Changes in Urban Healthcare Accessibility: An Analysis of Health-Related Outcomes Using a Synthetic Control Approach

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ABSTRACT

Chicago mayor Rahm Emanuel's 2012 decision to close six of the twelve municipally funded mental health clinics was met with historic public dissent from healthcare practitioners and patients alike. While the immediate reduction in healthcare accessibility for thousands of Chicago residents was analyzed under a qualitative lens, the long-term effect of the policy decision on health outcomes in the city is yet to be understood from a quantitative perspective. The empirical objective of this research is to determine whether a causal treatment effect of the clinic closures can be observed and quantified. This analysis relies upon synthetic control methodology to compare treated time-series outcomes in Chicago to a synthetic prediction of untreated outcomes to determine the causal effect of the policy decision. The findings of this analysis assert the importance of effective data collection on municipal-level health outcomes as a function of improving the validity of causal inferences on local policy decisions. This research illustrates potential barriers associated with the use of synthetic control methodology to analyze treatment effects at the municipal level, as well as illuminates' strategies that would improve future research on the application of synthetic control methodology to analyze municipal-level outcomes.

Keywords: mental healthcare, accessibility, synthetic control, treatment effect, substance abuse, drug-induced mortality

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I. INTRODUCTION

In early 2011, the Chicago Department of Public Health (CDPH) operated twelve community mental health centers, which were distributed evenly throughout the Chicago metropolitan region. By early 2012, the number of active community health centers in the city dropped to six. This significant change in accessibility came as a result of a social service consolidation plan crafted by Chicago's newly elected mayor, Rahm Emmanuel, which aimed to cut the municipal budget by $2.6 million and increase the CDPH's patient care capacity by outsourcing care provision to private providers (Coen, 2019). In addition to providing low-cost psychiatric treatment and therapy for thousands of qualifying patients, the community mental health clinics served as critical resources for affordable substance abuse care and recovery in the urban neighborhoods of the Chicago metropolitan area (Corley, 2012). Following immediate public uproar on the controversial decision, Mayor Emmanuel claimed that the policy would allow more Chicagoans greater access to social services from private psychiatric clinics receiving supplemental funding (Corley, 2012). Sophia Kortchmar, a member of the group Mental Health Movement, responded to this claim with, "We have heard a mountain of evidence…from consumers at these clinics, people who use these services, from therapists, from doctors, from allied organizations all across the city that say no, the transition plan is not working. People are falling through the cracks." (Corley, 2012).

The closure of the mental health clinics, although designed to allow residents within former catchment areas the ability to access any one of the remaining facilities, led to a significant reduction in overall accessibility to mental healthcare resources for Chicago residents (Lyderson, 2015). While catchment areas with traditionally higher levels of socioeconomic status enjoyed minimal changes in mental healthcare accessibility, traditionally underserved communities experienced significant reductions in access to mental healthcare. Although unintentional in the design of the policy, the Emmanuel Administration's social service consolidation plan drastically altered mental healthcare coverage in Chicago neighborhoods that needed it most. While news outlets conducted surveys and interviews on Chicago residents immediately following the 2012 clinic closures, these analyses are limited in their ability to depict the long-term causal effect that the decision maintained on health-related outcomes in the city of Chicago in the years following the closures (Hush, 2021). The lack of quantitative analyses regarding the effect of the social service consolidation plan on health-related outcomes has contributed to a gap in understanding on the unintended impact the decision has sustained on Chicago residents. It is this impact that I endeavor to define and conceptualize for the purpose of contributing to existing literature and future policy considerations.

This research serves to contribute to a limited but growing body of research in applied synthetic control methodology as a strategy for predicting causal treatment effects at the municipal level. The majority of research using synthetic control methodology analyzes outcomes at the state or national level in research areas wherein existing time-series data is bountiful. This research uses synthetic control methodology to determine whether a causal treatment effect can be identified and defined by analyzing mental health-related outcomes in the city of Chicago prior to and following the 2012 social service consolidation plan. The analysis compares annual time-series outcomes for deaths related to drug overdose per 100,000 residents in the city of Chicago against a synthetic prediction for the same variable. The synthetic prediction consists of a weighted average of annual health- and mortality-related donor variables from all 50 states and 38 large U.S. cities that serve to "match" the trends expressed in the actual time-series outcomes. The primary goal of this analysis is to determine whether synthetic control methodology can be effectively applied to predict a casual treatment effect on outcomes related to policy decisions at the municipal level.

