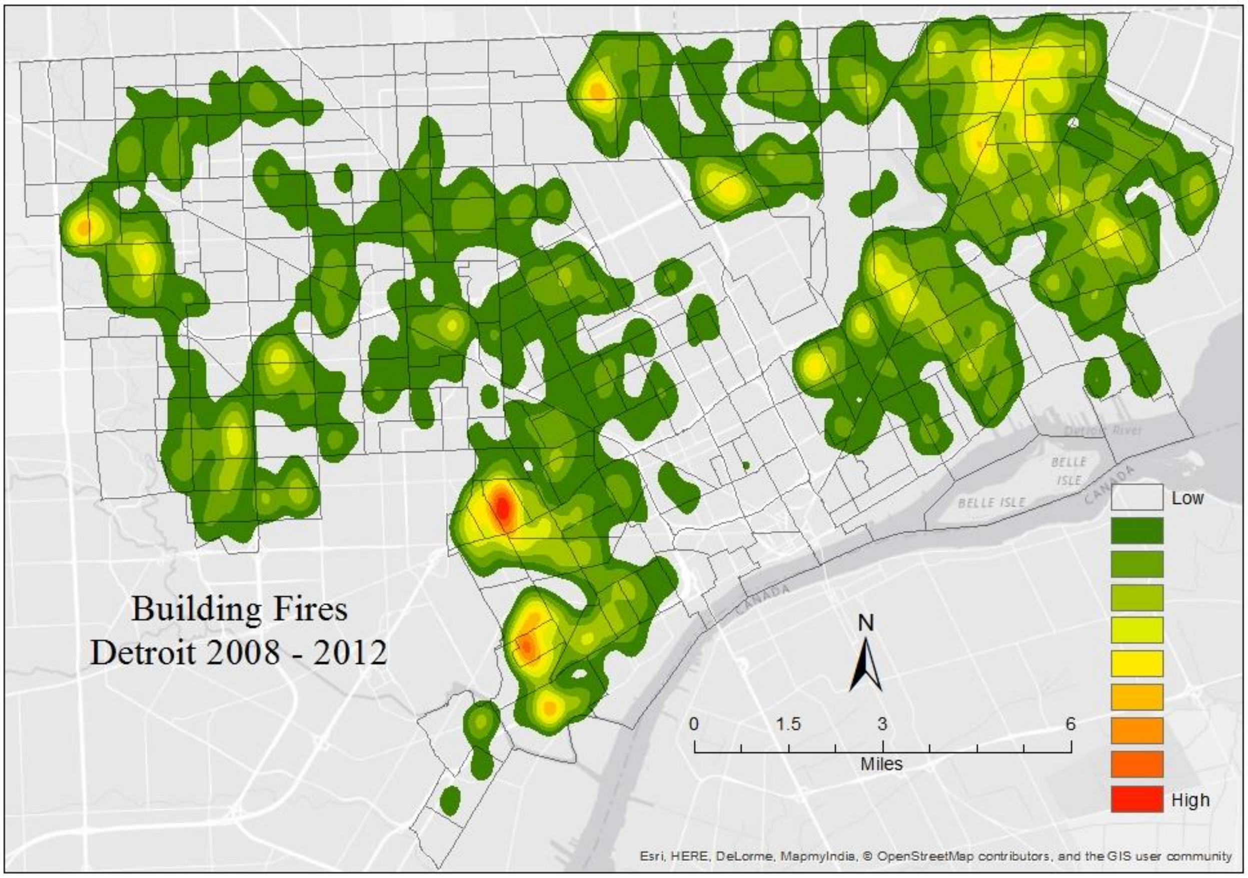


Table 2 shows the estimations for the spatial lag model. Since the previous analysis has shown that heteroskedasticity cannot be disregarded, the estimation is carried out using robust standard errors. The variation ratio is indicated to lie between 0.48 and 0.57 (0.40 and 0.41). As expected, most estimated coefficients as well as the corresponding z-statistics are now lower than before the spatial adjustment. This makes sense intuitively, as OLS previously may have overestimated the influence of the independent variables where no spatial parameter was present. Unemployment is now estimated to be 0.90 at a 95 percent confidence interval. Teenage unemployment is now only marginally significant in the baseline model, and not statistically significant in the augmented model. The baseline estimate of families with children is not significant anymore, either. Only the vacancy rate has gained slightly both in terms of its coefficient and its level of significance, whereas the level of abandonment has lost its statistical importance. The signs of the coefficients have not changed.

The poverty indicator is still highly significant and estimated to increase the number of fires by 0.60 (1.46) percent for each percentage point increase in poverty. With -0.009 (-0.017), the coefficient of the median income has only changed ever so slightly. The new lag variable rho is significant at a 99 percent interval with an estimated coefficient of at least 0.62. This result indicates that a high fire risk in one area increases the fire risk of a neighboring area.

Table 2 also exhibits the estimated results for the spatial error model. The variation within the variance ratio estimations is now higher than in the spatial lag model (0.50 – 0.58 (0.23 – 0.24)). The level of poverty per tract is still highly significant, where the coefficient of 0.89 (1.50) is slightly higher than in the spatial lag model. The estimated coefficient of the median income is also statistically significant with an estimated coefficient of -0.014 (-0.017). The level of vacant structures, and the rate of abandoned structures among them, is now significant, at least at a 95 percent interval. All other estimates are comparable to the spatial lag model, yet the estimated coefficients vary. The spatial error parameter lambda is estimated to be at least 0.87 and is significant at a 99 percent confidence level, indicating that spatially correlated errors exist.

Table 2: F1 All building fires; Spatial Lag and Spatial Error

VARIABLES	(1a) LAG	(1b) LAG	(2a) LAG	(2b) LAG	(1a) ERR	(1b) ERR	(2a) ERR	(2b) ERR
poverty	1.459***	0.597**			1.504***	0.894***		
	(0.278)	(0.270)			(0.303)	(0.274)		
median income			-0.0165***	-0.00926***			-0.0174***	-0.0144***
			(0.00322)	(0.00326)			(0.00353)	(0.00361)
unemployment	0.896**	0.481	0.946**	0.699*	0.857**	0.228	0.867*	0.388
	(0.411)	(0.365)	(0.426)	(0.406)	(0.429)	(0.350)	(0.449)	(0.398)
unempl 16-19	0.191*	0.114	0.192*	0.170*	0.193*	0.0974	0.194*	0.150*
	(0.0991)	(0.0900)	(0.101)	(0.0916)	(0.101)	(0.0821)	(0.103)	(0.0860)
unempl 20-24	-0.0301	-0.0230	0.0235	0.0708	-0.0319	-0.0383	0.0219	0.0725
	(0.131)	(0.106)	(0.132)	(0.121)	(0.131)	(0.102)	(0.131)	(0.115)
child	0.686	0.678*	0.883**	1.307***	0.573	0.470	0.809*	0.987**
	(0.445)	(0.377)	(0.431)	(0.381)	(0.484)	(0.387)	(0.466)	(0.402)
single parents	0.0572	0.0152	-0.0408	0.131	0.0915	0.0105	-0.0265	0.0943
	(0.200)	(0.185)	(0.208)	(0.196)	(0.210)	(0.184)	(0.220)	(0.196)
single m 15-17	2.354	1.178	1.890	1.177	2.529	1.257	2.088	1.171
	(1.905)	(1.324)	(1.908)	(1.524)	(1.880)	(1.312)	(1.892)	(1.529)
single m 18-24	0.326	0.436	0.155	-0.472	0.631	0.690	0.443	-0.144
	(1.316)	(1.065)	(1.395)	(1.261)	(1.298)	(1.000)	(1.384)	(1.163)
age 65	-1.720***	-1.950***	-2.077***	-1.955***	-1.997***	-1.698***	-2.376***	-1.781***
	(0.633)	(0.563)	(0.662)	(0.629)	(0.676)	(0.540)	(0.708)	(0.609)
housing value		-0.0719***				-0.0703***		
		(0.0154)				(0.0130)		
housing age		0.454***		0.441**		0.886***		0.960***
		(0.157)		(0.175)		(0.203)		(0.230)
vacancy		0.950***		1.263***		1.074***		1.305***
		(0.302)		(0.372)		(0.306)		(0.375)
abandonment		0.0461		0.0654		0.396**		0.415***
		(0.141)		(0.130)		(0.163)		(0.159)
Constant	-0.0972	1.067**	0.944*	0.359	3.064***	3.379***	4.183***	3.345***
	(0.441)	(0.452)	(0.525)	(0.506)	(0.346)	(0.505)	(0.461)	(0.667)
rho	0.762***	0.618***	0.768***	0.691***				
	(0.105)	(0.107)	(0.105)	(0.107)				
lambda					0.874***	0.937***	0.876***	0.946***
					(0.0959)	(0.0551)	(0.0927)	(0.0489)
Observations	283	283	283	283	283	283	283	283
Variance ratio	0.407	0.566	0.400	0.476	0.238	0.575	0.232	0.496

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

2.3.2.2 Unintentional building fires (F2)

This section of the analysis specifically investigates unintentional building fires, in other words, building fires where firefighters were able to rule out all other causes of ignition with certainty. As a result, only about 11.5 percent of all recorded data between 2008 and 2012 fall into this category and are part of the approximation. The estimated adjusted R^2-values are lower than in the previous regressions and range between 0.11 and 0.20. The estimation results also change substantially, once the dependent variable is narrowed down to just unintentional fires.

None of the four estimated models presented in Table 3 finds evidence for a significant correlation between poverty and fire risk, or the median income level and fire risk. However puzzling this result may seem at first glance, as it shows a very different outcome compared to prior studies, it makes sense intuitively, taking into account that these studies do not distinguish between different types of building fires. On second thought, it is hard to come up with a plausible reason that people living in poverty should be more prone to experience an unintentional fire than others, once the model is controlled for various socio-economic and other housing factors, as, by definition, unintentional fires happen more randomly than intentional fires.

Only four explanatory variables are consistently estimated to have significant impact on unintentional fire risk. First of all, this includes single parents. The estimates suggest that, for a one percentage point increase in the number of single parents, fire risk increases by 0.38 (0.45) percent, significant at least at a 95 percent interval. One explanation for this result might be given by the hypothesis raised earlier, in that single parents might find it harder to supervise their children than two-parent families. However, the estimation is weaker using the FGLS estimator. The rate of single males between 18 and 24 years old also appears to be positively correlated with fire risk, although mostly only at a marginal level of significance. Similar to the previous analysis, I find that areas with more single householders above the age of 65 years are less likely to experience an unintentional fire. The estimated coefficients are now slightly smaller than before. Finally, housing value is now strongly negatively correlated with unintentional fire risk. The estimations suggest that an increase in value by $10,000 decreases unintentional fire risk by between 0.04 and 0.06 percent.

Table 3: F2 Unintentional building fires; OLS and FGLS

VARIABLES	(1a) OLS	(2b) OLS	(1a) OLS	(2b) OLS	(1a) FGLS	(2b) FGLS	(1a) FGLS	(2b) FGLS
poverty	-0.0742	-0.275			-0.122	-0.295		
	(0.250)	(0.268)			(0.254)	(0.250)		
median income			0.00285	0.00358			0.00193	0.00396
			(0.00299)	(0.00329)			(0.00286)	(0.00283)
unemployment	0.269	0.153	0.355	0.329	0.277	0.216	0.191	0.0422
	(0.358)	(0.356)	(0.357)	(0.363)	(0.349)	(0.324)	(0.347)	(0.334)
unempl 16-19	0.0806	0.0417	0.0780	0.0742	-0.0350	-0.0476	-0.0168	-0.0168
	(0.0918)	(0.0920)	(0.0917)	(0.0940)	(0.0890)	(0.0858)	(0.0883)	(0.0881)
unempl 20-24	0.180	0.148	0.173	0.178	0.183*	0.122	0.180	0.171
	(0.120)	(0.118)	(0.120)	(0.121)	(0.110)	(0.100)	(0.111)	(0.107)
child	0.0308	-0.264	0.0304	0.0680	-0.379	-0.498	-0.453	-0.419
	(0.337)	(0.351)	(0.334)	(0.345)	(0.344)	(0.316)	(0.335)	(0.321)
single parents	0.451***	0.378**	0.477***	0.503***	0.292*	0.334**	0.340*	0.416**
	(0.154)	(0.164)	(0.157)	(0.169)	(0.174)	(0.162)	(0.175)	(0.181)
single m 15-17	0.700	0.472	0.720	0.659	1.091	-0.310	1.315	0.884
	(1.300)	(1.295)	(1.296)	(1.323)	(1.159)	(0.828)	(1.217)	(1.053)
single m 18-24	1.882*	2.312**	1.949*	1.882*	1.920*	1.762*	2.182*	1.522
	(1.052)	(1.043)	(1.053)	(1.065)	(1.136)	(0.981)	(1.143)	(1.117)
age 65	-2.097***	-2.202***	-2.000***	-1.990***	-2.426***	-2.465***	-2.341***	-2.132***
	(0.570)	(0.561)	(0.579)	(0.588)	(0.566)	(0.511)	(0.582)	(0.566)
housing value		-0.0431***				-0.0559***		
		(0.0106)				(0.0122)		
housing age		0.0899		0.0676		0.0257		0.0182
		(0.156)		(0.159)		(0.134)		(0.144)
vacancy		-0.185		0.0940		-0.0272		0.325
		(0.318)		(0.329)		(0.285)		(0.315)
abandonment		-0.0136		0.0149		-0.132		0.0169
		(0.139)		(0.143)		(0.125)		(0.134)
Constant	1.662***	2.240***	1.502***	1.403***	1.998***	2.590***	1.871***	1.705***
	(0.181)	(0.244)	(0.237)	(0.281)	(0.188)	(0.235)	(0.259)	(0.287)
Observations	283	283	283	283	283	283	283	283
R-squared	0.125	0.177	0.128	0.129	0.121	0.200	0.119	0.115

