# A Novel Approach to Understanding Small Area Variation Within Communities by Using Computer-Assisted Dispatch (CAD) Data

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Geographic variation in the incidence of time sensitive conditions (e.g. myocardial infarction (MI)[1] and stroke[2]) in the United States has been described by the Centers for Disease Control.[3] These annual estimates of stroke and MI mortality by both state and county are based on data from national administrative datasets (e.g. Medicare and National Vital Statistics).

For example, in Colorado, acute MI deaths by county can vary from 10.7/100,000 people to 148.7/100,000 people, almost a 14-fold difference. Although these county level variations are large, there is no data on how acute MI mortality may vary at a more granular level where interventions can be focused, such as census tract. Census tracts are geographic units comprised of approximately 4,000-6,000 people, in comparison to counties, which comprise approximately 100,000 people.[4]

In out-of-hospital cardiac arrest (OHCA), another very important time-sensitive condition, a small amount of research at the more granular, census tract level has been conducted.[5, 6] Data from two cities has shown that certain census tracts within a county have 2-3 times the incidence of OHCA and 1/5 the prevalence of bystander cardiopulmonary resuscitation (CPR). This "small area variation" in OHCA incidence and bystander CPR prevalence has been integral in driving efforts by the public health department, local organizations, policy makers, and healthcare professionals to target community-based educational interventions to promote greater recognition of OHCA and provision of bystander CPR by the public.

Given the fragmentation of the healthcare system, it is not surprising that there is little data on the small area variations of MI, stroke and OHCA. If a community wanted to understand its small area variation in the incidence of these diseases, it would have to combine data from multiple Emergency Medical Services (EMS) providers, emergency departments, and hospital systems. This is both time and resource intensive, and ultimately unpalatable to most communities. However, without this information, it is difficult to assess whether there are certain areas within a county that may be at higher risk than others for having these time-sensitive conditions and need to be targeted for public health interventions.

We propose a novel alternative approach to determining the incidence of time-sensitive conditions in the general population through the use of computer-assisted dispatch (CAD) and medical dispatch data. The vast majority of patients who come to the Emergency Department with time-sensitive conditions like MI, stroke, and OHCA come via EMS. Dispatch centers capture data on important variables: the time of 9-1-1 call, reason for the call (e.g. chest pain), level of response needed (e.g. basic versus advanced life support), time of police/EMS dispatch, reason for call, and severity of illness. For example, when a person identifies an emergent condition, 9-1-1 is called and EMS is activated to respond. The dispatcher must then go through a vast differential of diagnoses in the attempt to understand why the person has called, what the severity of the illness is, and what level of care should be sent to transport the patient. In many communities, this data is then linked to prehospital care records so that a final prehospital diagnosis and disposition is added to each record. In a smaller proportion of these 9-1-1 calls, records are also linked to the eventual hospital disposition.

While there are many CAD vendors used in the different 911 systems across the United States, the geographic and medical dispatch data is often captured in a standardized fashion, making it easier to collect and analyze, as compared to prehospital care records. If this data were analyzed, it would provide a snapshot of the incidence of these time-sensitive conditions, both at the national and local level. By analyzing this data, we may be able to determine key indicators of a community's health and the local small area variation. This data could then be linked to census data to determine the populations most impacted and identify the highest-risk neighborhoods within a community and the socio-econo-demographic characteristics associated with these high-risk neighborhoods.

This line of data inquiry has several important policy implications. While the Centers for Disease Control provide state- and county-level public health data on certain conditions, they does not specifically analyze MI, stroke, or OHCA data at a more granular level. Data from CAD could therefore be used to provide a more detailed picture of a community's health and potential targets for community-based interventions. It also would provide a community with the ability to compare itself to other demographically and economically similar areas throughout the U.S.

There are some important considerations about the use of CAD data for deriving smaller areas of geographic variation. First, selection bias can be considerable, as this approach assumes that the person from the community has called 9-1-1. There are cases in which people with MI, stroke, and OHCA may come by private vehicle, and this information would not be captured by CAD data. This could cause an underestimation of the true incidence of disease. Secondly, a medical dispatch determination of possible stroke, MI or OHCA may or may not be accurate. However, given that the majority of U.S. is using the same medical dispatch protocols for answering 9-1-1 calls and determining the possible diagnoses, this is less likely to have a large impact. Analyzing the subset of CAD records that are linked to prehospital care, emergency department, and/or hospital records could assess the impact of this potential limitation. This would provide an estimate of how accurately CAD data can predict MI, stroke, and OHCA.

The analysis of CAD data to determine geographic variation of time sensitive conditions is a first step in understanding how community health may differ at both a local and national level. Further research in this area must be done to see how CAD and medical dispatch-data derived estimates of MI, stroke, and OHCA incidence compare with other local and statewide datasets (e.g. NEMSIS[7] and Cardiac Arrest Registry to Enhance Survival[8]).

In time-sensitive conditions like MI, stroke, and OHCA, literally minutes can be the difference between life and death. As a result, it is imperative that we begin to use new approaches to data analysis to understand how these conditions vary across smaller areas, so that important public health efforts can be directed at the areas that are most in need.

## References


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