The empirical goal of this analysis is the development of a synthetic prediction for actual outcomes related to drug mortality in the city of Chicago following the 2012 community health clinic closures. The results of the synthetic control analysis suggest that although a treatment effect can be inferred, limitations in publicly accessible health-related outcomes for the city of Chicago contribute to a null synthetic prediction. The results of this analysis provide valuable insights into the application of synthetic control methodology on municipal-level outcomes. Further, these findings serve to indicate the importance of stronger data collection for municipal outcomes, specifically those which are health related, as well illuminates useful strategies on how future analyses can effectively measure causal treatment effects within small geographic areas.

II. REVIEW OF EXISTING LITERATURE

Substance Abuse Treatment Care

Existing literature on substance abuse treatment care indicates a relationship between the provision of substance abuse treatment and a variety of health-related outcomes. Studies on the effect of substance abuse treatment care primarily focus on how federal, state and local policies minimize the demand for illicit substance abuse and addiction within their boundaries (Swenson, 2015). Despite receiving significantly less funding than supply-side, police-based enforcement strategies, substance abuse treatment care posits itself as a promising approach to reducing the demand for illicit substance abuse (Swenson, 2015). Recent studies have analyzed the effect of an increase in access to substance abuse treatment centers on mortality outcomes at the county level. Findings from these studies indicate that increasing access to treatment care facilities decreases county-level mortality outcomes by a significant margin, with the most prominent reduction occurring in drug-induced deaths (Swenson, 2015). Further, such findings suggest that the benefits of an increase in access to substance abuse treatment care are more significant among racial minorities, as well as for households in urban counties maintaining relatively low levels of per capita income (Swenson, 2015). These findings support this analysis' use of drug-induced mortality as an outcome variable for understanding the treatment effect of 2012 social service consolidation plan.

A number of studies have analyzed the relationship between substance abuse treatment care and criminal behavior. Research within this branch of literature relies upon Goldstein's (1985) incredibly influential tripartite framework for the drugs-violence nexus, which states that drugs influences criminal behavior through psychopharmacological, economically compulsive, and systemic effects. By viewing substance abuse treatment through the lens of this framework, researchers have asserted that increasing the share of substance abuse care in a community could reduce the use of drugs that lead to violent behavior, as well as reduce general crime among drug users (Bondurant et al., 2016). Contemporary studies have further analyzed the relationship between substance abuse treatment centers and local crime. Evidence from these studies suggest that expanding access to substance abuse treatment centers significantly reduces the social costs associated with violent crime at the county level (Bondurant et al., 2016). Further, such evidence indicates that county-level rates of serious violent crimes, such as homicide and aggravated assault, are most dramatically reduced with the addition of a substance abuse treatment center into an area (Bondurant et al, 2016). The relationship between substance abuse care and crime serves as the logical basis for this analysis' use of crime-related outcomes to formulate the synthetic prediction for drug-induced mortality in the city of Chicago.

Contemporary analyses have explored the effect of substance abuse treatment provider behavior amidst healthcare reform. Such research aims to identify how healthcare provider care varies with an increase or decrease in financial support or tangible assets, such as community clinics. One study analyzes how Substance Use Disorder (SUD) treatment providers in Massachusetts responded to the state's gargantuan 2006 healthcare reform bill, which is cited to be the blueprint for the 2010 Affordable Care Act (Maclean & Soloner, 2015). Initial analysis indicates that the healthcare reform plan drastically increased the share of Massachusetts citizens with SUD treatment insurance, as well as improved overall care for existing and newly insured citizens (Maclean & Soloner, 2015). Compared to providers in states that did not experience significant healthcare reforms, Massachusetts providers increased admissions to SUD treatment centers by 17.1% annually (Maclean and Soloner, 2015). Overall, SUD treatment providers in Massachusetts maintained high levels of healthcare accessibility despite absorbing a high volume of new patients following the 2006 healthcare reform (Maclean & Soloner, 2015). These insights highlight the role that significant changes in access to healthcare resources maintain on health-related outcomes.