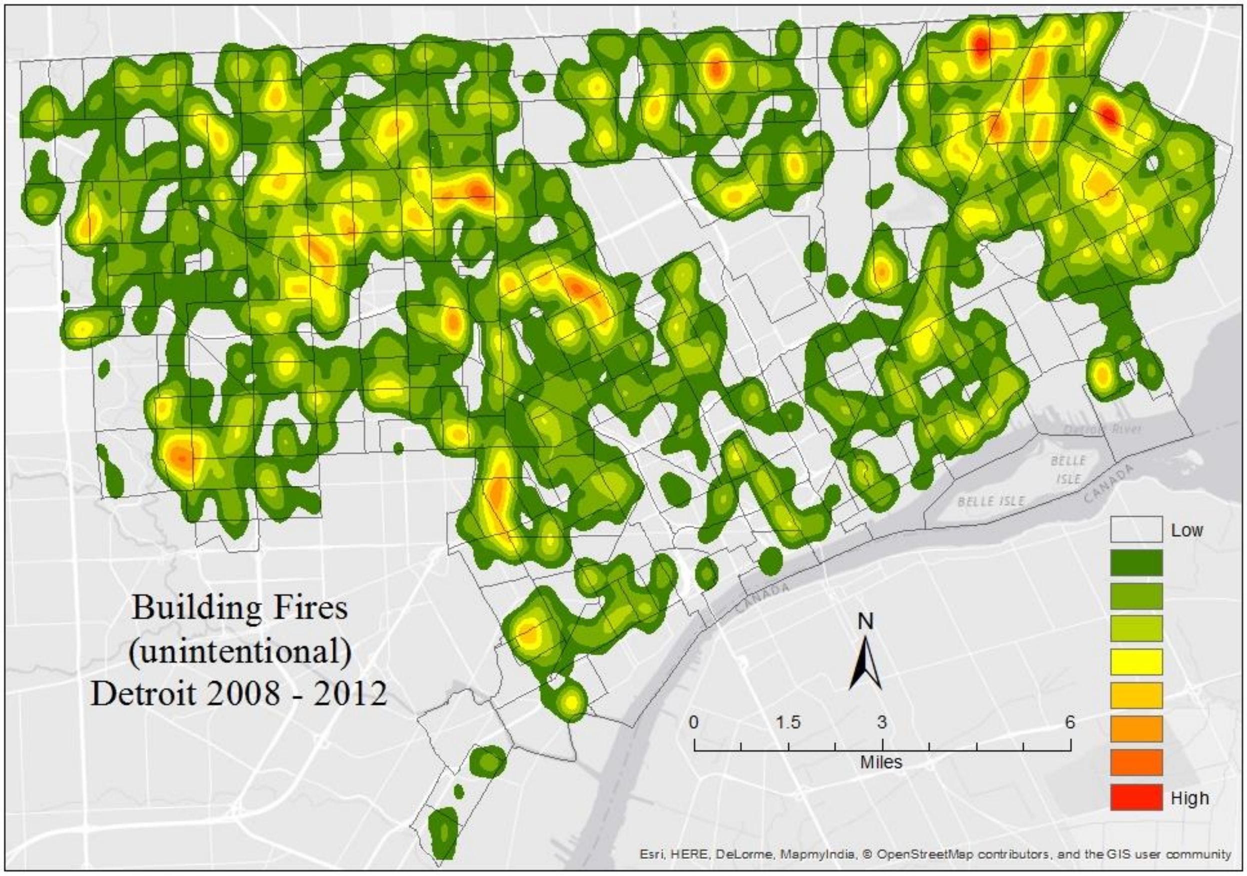
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As in the previous analysis, I test the data for spatial autocorrelation. With a Moran's I of at least 5.495 ($p-value = 0.000$), and a Lagrange multiplier of 15.970 ($p-value = 0.000$) (Model b: 4.953 ($p-value = 0.000$), a Lagrange multiplier of 12.483 ($p-value = 0.000$)), we can reject the null hypothesis of zero autocorrelation, and the use of a spatial regression model is justified.

Map 7 allows a closer visual examination of the unintentional building fire distribution in Detroit between 2008 and 2012. By comparing Map 6 to Map 7, we can see that the distribution is substantially different, and that a clear pattern is now harder to identify. It seems that fires are more randomly scattered across the city and that hotspots are now more numerous, yet mostly not as severe as before. There is also evidence for spillover effects from high frequency areas to adjacent areas, but only to a smaller extent than before. Again, the map gives the impression that fewer fires happen in the midtown and downtown areas along the Woodward corridor and Jefferson Avenue, respectively. Neighborhoods on the west side, and especially on the east side, appear to see more unintentional building fires than other areas.

Table 4 presents the estimation results for the spatial lag and the spatial error models. The variation ratio is now between 0.08 and 0.21, and smaller than before. None of the regression models finds a significant correlation between poverty, or median income, and the risk of unintentional building fires. The signs of the coefficients are consistent and their magnitude is slightly smaller compared to the models without spatial adjustment. As before, the estimation finds significant correlations between single parents, single males between 18 and 24, single residents above 65, housing value, and fire risk.

Map 7: Spatial distribution of unintentional building fires in Detroit 2008 - 2012



In addition, both spatial models find that old housing stock positively influences the risk of an unintentional building fire. The spatial error model, for instance, predicts an increase in fire risk of 0.58 percent for every one percentage point increase in the share of old housing stock. The spatial parameters, rho and lambda, are estimated to be positively significant at a 99 percent confidence interval. However, the coefficients of lambda are consistently smaller than before.

Table 4: F2 Unintentional fires; Spatial Lag and Spatial Error

VARIABLES	(1a) LAG	(1b) LAG	(2a) LAG	(2b) LAG	(1a) ERR	(1b) ERR	(2a) ERR	(2b) ERR
poverty	0.123	-0.126			0.245	0.131		
	(0.243)	(0.264)			(0.273)	(0.274)		
median income			0.000151	0.00112			-0.00121	-0.00272
			(0.00313)	(0.00343)			(0.00359)	(0.00384)
unemployment	0.0979	-0.0396	0.172	0.117	0.0487	-0.207	0.122	-0.0730
	(0.347)	(0.339)	(0.375)	(0.381)	(0.359)	(0.337)	(0.391)	(0.386)
unempl 16-19	0.0594	0.0206	0.0583	0.0544	0.0603	0.0177	0.0585	0.0473
	(0.0844)	(0.0892)	(0.0842)	(0.0842)	(0.0859)	(0.0860)	(0.0858)	(0.0823)
unempl 20-24	0.130	0.109	0.132	0.145	0.108	0.0808	0.117	0.131
	(0.109)	(0.100)	(0.110)	(0.108)	(0.109)	(0.0971)	(0.109)	(0.104)
child	-0.158	-0.397	-0.130	-0.0601	-0.252	-0.512	-0.200	-0.245
	(0.393)	(0.385)	(0.397)	(0.398)	(0.428)	(0.402)	(0.430)	(0.429)
single parents	0.338*	0.324**	0.349**	0.432**	0.317*	0.304*	0.322*	0.391**
	(0.174)	(0.162)	(0.174)	(0.174)	(0.180)	(0.165)	(0.181)	(0.178)
single m 15-17	0.350	-0.0463	0.320	0.113	0.325	-0.132	0.278	-0.0587
	(1.209)	(1.110)	(1.212)	(1.199)	(1.197)	(1.058)	(1.197)	(1.153)
single m 18-24	1.821*	2.116**	1.852*	1.672	1.864*	2.106**	1.867*	1.672
	(1.087)	(1.066)	(1.093)	(1.084)	(1.073)	(1.037)	(1.087)	(1.052)
age 65	-1.785***	-1.904***	-1.764***	-1.769***	-1.806***	-1.741***	-1.815***	-1.654***
	(0.594)	(0.572)	(0.602)	(0.596)	(0.620)	(0.575)	(0.633)	(0.604)
housing value		-0.0422**				-0.0419***		
		(0.0168)				(0.0153)		
housing age		0.280*		0.259		0.575**		0.578**
		(0.161)		(0.166)		(0.230)		(0.246)
vacancy		-0.178		0.0619		-0.192		0.00841
		(0.317)		(0.346)		(0.326)		(0.359)
abandonment		-0.0289		-0.00189		0.166		0.172
		(0.142)		(0.135)		(0.169)		(0.161)
Constant	0.428	0.763*	0.467	0.112	1.775***	2.030***	1.867***	1.632***
	(0.345)	(0.409)	(0.342)	(0.372)	(0.248)	(0.377)	(0.299)	(0.390)
rho	0.659***	0.734***	0.642***	0.725***				
	(0.139)	(0.128)	(0.141)	(0.137)				
lambda					0.740***	0.891***	0.723***	0.893***
					(0.152)	(0.0925)	(0.160)	(0.0943)
Observations	283	283	283	283	283	283	283	283
Variance ratio	0.154	0.207	0.154	0.158	0.077	0.189	0.076	0.138

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

2.3.2.3 Intentional building fires (F3)

After the overall not very fruitful, yet revealing, analysis of unintentional building fires, it is now interesting to investigate whether poverty can be a valid predictor of intentional, or, in other words, crime-related building fires. Together, these incidents account for about 12 percent of all building fires in Detroit during the period between 2008 and 2012. There is strong evidence, however, that the real number is significantly higher, as, for many building fires, the cause of ignition was still under investigation at the time the incident was recorded. These fires are marked "cause under investigation". That means that arson was highly suspected as the cause of the building fire, even though it had not been proven at that point of the investigation. By changing the outcome variable to intentional fires, and keeping the explanatory variables unchanged, I am able to investigate the causal determinants of these fires more carefully than previous literature was able to do.

The analysis is carried out for 275 census tracts, as eight had to be dropped due to lack of observations. Again, I use a standard OLS multiple regression as a reference point (see Table 5 for details). The first thing to notice is that with values between 0.24 and 0.38, the R^2-value is now higher as in the regression regarding unintentional building fires. Most importantly, the estimated coefficients of poverty are highest among the three different dependent variables. A one percentage point increase in poverty is predicted to lead to a 0.9 (2.0) percent increase in intentional building fires, significant at least at a 95 percent confidence interval. Similarly, a $1,000 increase in the median income causes a 1.8 (2.6) percent drop in the number of intentional building fires, significant at a 99 percent confidence interval. With a value of at least 1.27 (1.74), the level of overall unemployment has by far the highest impact on fire risk across F1 to F3. The fraction of families with children is again positively correlated with intentional fire risk, and strongly significant. Another interesting difference compared to the earlier regression analyses is that the share of elderly single householders is now only marginally significant at best, while the absolute value of its coefficient has decreased. The highly significant housing value and housing age specific coefficients have increased in absolute terms, compared to previous estimations; however, the level of vacancy and abandonment is not statistically significant anymore. Especially the latter result is somewhat surprising, as many of the arson- related fires occur in vacant, and especially abandoned, structures.

The FGLS estimation method delivers similar results to the OLS estimator, at least with respect to poverty and median income. The effect of poverty is now calculated to be 1.01 (2.10) percent, while median income accounts for a 2.0 (2.8) percent change. These are the highest coefficients measured among FGLS estimates. The effect of overall unemployment is strongly significant, and, with values of at least 1.18 percent, also the highest among the three models. The same assessment can be given to the absolute values of the housing value and housing age coefficients. The vacancy level is now significant, at least at a 95 percent confidence interval, and estimated to move in the same direction as fire risk. According to the estimates, a one percentage point increase in the level of vacancy now causes an increase in the number of fires between 1.17 and 1.50 percent. The coefficient of abandoned housing has increased slightly; however, the estimation is still far from significant.

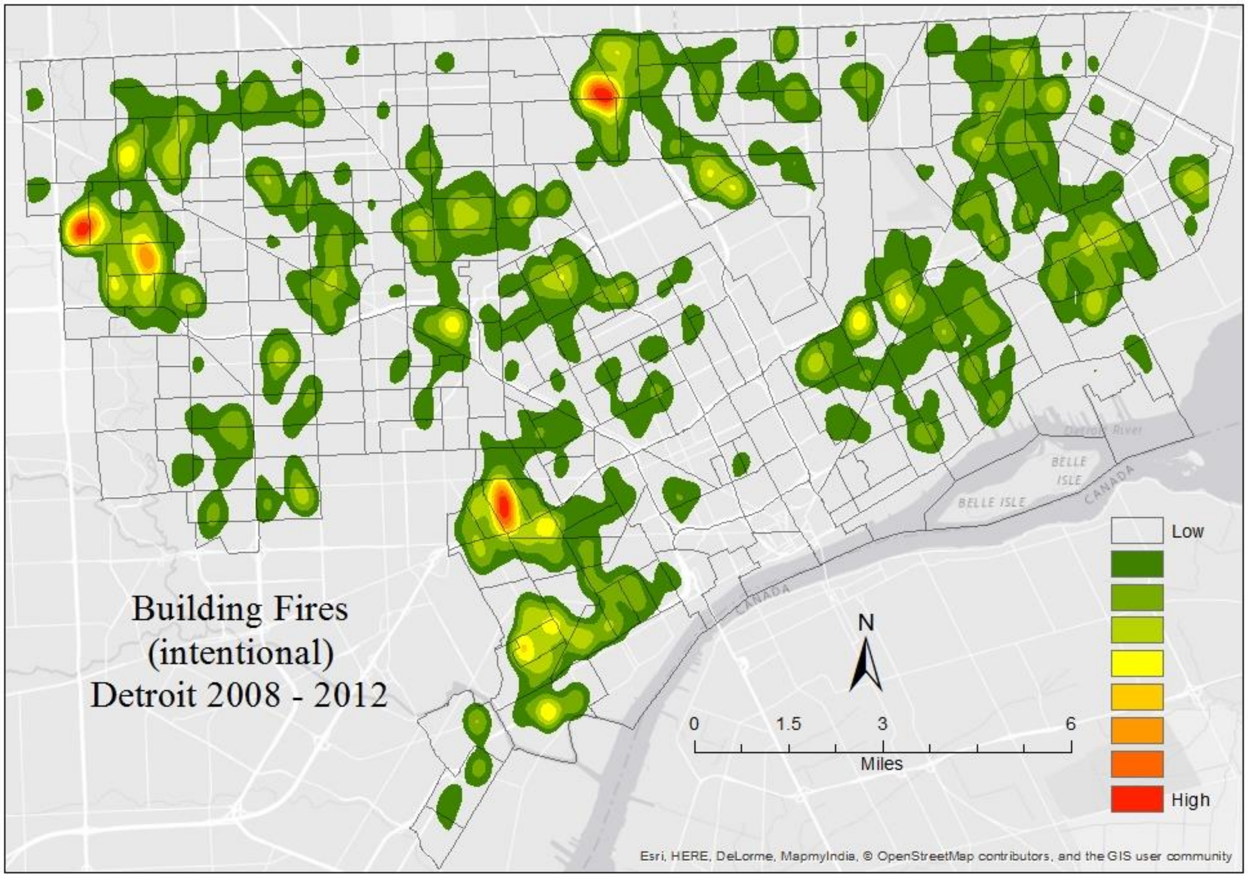
Table 5: F3 Intentional building fires; OLS and FGLS

VARIABLES	(1a) OLS	(1b) OLS	(2a) OLS	(2b) OLS	(1a) FGLS	(1b) FGLS	(2a) FGLS	(2b) FGLS
poverty	2.000***	0.900**			2.102***	1.006**		
	(0.420)	(0.415)			(0.432)	(0.413)		
median income			-0.0264***	-0.0179***			-0.0281***	-0.0200***
			(0.00504)	(0.00533)			(0.00450)	(0.00450)
unemployment	1.864***	1.266**	1.736***	1.518***	2.037***	1.179**	1.795***	1.343**
	(0.588)	(0.544)	(0.586)	(0.574)	(0.572)	(0.554)	(0.580)	(0.552)
unempl 16-19	-0.0971	-0.206	-0.0926	-0.123	-0.267*	-0.304**	-0.312**	-0.241*
	(0.152)	(0.141)	(0.150)	(0.148)	(0.145)	(0.138)	(0.146)	(0.139)
unempl 20-24	-0.0816	-0.0599	0.00846	0.0632	0.0246	0.0580	0.0765	0.224
	(0.197)	(0.180)	(0.195)	(0.190)	(0.188)	(0.171)	(0.188)	(0.176)
child	1.324**	1.243**	1.643***	2.002***	0.726	1.056*	0.876	1.788***
	(0.568)	(0.541)	(0.559)	(0.556)	(0.590)	(0.542)	(0.583)	(0.551)
single parents	0.00536	-0.0183	-0.139	0.103	-0.226	-0.124	-0.501	-0.0755
	(0.259)	(0.253)	(0.259)	(0.267)	(0.303)	(0.280)	(0.307)	(0.289)
single m 15-17	3.127	1.855	2.490	1.804	4.868***	2.776*	3.620**	1.255
	(2.136)	(1.972)	(2.114)	(2.078)	(1.681)	(1.545)	(1.740)	(1.813)
single m 18-24	0.534	0.310	0.359	-0.534	-0.375	-0.589	0.202	-1.110
	(1.765)	(1.620)	(1.752)	(1.710)	(1.874)	(1.636)	(1.895)	(1.736)
age 65	-1.317	-1.526*	-1.816*	-1.774*	-1.793**	-1.571*	-2.328**	-2.105**
	(0.955)	(0.873)	(0.960)	(0.939)	(0.897)	(0.865)	(0.912)	(0.938)
housing value		-0.102***				-0.106***		
		(0.0170)				(0.0186)		
housing age		0.676***		0.691***		0.764***		0.696***
		(0.238)		(0.251)		(0.227)		(0.239)
vacancy		0.877*		1.125**		1.170**		1.495***
		(0.485)		(0.517)		(0.485)		(0.502)
abandonment		0.0686		0.0964		0.0305		-0.138
		(0.215)		(0.227)		(0.204)		(0.213)
Constant	0.346	1.195***	1.953***	0.927**	0.676**	1.256***	2.588***	1.328***
	(0.315)	(0.380)	(0.390)	(0.443)	(0.329)	(0.392)	(0.454)	(0.467)
Observations	275	275	275	275	275	275	275	275
R-squared	0.237	0.383	0.250	0.305	0.279	0.424	0.323	0.376

Standard errors in parentheses

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

Map 8: Spatial distribution of intentional building fires in Detroit 2008 - 2012



With a Moran's I of at least 5.663 ($p - value = 0.000$), and a Lagrange multiplier of 17.151 ($p - value = 0.000$) (Model b: 6.180 ($p - value = 0.000$), a Lagrange multiplier of 20.629 ($p - value = 0.000$)), there is strong evidence that the use of a spatial regression model is also justified in case of intentional building fires. Map 8 graphically illustrates the distribution of intentional building fires across Detroit. The patterns appear very different compared to the density map of unintentional fires. It is now obvious that intentional fires are heavily clustered in only a few areas of Detroit. These areas can be found in the west, the southwest, north of Highland Park, and, to a minor extent, on the east side of Detroit.

Table 6 present the results for both spatial regression models. With a value between 0.90 (1.94), and 1.34 (2.05), both spatial lag and spatial error models estimate a very strong and highly significant correlation between poverty and intentional fire risk. Similar to this result, the coefficient of median income is significant at a 99 percent interval, and its value ranges between -0.018 (-0.026) and -0.025 (-0.029). Both spatial regression models estimate a significant correlation for housing value, housing age, and vacancy rate. In addition, the spatial error model reports a significant effect of the level of abandonment, according to which a one percentage point increase in abandoned housing leads to a 0.57 (0.59) percent increase in intentional building fire risk. Again, the spatial parameters, rho and lambda, are estimated to be positively significant at a 99 percent confidence interval. The coefficients of lambda are now slightly higher than in the previous analysis, emphasizing the importance of the spatial setting.

In summary, all variations of regressions, adjusted for heteroskedasticity, spatial interaction of the dependent variables, as well as spatial autocorrelation, find strong evidence for the positive correlation between poverty and fire risk. Furthermore, all variations of regressions find strong evidence for the negative correlation between median household income and fire risk. This seems to hold true for building fires in general and for intentional fires in particular. No such conclusion can be drawn easily for the influence of vacant and abandoned structures on fire risk, as their influence on the dependent variables is not consistent across all different types of analyses. If anything, then the prediction power seems to be greater with regard to intentional building fires when adjusted for spatial autocorrelation.

Table 6: F3 Intentional fires; Spatial Lag and Spatial Error

VARIABLES	(1a) LAG	(1b) LAG	(2a) LAG	(2b) LAG	(1a) ERR	(1b) ERR	(2a) ERR	(2b) ERR
poverty	1.935***	0.901**			2.051***	1.335***		
	(0.407)	(0.407)			(0.439)	(0.426)		
median income			-0.0259***	-0.0178***			-0.0286***	-0.0252***
			(0.00483)	(0.00499)			(0.00524)	(0.00552)
unemployment	1.702***	1.167**	1.561***	1.370**	1.698***	0.831	1.462**	0.937
	(0.594)	(0.555)	(0.605)	(0.587)	(0.613)	(0.531)	(0.632)	(0.572)
unempl 16-19	-0.153	-0.236*	-0.149	-0.164	-0.115	-0.217*	-0.112	-0.144
	(0.151)	(0.139)	(0.151)	(0.145)	(0.152)	(0.125)	(0.152)	(0.133)
unempl 20-24	-0.0792	-0.0572	0.00896	0.0615	-0.0614	-0.0512	0.0277	0.0898
	(0.192)	(0.164)	(0.189)	(0.176)	(0.191)	(0.161)	(0.186)	(0.168)
child	1.141**	1.149**	1.446**	1.844***	1.092*	0.976*	1.461**	1.586***
	(0.578)	(0.494)	(0.561)	(0.520)	(0.595)	(0.517)	(0.576)	(0.534)
single parents	0.0305	-0.00370	-0.111	0.106	0.113	0.00655	-0.0725	0.0760
	(0.288)	(0.272)	(0.292)	(0.285)	(0.296)	(0.267)	(0.304)	(0.276)
single m 15-17	2.972	1.657	2.355	1.557	3.220	1.945	2.540	1.641
	(2.413)	(1.843)	(2.404)	(2.015)	(2.392)	(1.751)	(2.415)	(1.984)
single m 18-24	0.618	0.342	0.442	-0.444	1.147	0.841	0.968	0.0459
	(1.863)	(1.632)	(1.936)	(1.839)	(1.862)	(1.562)	(1.928)	(1.758)
age 65	-1.031	-1.282	-1.520*	-1.490*	-1.463	-1.230	-1.995**	-1.517*
	(0.899)	(0.829)	(0.890)	(0.889)	(0.941)	(0.805)	(0.937)	(0.876)
housing value		-0.0962***				-0.0987***		
		(0.0169)				(0.0133)		
housing age		0.621***		0.625**		1.199***		1.325***
		(0.225)		(0.249)		(0.290)		(0.333)
vacancy		0.980**		1.216**		1.184**		1.324**
		(0.474)		(0.541)		(0.468)		(0.537)
abandonment		-0.0189		-0.0114		0.587**		0.572**
		(0.203)		(0.203)		(0.235)		(0.245)
Constant	-0.923**	0.143	0.625	-0.253	0.332	0.686	2.067***	0.985
	(0.455)	(0.530)	(0.534)	(0.545)	(0.420)	(0.632)	(0.525)	(0.733)
rho	0.695***	0.553***	0.708***	0.666***				
	(0.167)	(0.192)	(0.161)	(0.175)				
lambda					0.764***	0.910***	0.792***	0.921***
					(0.153)	(0.0740)	(0.140)	(0.0675)
Observations	275	275	275	275	275	275	275	275
Variance ratio	0.252	0.391	0.264	0.317	0.229	0.583	0.248	0.522

Robust standard errors in parentheses

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

2.4 Discussion

The previous analysis raises many questions, carries policy implications for the city of Detroit, and potentially also for other cities that deal with similar problems. It also leaves room for extensive future research, especially in the field of economics. I would like to address briefly only two of these issues.

First, if this analysis has demonstrated one thing, it is that poverty, and especially intentional building fires, are closely linked together. Intentional building fires account for 12 percent of all building fires over the observed period. If "suspicious" building fires were added to that fraction, in other words, fires in cases where arson was highly suspected at the point of investigation when the data were recorded but could not be proven, then the number would increase to 40 percent of all building fires. Therefore, more emphasis on arson investigation, but also a better understanding of the determinants of intentional fires, followed by counteracting measures to prevent them from happening in the first place, may potentially decrease the overall number of building fires dramatically.

Second, from an economic standpoint, these findings call for a theoretical framework to determine the value of urban fire service, as this area of research has been largely neglected up to this point. By that I mean a framework not only in terms of insurance claims, or from a business perspective with regard to the forgone contribution towards productivity, but in a more general sense with a focus on individual utility and social well-being.

2.5 Conclusion

This chapter analyzes the correlation between poverty, median income, and fire risk in an urban environment. In line with previous literature, I find relatively small, yet persistent, effects. A one percentage point increase in the number of households living below the poverty line translates to a 0.60 and 1.64 percent increase in the number of building fires. By focusing only on intentional fires, the effect rises to 0.90 – 2.10 percent. I also find that a decrease of $1,000 in the level of median income corresponds to a 1.03 – 2.00 percent increase in building fires, and to a 1.78 – 2.86 percent increase in intentional building fires. These findings stand in sharp contrast to the estimations for unintentional building fires, where no significant correlation between poverty, median income, and fire risk can be recorded. Furthermore, I find ambiguous estimations for the effect of vacant and abandoned housing. However, there is some evidence that both are positively affecting fire risk. Finally, there is strong evidence that fires are clustered and that spatial autocorrelation has to be adjusted for.

More research in the field of economics, both empirically and theoretically, is needed to understand better the cause of fires in an urban environment, their economic implications, and ways to counteract, or better still, to prevent them in the future.

CHAPTER 3 "FIRE RISK AND FIRE STATION SITING IN DETROIT – THE ISSUE OF DISTRIBUTIONAL EQUITY"

3.1 Introduction

This research investigates the link between quality of public service provision and available budget with respect to two aspects of distributional equity, equality and need. Effective July 1st, 2012, the implementation of a new, smaller budget made it imperative for the Detroit Fire Department to decrease labor input on any given day. Fire stations had to be closed, leading to a less dense fire station grid in some areas of the city for the remainder of the year.

To motivate this study, I review excerpts of relevant literature on criteria determining optimal fire station siting. The research question is then addressed empirically by analyzing fire incident micro data for the year 2012, collected by Detroit's fire department.

First, I compare Detroit fire incident data from 2012, before and after the change in budget, in a simple OLS framework to find out whether fire response time as a quality indicator of public fire service has changed significantly as a consequence of the change in budget.

In a second step, I introduce box plots and first-difference analysis in order to address the matter of equity interpreted as equality of public service distribution. Performing intra-city panel comparison on census tract level, I am able to investigate whether fire response time has changed uniformly across Detroit, or if tracts in the peripheries of former stations experience more dramatic changes in service quality than others.

After I briefly review the connection between fire risk and various socio-economic factors, I assess the change in budget with regard to equity interpreted as need. Finally, I create an index to determine potential fire risk, before the theory is then tested with various forms of variance analyses using Detroit micro data.

3.2 Literature Review

One of the most important decisions, if not the paramount decision, a fire department has to make is where to site its stations in a given area, such as a city. It is therefore no wonder that a great body of literature exists regarding this question, covering both theoretical models and addressing the application of these models to real world examples. One further complication to this already challenging task is that cities find themselves in a constant state of flux, which means that planners have to deal with cycles of development, decay, and redevelopment, continuously changing the demands on fire service. The purpose of this section is to highlight some of the important achievements made in this field, and to show how this study might still be able to fill a small, yet important, niche.

As early as 1968, Hogg attended to the optimal siting of fire stations. She pointed out that the optimum is achieved when no alteration of the station locations can decrease the total spread of all fires, measured in monetary terms. Following standard economic theory, Hogg then further specified the optimum by comparing the marginal cost and marginal benefit of an additional fire station. Applying her theory to the city of Bristol, United Kingdom, she developed an algorithm determining where an additional fire station should be positioned, in order for its impact to be maximized.

Toregas et al. (1971) used linear programming in a constrained optimization setup to figure out the minimum number of emergency service facilities, such as fire stations, to cover any given area. As a constraint in this so-called *location set covering problem (LSCP)*, they used maximum response time within which a response unit must be able to arrive on scene. In 1972, Toregas and ReVelle enhanced previous findings by acknowledging that some sort of social utility measurement should also alter the decision-making process of optimal fire station location. As the task of need and desire determination is quite a difficult one for decision makers, the authors proposed a preference curve, where various values of maximum distance were linked to levels of necessary funding.

In 1972, Guild and Rollin investigated the optimal number of fire stations with a focus on graphic, ready-to-use representation of scenarios, given a multitude of assumptions. In so doing, they took into account area size and workload per station, as well as other factors, such as the average cost of running a fire station versus the average cost of fire loss.

Plane and Hendrick (1977) calculated the optimal siting of fire stations for Boulder, Colorado. In collaboration with the city council, the researchers set out to develop a more efficient method of service provision. Their goal was to maintain the status quo in service quality while providing service at a lower cost. Similarly to previous works, a set-covering problem was defined and evaluated based on a number of constraints. These included the maximum permitted response time, as well as a set of areas imposing an increased fire hazard, and, thus, potentially requiring more attention by the fire service. As a result, the new proposed configuration allowed the closing of several fire stations, while response time was decreased or at least held constant.

Kolesar and Blum (1973) developed an index to describe the relationship between the number of fire stations and the average distance traveled by a fire service company. According to their model, the expected distance (*D*) between the nearest fire station and points where fires could occur is determined by the quotient of a constant of proportionality (*K*) and the square root of the number of fire stations (*N*), for any given area (*A*). Therefore, $D=K/(N/A)^{1/2}$, which can be used to assess resource allocation plans, given certain response time requirements.

Over time, more sophisticated programming tools and models, accounting for previously omitted variables, evolved. ReVelle (1991) presented various improved optimization models.

Based on the *maximum covering location problem (MCLP)*, developed by Church and ReVelle (1974), which additionally accounted for demand frequency and individual siting cost, *additional coverage models* were created. For instance, these models accounted for a situation where emergency units are busy at the time an additional call is received. In addition, *probabilistic models* were developed and further improved.

Badri et al. (1998) employed a multi-objective programming approach to assist the city of Dubai with the restructuring of their fire station grid. Taking into account eleven strategic goals, such as demand, distance, time, and water availability, the authors found that the original setup is only 60 percent efficient. They also documented the difficult task of accurately implementing fire engine travel times, as well as the challenge of finding an adequate solution depending on which of the sometimes conflicting goals the planner wants to maximize.

In the more recent past, the use of geographical information systems (GIS) has become standard to determine optimal station siting. Liu and Huang (2006), for instance, used a combination of GIS spatial representation capabilities and ant colony optimization algorithms to improve transport routes for fire service vehicles in Singapore. Taking into account a multi-objective framework, the authors succeeded in finding the optimal location for additional stations so as to reduce response time from eight to five minutes.

Chevalier et al. (2012) developed a decision-aiding tool for planners to find the optimal location for fire stations in Belgium. Their contribution to the already existing body of literature is highlighted by the innovative risk modeling approach implemented on a national scale. Based on eleven years of national survey data, collected from all 251 fire stations, the authors constructed maps to visualize fire risk patterns across the country. Based on this information, the authors then developed a heuristic to determine a fire station grid that minimizes cost, while meeting various other quality constraints.

Finally, Murray (2013) addressed the optimal location problem in response to efforts by the Elk Grove, California, Fire Department to accommodate expected population growth with a number of additional stations. Here, the achievement of response time was imperative. Using GIS and variations of the MCLP, the author estimated the number of additional fire stations necessary, based on radii response time analysis. He also calculated various other scenarios, including larger areas of operation per fire station and corresponding effects on total costs.

After this brief investigation into examples of previous studies, it seems that the vast majority of them are concerned with service efficiency, and only a few of them explicitly account for factors determining fire risk. Furthermore, it seems that up to this point no effort has been made to link the question of optimal fire station location to the issue of distributional equity. Therefore, this first attempt, proposed in this paper, can contribute to existing literature and will hopefully attract further research in the same direction.

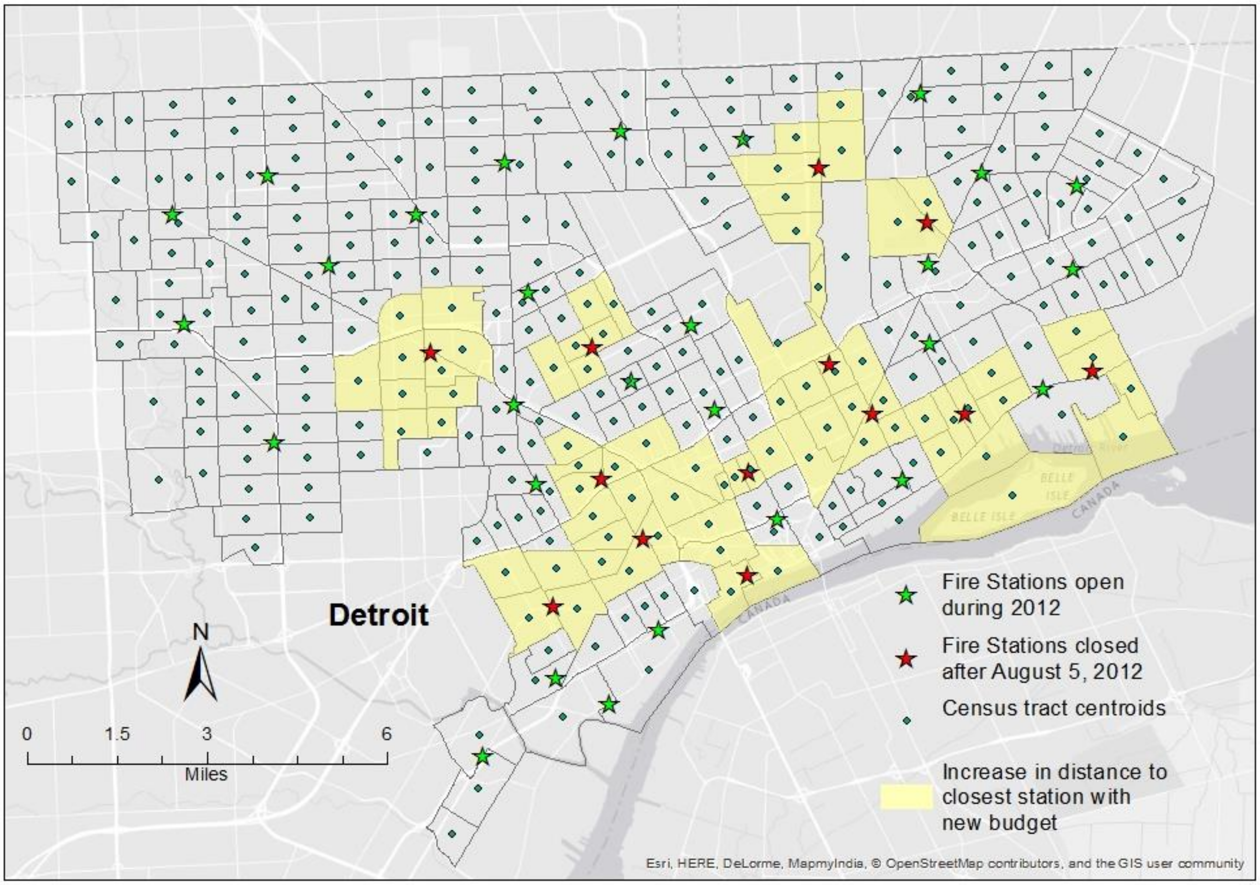
3.3 Empirical Analysis

3.3.1 Research question and data

Map 9 shows the city of Detroit, divided into census tracts. The stars mark the locations of all fire stations. With the implementation of a new, smaller budget at the beginning of July, 2012, the number of firefighters on duty per day decreased by about 30 percent for the remainder of the year. To accommodate this change, 13 of the 42 fire stations previously in operation across Detroit were closed. These stations are represented in the map by red stars. The remaining 29 stations (green stars) stayed open for the remainder of the year. As the fire station grid becomes less dense, it seems obvious that overall travel distance from the remaining stations to the site of operation increases, which would lead to an increase in travel time and, thus, in total response time.

The following section sets out to find evidence for a significant correlation, supporting this hypothesis. However, as the map shows, the station closing has taken place primarily in the central and downtown areas of the city, whereas the western, northern, and eastern outskirts seem to be largely unaffected by the changes. Correspondingly, the yellow shaded areas show census tracts where distance from census centroid to nearest fire station has increased after the implementation of the new budget. Based on these observations, the remaining sections of this chapter seek to analyze whether the closing of fire stations had an effect on various interpretations of distributional equity of fire service, in particular equity in terms of equality and equity in terms of need.

Map 9: Detroit fire stations 2012



The data used for this analysis are provided by the Detroit fire department. The raw data set consists of every incident the fire service responded to in 2012. The data are collected electronically, using a combination of CAD- (computer-aided dispatch) data and NFIRS- (National Fire Incident Reporting System) data. The time period from December 11th, 2012 to December 16th, 2012 is not provided in the data set due to systemic malfunction. All incidents in the data set are consistently marked as “priority 1 incidents” and handled by the fire department. No exclusive runs by the emergency medical services (EMS) are included. Furthermore, I only take into account records indicated as “building fire”, in order to ensure a homogeneous data set. Following Upson & Notarianni (2012), I drop observations with a response time of 0.00min, as these may not be accurate due to system failure and human error. After data cleaning, the sample consists of N =

5,731 observations. The data are then matched to American Community Survey data (ACS), in order to acquire information regarding socio-economic specifications of an area where a fire-related incident took place. I use data collected over a 5-year period, 2008 – 2012, for all 297 census tracts of Detroit.

3.3.2 Fire response time and budget

This first part of the analysis aims to provide insight into the effect of a change in budget on the quality of public fire service. *Total fire response time* is used as the dependent variable. It is a common indicator of service quality for police, fire, and EMS. Defined as the aggregate of *turnout time* and *travel time,* this indicator is recorded routinely by public safety organizations (Flynn, 2009). Definitions are provided by the National Fire Protection Agency (NFPA) and its "1710" guide for "Standard for the Organization and Deployment of Fire Suppression Operations, Emergency Medical Operations, and Special Operations to the Public by Career Fire Departments" (NFPA, 2010). According to these guidelines, turnout time begins with the audible or visible notification of the emergency response unit (ERU) and ends with the beginning of travel time, which ends with the arrival of the ERU on scene. The NFPA also provides performance objectives for professional fire services, according to which turnout time should not exceed 80 seconds, while travel time should not be greater than 240 seconds. These goals ought to be achieved in 90 percent of all cases.

Independent variables are composed of a categorical variable, capturing the effect of the change in budget, as well as various other control variables. Although the budget was officially implemented on July 1st, 2012, the adjustments did not take place instantly. Records show that some of the 13 stations to be closed responded to emergency calls until August 5th, 2012. Therefore, I define the categorical variable *budget change* as the time periods from January 1st, 2012 to

August 5th, 2012, and from August 6th, 2012 to December 31st, 2012. For reasons already explained above, I would expect a positive correlation between total response time and this categorical variable. Secondly, I control for *travel distance*, as it seems only logical that this control variable is strongly positively determining travel time. The variable is constructed as the shortest distance a fire engine can possibly take from its station to the incident, given prevailing infrastructure and traffic regulations compliance.

Following Upson and Notarianni (2012), I also include *time of day*, a categorical variable accounting for different periods of a 24-hour shift, when an emergency call is received by the ERU. The shift is divided into three sections, daytime: 6am to 6pm, evening: 6pm to midnight, and nighttime: midnight to 6am. The authors find a significant increase in response time for calls received during nighttime, which is why I would expect a similar result for this analysis. Next, I control for *seasonal effects* by coding another binary variable, which compares late spring to late summer months (mid-March to mid-October) with the remaining seasons of the year. A higher workload, typical for these months, may increase response time. *Weather conditions* is another dummy variable which indicates days in which fire response time might be extended due to severe weather conditions such as heavy rain, fog, or snow.

Next, I account for *housing density* in a census tract, calculated as the number of housing units per acre. The idea is that greater housing density might lead to higher traffic volume and street congestion, which would increase response time. Similarly, I control for *population density*, constructed as the number of people residing in a census tract per acre, as Detroit displays a very different structure across various geographical areas. The core, midtown and downtown, along the Woodward Avenue corridor, is very different in density, infrastructure, and level of occupancy compared to the more suburban, or even "rural", areas in the east and the west. Likewise, the fire station grid is much denser in the midtown and downtown region, which would imply a negative correlation between this control variable and response time.

Additionally, I account for the median *housing unit value* in a census tract. The logic behind this is that, following classic fire station location strategies, stations are located close to areas where the potential damage of a fire is relatively higher than in other areas, for instance, close to public buildings such as schools, or private buildings such as office buildings (Lucy, 1981). Therefore, housing unit value might be negatively related to response time. Finally, I include the number of *vacant units* per 1000 housing units of a tract where a fire occurred. The correlation to fire response time is ambiguous. On the one hand, a higher level of vacancy could indicate less activity in the area, which in turn could lead to a lower response time. On the other hand, literature shows that high vacancy might lead to an increased number of fires, either accidental or intentional, especially when vacant buildings are actually abandoned. Therefore, the volume of fires to be handled by fire stations might increase, and with it response time (see, e.g., Shai, 2006).[5]

I use a simple OLS framework to estimate the model. It takes the following classic form:

$$y = f(\boldsymbol{X}) + \epsilon, \tag{45}$$

where y is the dependent variable, $\boldsymbol{X}$ is a vector of all independent variables, and ϵ is the random error term. Various standard tests are carried out to ensure that the Gauss-Markov assumptions for unbiased model specification are met. A maximum variance inflation factor-test score of 1.68 indicates that multi-collinearity does not pose a severe problem to the model. I perform a Breusch-Pagan-test for homoskedasticity which finds significant evidence for the presence of heteroske-

[5] Table 4 of the appendix summarizes the variables determining the econometric model as well as their definitions. Additional summary statistics for key explanatory variables can be found in the appendix, Table 5.

dasticity ($chi2 = 58.22, where\ Prob > chi2 = 0.00$). The White-test also suggests that homoskedasticity cannot be assumed for the model ($chi2 = 93.62, where\ Prob > chi2 = 0.0028$) Therefore, the model is estimated using robust standard errors.

Table 7 shows the results of this first regression. According to the R^2-value, 13.9 percent of the variance in response time is explained by the model. Although this doesn't seem particularly high, it is not unusual when dealing with noisy micro data. As expected, fire response time does significantly increase after the closing of the 13 fire stations, and the estimated coefficient of budget change is the highest among all explanatory variables. According to the calculations, the new budget is responsible for an increase in response time of almost 30 seconds compared to the situation before.

Also not a surprise is the strong correlation between distance traveled and response time. The results suggest that response time increases by about 5 seconds for every tenth of a mile increase in travel distance. Fire response time at times other than between midnight and six o'clock in the morning is considerably shorter than during the latter. An explanation might be that firefighters on duty are asleep during the night, and need time to get up and put on their gear, before they can go on a run. The data also suggest a seasonal effect, according to which response time in the summer months is longer than in the winter months. This might be explained by the higher building fire rate in the summer months, leading to a higher workload for fire companies. Weather conditions turn out non-significant, which might partly be explained by the crudeness of this independent variable, as it does not distinguish between light drizzle and heavy rain, nor does it take into consideration when the precipitation occurred during the day. Carmichael et al. (2004) propose a weather index which, among other things, accounts for temperature, precipitation, and sea level pressure. Such a complex index requires very detailed data, which, unfortunately, were not obtainable while preparing this study. Meeting the expectations, housing density is statistically positively related to fire response time, while population density is significantly inversely related. The median value per housing unit and census tract shows no significant correlation, which means there is no evidence for the claim that the fire service response time is influenced by the value of a building. Finally, the higher the number of vacant units per tract the lower the fire response time, although the estimated coefficient turns out to be very small.

Table 7: Fire response time determinates

VARIABLES	(OLS) response time
budget change	0.462***
	(0.0477)
distance	0.768***
	(0.0363)
t = 0600h-1800h	-0.574***
	(0.0534)
t = 1800h-0000h	-0.676***
	(0.0551)
season	0.164***
	(0.0455)
weather	0.0652
	(0.0450)
housing density	0.0406**
	(0.0181)
population density	-0.0331***
	(0.00627)
housing value	-0.000166
(in thousands)	(0.00109)
vacancy	-0.000968***
	(0.00024)
Constant	4.183***
	(0.156)
Observations	5,731
R-squared	0.139

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.3.3 Budget and equality of service distribution

The previous analysis reveals that there is strong evidence for the influence of the change in budget on fire response time. The question is now whether, aside from the overall observable increase, various areas of the city have been affected differently, and, thus, the level of distributional equity has changed compared to the situation before the new budget was implemented. To find out, I follow Lucy (1981) and Talen (1998), and their work regarding equity in the provision and distribution of local public services. Building on the works of Rawls (1971), Rescher (1966), and Musgrave (1959), Lucy (1981) discussed five dimensions of equity, equality, need, demand, preferences, and willingness to pay, which can support a local planner in deciding on a "fair" allocation of resources. Later on, Talen (1998) utilized these concepts, and developed "equity maps" to present single dimensions of distributional equity graphically.

Applying their framework to the issue discussed here in this chapter, I use fire response time as a service quality indicator, in order to test for equality of service provision. Perfect equality would be reached if one uniform value of response time could be recorded for every building fire throughout the city. For obvious reasons, this goal seems to have mostly theoretical relevance, as it is downright impossible to achieve such a situation in the real world. Taking the variance in response time before the change in budget, for instance, we see that it is very obvious that service distribution is nowhere near perfect equality. However, relatively speaking, it is possible to analyze whether the change in budget caused a shift towards the fulfillment of this goal, or away from it.

To find out, Table 8 presents some descriptive statistics of response time before and after the change in budget with regard to individual building fires in Detroit. After the change, the standard deviation of response time increased from 1.62 to 2.00, indicating a larger variation within the data, and, thus, lower service equality. This observation makes intuitive sense, as the overall median distance from census tract centroid to closest operational fire station increased from 0.73 miles to 0.91 miles as a result of the budget change. Greater travel distance per run leads to greater infrastructural heterogeneity and uncertainty en route and, thus, also to greater variation in response time.

The validity of this logic can be further tested by dividing the data into smaller subsets of treatment and control groups. As already pointed out at the beginning of this section, the yellow shaded census tracts, displayed in Map 9, are the ones which actually faced the increase in minimum distance from their centroid to the closest operational fire station after the closing of the 13 fire stations. Building fires within these tracts are regarded as the treatment group, whereas records of building fires in the remaining tracts form the control group. Looking at the treatment group first, Table 8 reports an increase in standard deviation from 1.56 before the change in budget to 2.01 after it, while the median distance to the nearest fire station has almost doubled from 0.64 miles to 1.2 miles. The standard deviation of the control group has changed from 1.63 to 1.94, while the median distance to the closest fire station was 0.80 miles for the entire year, 2012. In other words, standard deviation used to be greater in the control group before the change, while after the change it is greater in the treatment group. As it turns out, the difference in standard deviation between treatment and control groups on the individual level has increased from 4.6 percent before, to 7.6 percent after, the station closing. This would suggest that service distribution is now less equal than before the budget change. Looking at median response time values of census tracts, however, we see that the results are different. Taking into account that, due to lack of observations, 38 census tracts have to be excluded from the analysis, now $N = 259$, I find that despite the overall increase in variation, the difference in standard deviation between treatment and control groups on census tract level has decreased from 19.4 percent to 11.5 percent. This result suggests a more equal service distribution after the change in budget, at least with regard to aggregated treatment and control group data.

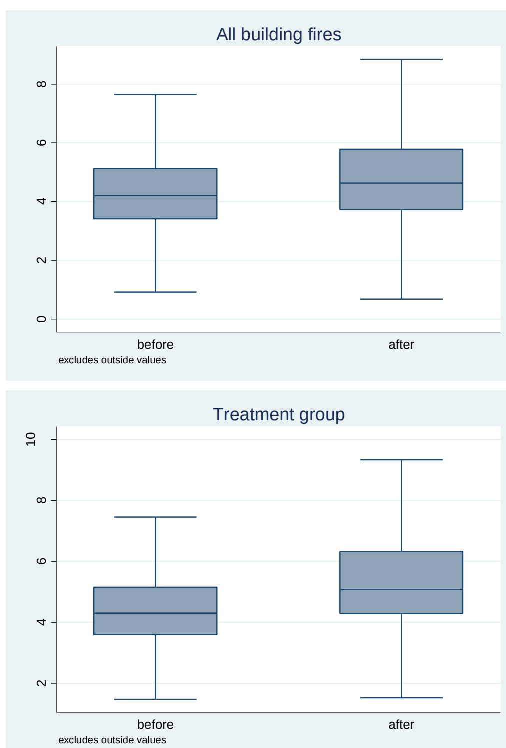
Table 8: Descriptive statistics response time, in minutes

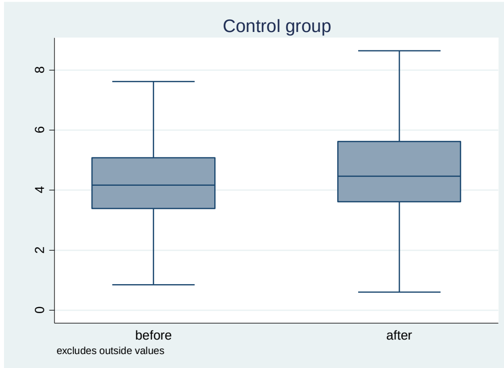
response time	N	mean	sd	min	max
individual					
before change	3,649	4.376	1.617	0.120	18.62
after change	2,170	4.957	2.003	0.120	17.73
before change treatment group	845	4.452	1.562	0.150	14.22
after change treatment group	550	5.452	2.101	0.170	17.32
before change control group	2,804	4.353	1.633	0.120	18.62
after change control group	1,620	4.789	1.941	0.120	17.73
census tract					
before change	259	4.252	0.838	2.05	8.75
after change	259	4.801	1.0699	1.99	9.09
before change treatment group	64	4.353	0.728	2.99	6.37
after change treatment group	64	5.152	0.968	3.48	7.98
before change control group	195	4.217	0.8696	2.05	8.75
after change control group	195	4.686	1.079	1.99	9.09

Figure 2 shows simple box plots to graphically approach the question of distributional equality of fire service. Following a similar line of reasoning as in the previous discussion, I plot fire response time before and after the change, and also compare the treatment with the control group, using Detroit census tracts. For this analysis, I exclude outliers, since I'm predominantly interested in the overall trend in the data distribution. The graph for all building fires shows an increase in median response time from 4.20 to 4.60 minutes, which is accompanied by a positive skew in the distribution. It also shows that the inconsistency within the 25th and the 75th percentile has increased. Furthermore, it appears that the whiskers (representing the minimum and the maximum values) increased in length, indicating a wider overall spread in the data. Looking at the treatment group, we note that the effect of the budget change becomes even more apparent. The

50th percentile has increased from 4.30 to 5.08 minutes. The variation within the two middle quartiles has increased as well, and ranges from 4.28 to 6.32 minutes after the change. The overall spread is now also greater than before. Finally, the median response time value for the control group has increased from 4.17 to 4.47 minutes, while the variation within the box after the change is very similar to the one within the treatment group at that point in time. The overall spread is again greater than it was before. Furthermore, the gap between treatment and control groups in terms of the 25th percentile has gone up from 0.22 to 0.68, and the gap for the 75th percentile has also widened from 0.07 to 0.7. Summarizing these observations, we can say that all three graphs suggest an increase in data variation due to the change in budget, and hence, one might argue that overall service equality has decreased.

Figure 2: Box plot response time and budget change





Apart from descriptive and graphic analyses, it is also possible to use quantitative methods to explore the effect of the station closings on distributional equality. Two aspects are of interest. The first, more general question, is whether there exists a measurable effect in the change in median travel distance on the change in fire response time. The second, equality-specific question, is whether areas directly affected by the closing of stations in terms of the minimum distance to the closest station differ significantly from others. To find out, I use panel data analysis on the census tract level and employ a two period, first-difference strategy. The model takes the following general form, following Greene (2008):

$$y_{it} = \theta_t + \boldsymbol{x}'_{it}\beta + \gamma T_i + u_i + \varepsilon_{it},\ t = 0, 1, \tag{46}$$

where y is the dependent variable, θ_t is the constant term, $\boldsymbol{x}'_{it}$ is a vector of exogenous variables, T_i is the treatment dummy variable, u_i is the group-specific random element, and ϵ is the zero mean disturbance. Applying this framework to the specific problem in question, we acquire the following, where subscript i represents different census tracts:

$$\Delta response\ time_{it} = (\theta_1 - \theta_0) + \ \Delta distance_{it} + \gamma \Delta T_i + \Delta\varepsilon_{it}. \tag{47}$$

Employing the first-difference approach here seems justified, as, besides the advantage of removing any latent heterogeneity from the model, it is a common approach to quantify the effect of a policy change, or the effect of a certain treatment, separating two periods of time. Therefore, the first-difference estimator seems capable of capturing the effect of the newly implemented budget; more specifically, it seems capable of estimating the effect of the station closing program on post-closing response time. By separating census tracts into two groups, we find it is then possible to obtain additional information on the effect on distributional equality.

For every census tract, I calculate the median response time, as well as the median distance traveled by fire companies to tackle building fires, before and after the implementation of the new budget. Following Map 9, we create a treatment variable in the form of a simple dummy to identify treatment and control groups. Again, the data set consists of 259 observations over two periods. According to the table, a strong overall variation in median response time (1.99 – 9.09 minutes) exists in the data. With a standard deviation of 0.998, response time follows a normal distribution; however, the data are distributed around an overall mean of 4.52 minutes. Furthermore, the "between standard deviation" is greater than the "within standard deviation", indicating a greater variation from one census tract to the other, compared to the variation for a single census tract from period one to period two. The overall standard deviation of travel distance is 0.56, with a mean of 1.24 miles and a data spread between 0.25 and 3 miles. The between standard deviation is now about twice the level of the within standard deviation. Dividing the data into treatment and control groups again brings out a slightly more detailed picture. Now, the spread in the control group is greater. The treatment group response time values for between and within variation are similar to each other, while the within variation is greater than the between variation with regard to travel distance.[6]

[6] Table 6 of the appendix provides summary statistics on the variables used in the regression.

Table 9 presents the results of the first-difference estimation. It shows that there is evidence for a positive significant correlation between the change in travel distance and the change in response time, at least at a 90 percent confidence interval. A coefficient of 0.342 would suggest that a change of one mile in travel distance from one period to the next translates into a change of about 20 seconds in response time. Moreover, the estimations show a strong significant difference between the treatment and control groups among census tracts. With a positive coefficient of 0.568 at a 99 percent confidence interval, the first-difference estimator suggests a higher change in median response time of about 34 seconds per run for census tracts in the treatment group, compared with the control group.

Table 9: Response time and distance change

VARIABLES	(First-difference) Δ response time
Δ distance	0.342*
	(0.1769)
treatment	0.568***
	(0.1744)
Observations	259
R-squared	0.144

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Overall, it appears that, depending on the viewpoint, the change in budget had ambiguous effects on distributional equality. On the one hand, there is evidence that overall variation in response time has increased together with mean values, and that it had a different effect on the treatment group than it had on the control group. On the other hand, it seems that comparing the two groups in terms of difference of within-group variation, the gap between them has narrowed from one period to the next.

3.3.4 Budget and need satisfaction

Lucy (1981) and Talen (1998) describe a second manner of interpreting equity from a planner's point of view, which is the concept of need satisfaction. In contrast to the previous interpretation of equity as equality, this concept willingly accepts and even demands the unequal treatment of unequals. More precisely, instead of aiming for a most uniform treatment of individuals, equity interpreted as need satisfaction aims to allocate resources towards individuals who are relatively worse off than others in any given comparable aspect or dimension. Using this understanding in the context of fire protection, one might argue that special attention should be given to individuals facing a higher fire risk than others, or, more generally speaking, to areas, where the probability of building fires is higher than in others. This part of the paper analyzes the effect of the change in budget on equity interpreted as need. In so doing, I present means to link individual socio-economic and other factors to quality of fire service.

In its simplest form, an indicator determining fire risk in a certain area could be calculated ex post on the basis of standardized fire incident frequency, such as building fires per 1000 housing units in a given period of time. We can then go one step further, and ask what actually determines the incident frequency. An extensive body of literature addresses influential factors where, for instance, many of them find the level of poverty to be positively correlated with fire risk and some of them the level of unemployment (see, e.g., Gunther (1981), Fahy and Norton (1989), Chhetri et al. (2010)). Others note that housing age, the level of vacancy, and the rate of abandoned structures may also positively influence fire risk (see, e.g., Accordino (2000), Shai (2006)). Consistent with the concept of equity interpreted as need, one might therefore argue, for instance, that areas with a relatively higher poverty rate need better fire service than other areas where the poverty rate is relatively lower. A similar argument could be made for housing age, vacancy, abandonment, or any other determining factor.

Taking Detroit as an example, I suggest that a more tangible approach is the following. In a first step, it is possible to calculate the median value of census tract poverty levels among households across Detroit, where I again resort to 5-year ACS data. It is then easy to figure out which areas face a poverty level above, and which areas face a poverty level below, this value. In a second step, we can calculate the median of any desired quality of service indicator. Since we have already seen that fire response time is strongly positively correlated with travel distance, we can again use the distance from the census tract centroid to the nearest fire station as an indicator of service quality. Following the above logic, we would accept a negative deviation from the poverty median in combination with a positive deviation from the median in terms of distance to the nearest fire station, and vice versa. A perfectly fair situation would then be achieved where the deviations of both variables cancel each other out; in other words, where the sum of both values is equal to zero.

Figures 3 and 4 show the percentage deviation from the median both for the level of poverty as well as for the minimum distance between centroid and the closest fire station for every tract before and after the station closing. The observations are ranked according to the deviation from poverty median, starting with the minimum. Note that five census tracts had to be excluded from the analysis, due to lack of data availability.[7] In a perfectly fair fire service distribution, we would expect a symmetrical formation of individual observations around zero, so that the chart would appear somewhat like an hourglass. However, inspecting both charts, we observe that no such conclusion can be drawn, nor can a trend be spotted easily. Moreover, simply by visual inspection,

[7] Census tracts 9850, 9852, 9853, 9855, and 9859 had to be excluded from the analysis.

it is not possible to determine whether the change in budget has caused a significant shift towards or away from the fulfillment of perfect equity.

Figure 3: Poverty and minimum travel distance before

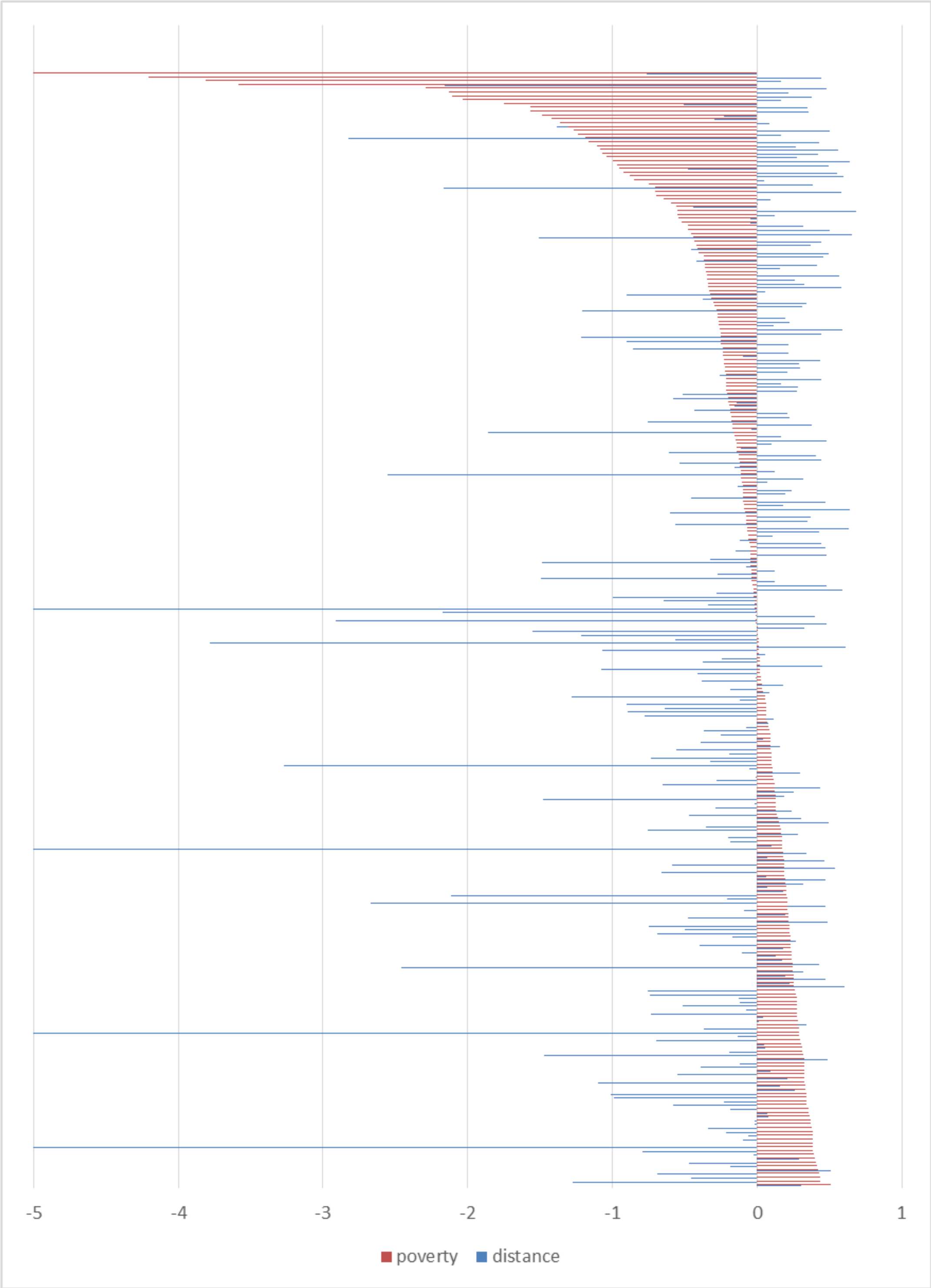
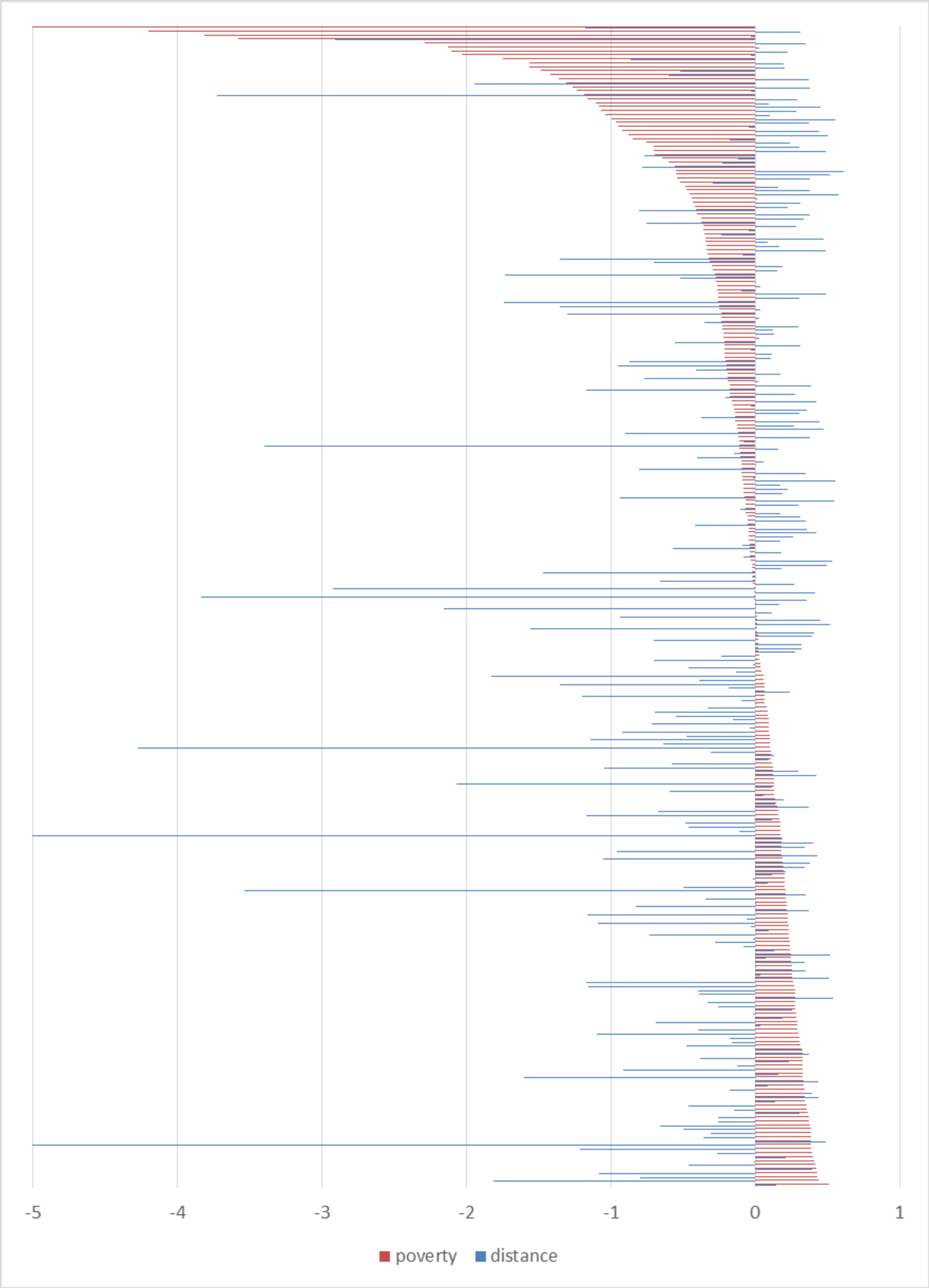


Figure 4: Poverty and minimum travel distance after



To get a better hold of the data, Figures 5 and 6 only show observations of the control group; in other words, observations where the minimum distance to the closest fire station hasn't changed with the new budget. Although far from being perfect, it appears that, for many observations, poverty and distance deviation move in the opposite direction, indicating the unequal treatment of unequals. Furthermore, it seems that the number of observations, which are deviating negatively from the distance median, has increased after the new budget was implemented. This observation seems plausible, as the overall median has also increased.

Figure 5: Poverty and minimum travel distance control before

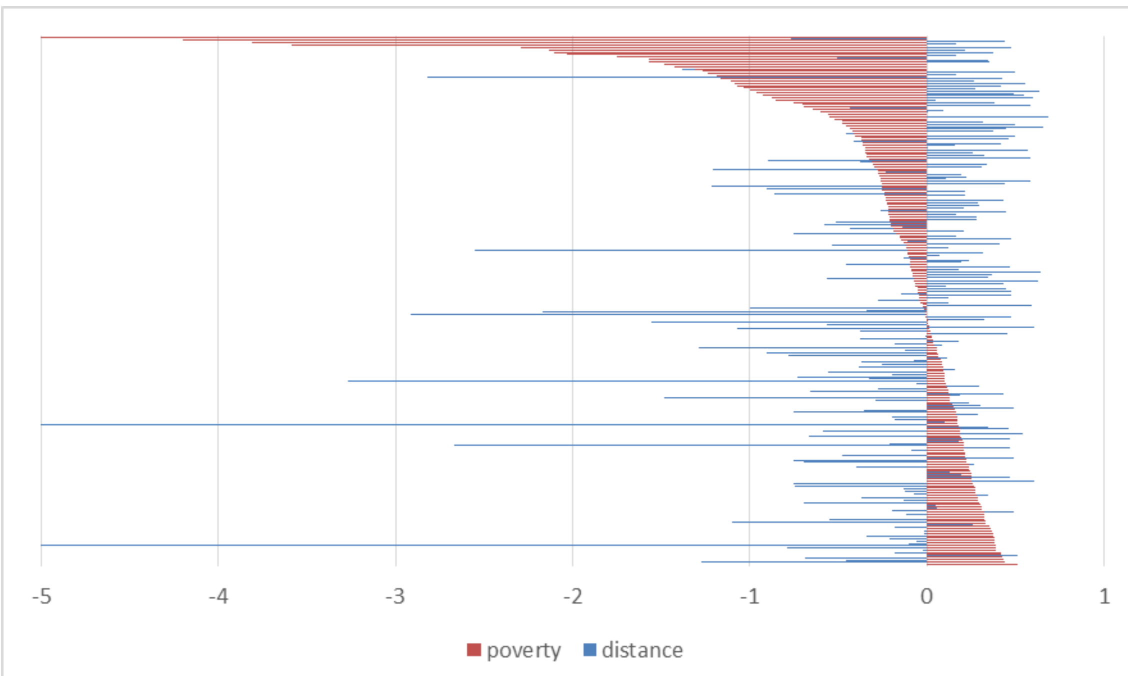


Figure 6: Poverty and minimum travel distance control after

Finally, observations of the treatment group are presented in Figures 7 and 8. Before the change in budget, no symmetrical distribution is apparent; however, it seems that the majority of the observations display a negative deviation from the distance median. That would suggest that quality of service tends to be relatively high, even in areas where fire risk is lower than it is in other areas of the city. Whereas no symmetrical distribution can be recorded after the change in budget, either, the distribution of distance deviations is now almost the complete opposite of what we could observe before the change. It seems that now, with only few exceptions, the observations deviate positively from the median. In other words, quality of service is now relatively lower, even in areas that face a higher fire risk than others.

Figure 7: Poverty and minimum travel distance treatment before

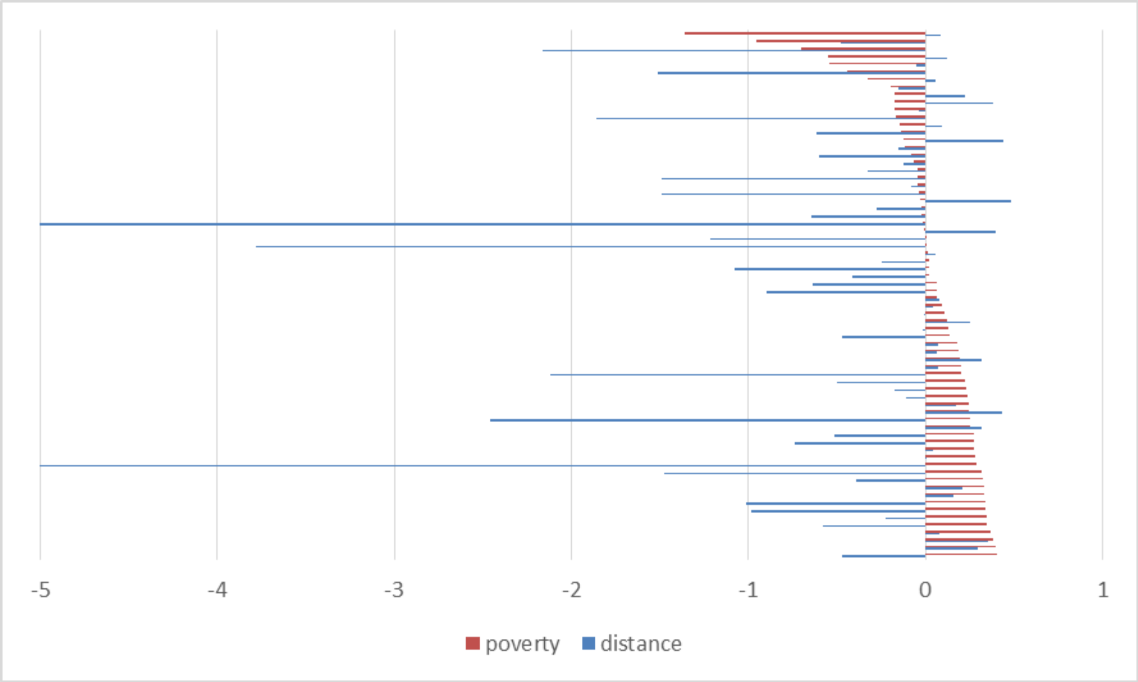
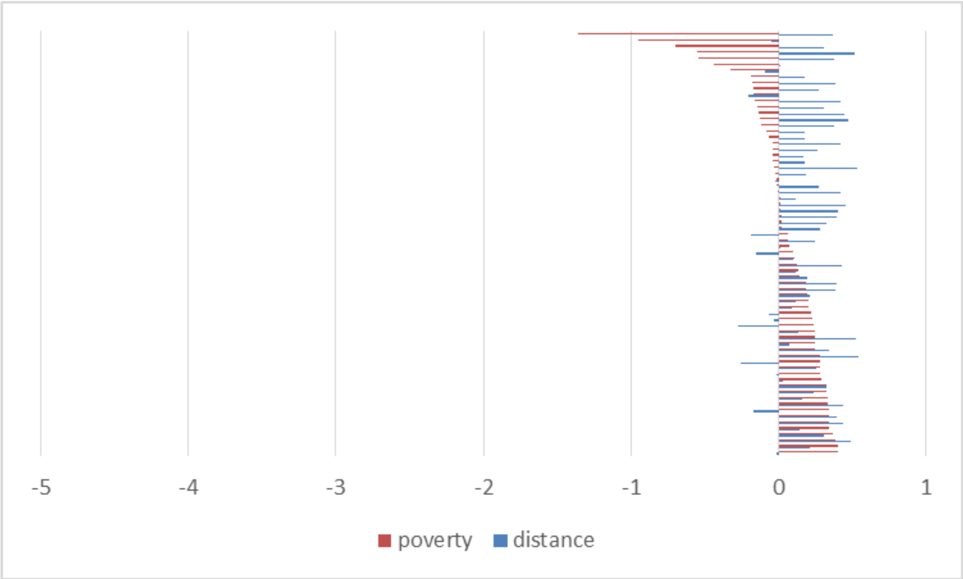


Figure 8: Poverty and minimum travel distance treatment after



Especially with regard to the treatment group, the observations suggest that the change in budget caused a shift away from the goal of perfect equity interpreted as need.

Based on this preliminary assessment, I employ statistical analyses to test its validity, and to find additional evidence for or against need satisfaction as a result of the change in budget. A technique appropriate for this type of investigation is the analysis of variance (ANOVA). Performing a simple one-way variance test, I'm able to compare the difference in means of a certain normally distributed dependent variable with respect to various groups of an independent, categorical variable. The null hypothesis is that groups do not significantly differ in their group means. In step one, I look at poverty both for the control and the treatment groups. Table 10 presents the results. With a ratio of 222 to 70, the control group is more than three times as large as the treatment group. As this inequality may lead to distortions in the estimated results, I also take a random sample of 50 observations for both groups. The results for this sample analysis are reported in parentheses; the full description can be found in the appendix (Table 7). Normal distribution is verified through histograms. The mean poverty level of the treatment group is 0.432 (0.430), whereas the same value for the control group is 0.382 (0.387). With an F-statistic of 7.82 (2.84) and a significance level of $p < 0.01$ ($p < 0.1$), we can reject the null hypothesis, and conclude that the mean poverty level significantly differs between groups. Based on these findings, I perform a similar analysis with regard to the minimum distances to the closest fire stations for both groups before and after the cut in budget. Before the change, the control group has a mean distance value of 0.863 (0.920), and the treatment group exhibits a value of 0.643 (0.634). The between group difference (F-statistic = 15.19 (13.36)) is significant at a 99 percent confidence level. However, looking at the results for the comparison after the station closing, we find that the mean of the control group is unchanged (distance from fire station unchanged), while the mean of the treatment group has increased to 1.233 (1.20) miles, which is double the distance. The F-statistic has increased drastically to 42.46 (12.53) and is strongly significant. Based on this test, I conclude that, compared to the control group, both mean values of poverty and distances are significantly higher in the treatment group after the budget change. This indicates a shift away from perfect distributional equity interpreted as need satisfaction. The change had the effect of worsening distributional equity.

Table 10: ANOVA results

	N	Mean	sd	SS	df	MS	F-stat
poverty							
treatment	70	0.432	0.112				
control	222	0.382	0.137				
between group				0.134	1	0.134	(7.82)***
within group				4.984	290	0.017	
total	292	0.394	0.133	5.119	291	0.018	
distance before							
treatment	70	0.643	0.304				
control	222	0.863	0.439				
between group				2.567	1	2.567	(15.19)***
within group				49.005	290	0.169	
total	292	0.810	0.421	51.572	291	0.177	
distance after							
treatment	70	1.233	0.324				
control	222	0.863	0.439				
between group				7.298	1	7.298	(42.46)***
within group				49.848	290	0.172	
total	292	0.952	0.443	57.146	291	0.196	

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

After this one-dimensional approach towards fire risk, we can now propose an index to accommodate various dimensions of fire risk. As mentioned previously, this might enable us to construct a more accurate probability of fire risk, based on socio-economic, housing, and other influential factors. Following Watts and Kaplan (2001), who develop an index to evaluate fire risk of historic buildings, the index could take the following general multi-dimensional linear form:

$$\Pi_i^F = \sum_{i=1}^{n} w_i D_i, \tag{48}$$

where Π^F indicates fire risk, D represents dimensions determining fire risk, and w denotes weights attributed to the various dimensions of D with respect to geographical area i. Following the above line of reasoning, equation 3 can be rewritten as follows:

$$\Pi_i^F = \sum_{i=1}^{n} (w_{s_i} S_i + w_{h_i} H_i), \tag{49}$$

where $[S, H]$ symbolize socio-economic and housing factors, respectively. For the purposes of this study, I chose two indicators for each dimension, and, for simplicity, set $w_i = 1$. The weights could, for instance, be based on level of significance, or coefficient value. After the adjustment, equation 4 takes the following simplified form:

$$\Pi_i^F = \sum_{i=1}^{n} (poverty_i + unemployment_i + housing\ age_i + vacancy_i), \tag{50}$$

where unemployment is measured as the share of unemployed among the labor force, housing age is defined as the share of old housing stock, built before 1939, and vacancy is the share of vacant structures per tract. The data are based on ACS 5-year census tract estimates for 2012. All variables are recorded in percentage form. After the index is calculated, it is standardized, so that $\Pi_i^F = [0,1]$.

Table 11 shows the results of the one-way ANOVA estimation. Note that one census tract (9851) had to be dropped from the analysis due to lack of observations. Therefore, the control group consists of 222 observations, while the treatment group consists of 69 observations. As before, I generate a random sample of 50 observations for each group, reported in parentheses. The full description can be found in the appendix (Table 8). In both cases, the Bartlett's test result is insignificant, suggesting that unequal variance between groups is not an issue. The mean value of the fire risk index for the control group is 0.529 (0.535), while the mean for the treatment group is

0.640 (0.645). With a value of 26.74 (12.85), the F-statistic suggests a significant difference between group means at a 99 percent confidence interval. This result confirms previously obtained, one-dimensional estimates.

Table 11: ANOVA results fire risk index

	N	mean	sd	SS	df	MS	F-stat
risk index							
treatment	69	0.640	0.143				
control	222	0.529	0.160				
between group				0.651	1	0.651	(26.74)***
within group				7.030	289	0.024	
total	291	0.556	0.163	7.680	290	0.027	

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

In summary, it appears that the goal of perfect equity interpreted as need satisfaction is not achieved either before or after the fire station closing in Detroit. However, the data suggest the change in budget shifted fire safety further away from perfect need satisfaction.

3.4 Discussion

The analysis presented in this paper on the topic of distributional equity carries various interesting implications, some of which I would like to address briefly in this section. First of all, it is clear that the accomplishment of this study can only be described as small, considering the vast and complex topic of distributional equity in the context of public service provision. Many experts in the field will have very good arguments to demonstrate why economists should primarily be concerned with aspects of maximizing efficiency, rather than equity. However, equity is a fundamental aspect of welfare economics that has been ignored by many, simply because of a lack of good answers to admittedly difficult questions. As the literature review has shown, most public planners have moved towards a multi-dimensional, constrained optimization approach when it comes to determining the optimal location of fire stations. Equity offers a very rich additional dimension, which should find significant consideration in the siting process. As the preceding analysis with respect to Detroit has shown, accounting for quality may lead to a very different outcome of station siting. I have shown that simple fire risk indexes can be created, extensively refined, and linked to quality of service indicators. More research in this direction is desirable and necessary.

One major shortcoming of this study is that budget constraints, and especially the question of who should pay for fire service, have been generously ignored. Planning based on need might explain, in contrast to common practice, why low income regions, or areas with a high fire risk score, should receive more attention by fire service than others, including a denser fire station grid and shorter response times. While public fire service is financed largely through tax money, one can rightly ask how people facing increased fire risk, who are therefore also likely to be poorer than others, are supposed to pay more for the service they need. Without any doubt, these concerns are justified and impose a huge challenge on policy makers, social planners, and society in general, as priorities may have to be rearranged.

Another important extension to this study involves the issue of flexibility in station (re-) location. Since cities, and therefore also fire risk factors attached to them, are changing constantly, so may fire service have to adjust constantly to accommodate these changes. A new form of station flexibility at a reasonable cost has to be developed and evaluated in the wider scheme of economic well-being.

Finally, this study also fails to come up with an optimal fire station siting plan. However, based on the ideas proposed in this preliminary work, future in-depth investigation is necessary to develop an optimal plan, which is far beyond the scope of this research.

3.5 Conclusion

The goal of this study is to analyze public fire service in Detroit for the year 2012 with regard to two aspects of distributional equity, equality and need. This study especially sets out to find any differences in these dimensions based on the change in budget in the middle of 2012.

Literature shows that most models are concerned with the efficient provision of public fire service, and that the question of equitable provision of public fire service plays only a minor role.

A multiple linear regression with cross-sectional data from the year 2012 is performed to find out which factors determine fire response time as an indicator of service quality. I find evidence for various factors significantly influencing fire response time, chief among which is travel distance, which is highly positively correlated with response time. I find that response time has significantly changed as a result of the change in budget. Thereafter, I demonstrate how minimum distance to the closest fire station has changed in some areas of Detroit due to the change in budget, while other areas have not been affected directly.

I find ambiguous evidence for the effect of the change in budget on distributional equity interpreted as equality. While there is no doubt that overall service quality in terms of response time or travel distance has deteriorated, it is not fully clear whether service allocation is now more unequal than before.

Thereafter, I perform various tests and propose a fire risk index to analyze the change in budget with respect to need satisfaction. I find strong evidence that, after the change, the allocation is less fair than before.

APPENDIX 1

Table A 1: Equity and need of fire service, summary statistics

poverty				before	response time		after
group	percentage	count		count	group	minutes	count
1	$0 \geq x \leq 0.307$	27		60	1	$0 \geq x \leq 3.8$	32
2	$0.307 > x \leq 0.383$	44		49	2	$3.8 > x \leq 4.3$	35
3	$0.383 > x \leq 0.486$	57		39	3	$4.3 > x \leq 4.8$	40
4	$x > 0.486$	48		30	4	$x > 4.8$	71
total		176		176			176
mean	0.42			4.18			4.6
min	0.178			2.54			2.43
max	0.679			6.37			7.21

APPENDIX 2

Figure A 1: Distribution of all building fires per 1000 housing units and census tracts

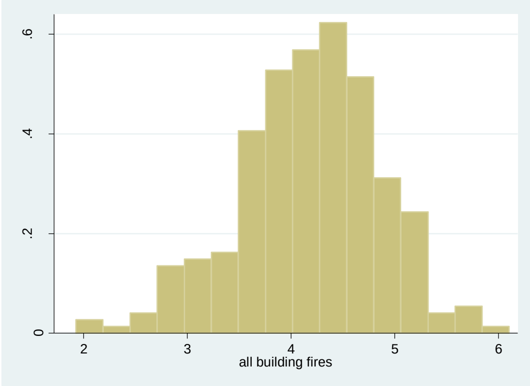


Figure A 2: Distribution of unintentional building fires per 1000 housing units and census tracts

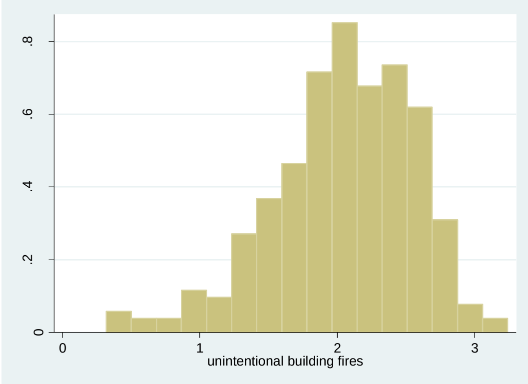


Figure A 3: Distribution of intentional building fires per 1000 housing units and census tracts

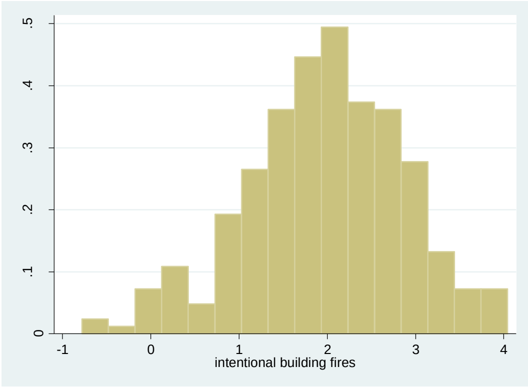


Table A 2: Defined variables

	Definition
Dependent Variable	
all building fires (F1)	A continuous variable indicating the number of building fires per 1000 housing units (in log form). (CAD, NFIRS)
unintentional building fires (F2)	A continuous variable indicating the percentage of unintentional fires per 1000 housing units (in log form). (CAD, NFIRS)
intentional building fires (F3)	A continuous variable indicating the percentage of intentional fires per 1000 housing units (in log form). (CAD, NFIRS)
Independent Variables	
Socio-economic	
poverty	A continuous variable indicating the percentage of households living below the poverty level. (ACS)
median income	A continuous variable indicating the median household income (in thousands). (ACS)
unemployment rate	A continuous variable indicating the number of unemployed people. 16 years and over, as a percentage of the civilian labor force. (ACS)
unemployment rate 16 - 19	A continuous variable indicating the level of unemployment among 16 and 19 year old. (ACS)
unemployment rate 20 - 24	A continuous variable indicating the level of unemployment among 20 and 24 year olds. (ACS)
child	A continuous variable indicating the percentage of households having one child or more. (ACS)
single parents	A continuous variable indicating the percentage of households where a child 18 years old or younger is raised by a single parent. (ACS)
single male 15-17	A continuous variable indicating the percentage of single males between 15 and 17 years old among all males 15 years and older. (ACS)
single male 18-24	A continuous variable indicating the percentage of single males between 18 and 24 years old among all males 15 years and older. (ACS)
age 65	A continuous variable indicating the percentage of households with one householder >=65years old living alone. (ACS)
Housing	
housing unit value	A continuous variable indicating the dollar value per housing unit (in ten thousands). (ACS)
housing unit age	A continuous variable indicating the percentage of building stock built prior to 1939. (ACS)
vacancy rate	A continuous variable indicating the percentage of vacant structures. (ACS)
abandoned structures	A continuous variable indicating the percentage of abandoned structures as a fraction of vacant structures. (ACS)

Table A 3: Summary statistics

VARIABLES	N	mean	sd	min	max
building fires	283	4.186	0.674	1.928	6.103
unintentional fires	283	2.043	0.512	0.318	3.241
intentional fires	275	1.973	0.894	-0.780	4.044
poverty	283	0.394	0.132	0.0620	0.790
median income	283	27.61	11.35	10.36	82.43
unemployment	283	0.289	0.104	0.0530	0.675
unemployment 16-19	283	0.604	0.335	0	1
unemployment 20-24	283	0.397	0.264	0	1
child	283	0.283	0.0991	0.0180	0.581
single parents	283	0.700	0.203	0	1
single male 15-17	283	0.0338	0.0241	0	0.224
single male 18-24	283	0.0443	0.0280	0	0.152
age 65	283	0.104	0.0574	0	0.299
housing value	283	6.112	3.149	1.980	27.86
housing age	283	0.354	0.219	0	0.864
vacancy	283	0.299	0.113	0.0484	0.597
abandonment	283	0.593	0.236	0	1

APPENDIX 3

Table A 4: Defined variables

	Definition
Dependent Variable	
total fire response time	A continuous variable, indicating the time it takes the fire service to arrive on scene, after an emergency call is received. (CAD, NFIRS)
Independent Variables	
budget change	A categorical variable, 0 for the time before the budget was implemented, 01/01/2012 – 08/05/2015 and 1 for the time after the budget was implemented, 08/06/2012 – 12/31/2012. (CAD, NFIRS)
distance	A continuous variable, indicating distance traveled from station to location of incident, in miles. (CAD, NFIRS)
time of the day	A categorical variable, 1 if t = 0600h-1800h, 2 if t = 1800h-0000h, 3 if t = 0000h-0600h. (CAD, NFIRS)
season	A categorical variable, 0 for 01/01/2015 - 03/14/2015 and 10/16/2015 – 12/31/2015, 1 for 03/15/2012 – 10/15/2012, 1 for 10/16. (CAD, NFIRS)
weather	A categorical variable, 0 if no rain, fog or snow was recorded that day, 1 otherwise.
housing density	A continuous variable, constructed as the number of housing units per acre in one census tract. (ACS)
population density	A continuous variable, constructed as the number of people per acre in one census tract. (ACS)
housing unit value	A continuous variable, indicating the dollar value per housing unit, in ten thousands. (ACS)
vacancy	A continuous variable, indicating the number of vacant units per 1000 housing units in one census tract. (ACS)

Table A 5: Summary statistics regression 1

VARIABLES	N	mean	sd	min	max
response time	5,819	4.593	1.793	0.120	18.62
distance	5,818	1.226	0.626	0.100	3.500
housing density	5,731	4.364	1.541	1.326	10.46
population density	5,731	9.245	4.360	0.729	24.33
housing value (in thousands)	5,731	53.51	22.43	19.80	278.6
vacancy (per thousand housing units)	5,731	316.0	103.1	48.40	597.4

Table A 6: Summary Statistics panel

VARIABLES		mean	sd	min	max		Obs
response time	overall	4.526	0.998	1.99	9.09	N =	518
	between		0.836	2.385	7.825	n =	259
	within		0.548	2.121	6.931	T =	2
distance	overall	1.237	0.560	0.25	3	N =	518
	between		0.504	0.325	3	n =	259
	within		0.245	0.337	2.137	T =	2
treatment							
response time	overall	4.752	0.942	2.99	7.98	N =	128
	between		0.6998	3.235	6.805	n =	64
	within		0.634	2.792	6.712	T =	2
distance	overall	1.395	0.571	0.25	2.7	N =	128
	between		0.381	0.775	2.35	n =	64
	within		0.427	0.495	2.295	T =	2
control							
response time	overall	4.452	1.006	1.99	9.09	N =	390
	between		0.864	2.385	7.825	n =	195
	within		0.517	2.047	6.857	T =	2
distance	overall	1.185	0.548	0.25	3	N =	390
	between		0.529	0.325	3	n =	195
	within		0.143	0.385	1.985	T =	2

Table A 7: ANOVA results sample

	N	mean	sd	SS	df	MS	F-stat
poverty							
treatment	50	0.430	0.116				
control	50	0.387	0.139				
between group				0.04734	1	0.047	(2.84)*
within group				1.606	98	0.016	
total	100	0.409	0.130	1.652	99	0.017	
distance before							
treatment	50	0.634	0.294				
control	50	0.920	0.470				
between group				2.053	1	2.053	(13.36)***
within group				15.060	98	0.154	
total	100	0.777	0.416	17.113	99	0.173	
distance after							
treatment	50	1.200	0.302				
control	50	0.920	0.470				
between group				1.957	1	1.957	(12.53)***
within group				15.304	98	0.156	
total	100	1.060	0.418	17.261	99	0.174	

Table A 8: ANOVA results fire index sample

	N	mean	sd	SS	df	MS	F-stat
risk index							
treatment	50	0.645	0.149				
control	50	0.535	0.159				
between group				0.304	1	0.304	(12.85)***
within group				2.320	98	0.024	
total	100	0.590	0.163	2.624	99	0.027	

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ABSTRACT

ECONOMIC WELFARE OF FIREFIGHTING SERVICE IN DETROIT

by

MATTHIAS JUNG

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Advisor: Dr. Michael Belzer

Major: Economics

Degree: Doctor of Philosophy

Chapter 1 is concerned with the effect of public fire service quality on individual utility. I develop a theoretical model to account for fire risk as a function of socio-economic, housing, and spatial factors. I review relevant literature on certain inherent public fire service issues regarding technology and cost structure before I briefly discuss the importance of public fire service with regard to overall social welfare. Finally, I employ equity mapping in a case study to assess the effect of a budget cut on equity of fire service allocation in Detroit.

Chapter 2 examines whether socio-economic factors, various aspects of housing, and spatial features can explain differences in building fire risk across Detroit. Using a complete Detroit fire incidents data set for the years 2008-2012, matched by census tract to American Community Survey (ACS) data for the same period, I employ kernel density mapping and spatial regression techniques to address the research question. Estimations suggest a positive correlation between poverty and fire risk, especially with regard to intentional building fires. In the case of unintentional building fires, no such conclusion can be drawn easily. I find evidence for fire clustering and spillover effects.

Chapter 3 approaches the question of optimal fire station siting in Detroit from a welfare economics viewpoint. Therefore, I assess the effects of a decrease in public budget in 2012 on distributional equity. First, regression analysis is used to determine the effect on response time as an indicator of fire service quality. Second, I use various statistical measures to evaluate intra-city service distribution with respect to equality. Third, I develop a fire risk index and link it to service quality to determine need satisfaction. I find ambiguous effects on distributional equality, while there is strong evidence of the change in budget having a negative effect on equity interpreted as need.

AUTOBIOGRAPHICAL STATEMENT

Author:

MATTHIAS JUNG, born June 22nd, 1984 in Fürstenfeldbruck (Germany)

Education:

2011 - 2015	PhD Economics at Wayne State University, Detroit (USA); Fields: Labor Economics, Health Economics (Thesis: "Economic welfare of firefighting service in Detroit")
2008 – 2009	MA Economics, Wayne State University, Detroit (USA); Field: Industrial Organization
2003 – 2009	"Diplom-Kaufmann", University of Augsburg (Germany); Fields: Health Economics, Public Sector Management (Thesis: "Prevention and flexibility regarding potential poverty in different population groups")

Fields of Research:

Welfare economics

Microeconomics

Poverty

Individual well-being

Public sector management

Awards:

2015	"Mendelson Endowed Award" for outstanding research, Wayne State University, Department of Economics, Detroit (USA)
2009	"PCI-Award" for an outstanding diploma thesis, University of Augsburg (Germany)