Urban Healthcare Accessibility

The concept of accessibility broadly refers to one's "potential for interaction"; that is, how easily accessible opportunities are within a given region according to their respective spatial distribution (Farber & Marino, 2017). Whereas measurements of accessibility identify spatial factors that hinder or support the use of resources within a given region, measurements of utilization rely upon non-spatial factors to determine the degree to which individuals within a given area truly access opportunities (Hawthorne & Kwan, 2012). Existing literature typically defines non-spatial factors as socioeconomic or transportation-related barriers to access, such as a given area's demographic makeup or average household income (Luo & Wang, 2003).

Potential accessibility is defined as one's potential to access opportunities within a region and is primarily dependent on a given area's spatial factors, such as transit availability and physical design (Luo & Wang, 2003). In contrast, revealed accessibility refers to the actual utilization of healthcare resources within a given area and is dependent on both spatial and non-spatial factors (Luo & Wang, 2003; Wang, 2012). Although spatial accessibility is an effective measurement of the physical barriers to access that exist within a given environment, a given area's spatial access does not guarantee that services offered within a region will be utilized by the population (Luo & Wang, 2003). Contemporary research on healthcare accessibility utilizes both spatial and non-spatial factors to determine how socioeconomic and demographic characteristics contribute to spatial access within a given region (Wang, 2012).

Research on healthcare accessibility and utilization within the urban environment primarily seeks to determine the effect of existing urban infrastructure on urban residents' ability to access healthcare services "when and where they are needed" (Hawthorne & Kwan, 2012). Researchers in the field of urban healthcare accessibility rely on a plethora of mixed-method research strategies for effective measurement (Wang, 2012). Whereas research on urban healthcare accessibility has traditionally relied upon GIS data to map urban residents' relative proximity to healthcare services, contemporary research looks to extend GIS measurements to account for "perceived distance", which is dependent on a number of socioeconomic factors. (Hawthorne & Kwan, 2012). Indeed, poor spatial access is significantly correlated with lower urban healthcare accessibility and utilization; however, recent studies indicate that low-income urban residents are significantly less likely to utilize healthcare resources *despite* living within close proximity to quality services (Hawthorne & Kwan, 2012; Wang, 2012). Thus, studies that solely rely upon measurements of potential spatial accessibility fall short in depicting the true barriers that urban residents face in accessing healthcare services. A 2003 study on potential spatial accessibility to healthcare services in the city of Chicago utilized a mixed-method research approach to determine that the city experienced significant, yet minimal variance in healthcare accessibility (Luo & Wang, 2003). However, the researchers conceded that their evidence did not distinguish those dependent on public transit who, as the researchers concluded, would experience significantly lower levels of accessibility (Luo & Wang, 2003).

A growing body of research indicates a strong correlation between healthcare accessibility and a given urban environment's socioeconomic and demographic makeup. Contemporary studies exploring this relationship have indicated that minorities and low-income Americans experience adverse barriers to care and detrimental health outcomes across numerous measures (Sommers et al., 2017; Mahmoudi & Jensen, 2012). Further, recent research on specific barriers to urban healthcare have found that significant racial and economic disparities exist in affordability of care, perceived quality of care and access to timely outpatient care (Sommers et al., 2017). Most relevant within these findings are the racial and ethnic disparities in access to timely outpatient care, as these measurements are likely correlated to urban transit accessibility and affordability. In considering the majority of urban environments in the United States, low-income and minority communities face inadequate public transportation and poor physical space, which leads to a number of life-threatening health consequences, including chronic and cancerous respiratory illnesses (Sommers et al., 2017; Mahmoudi & Jensen, 2012). Although researchers have a limited understanding of the long-term causal factors of such inequalities in healthcare accessibility, most researchers conclude that racial and socioeconomic disparities in health insurance coverage are a critical factor in determining one's accessibility to healthcare coverage and affordability of care (Sommers et al., 2012). Yet, despite evidence that increased healthcare insurance coverage could narrow these disparities, a number of spatial factors have been found to remain significant in hindering the ability of low-income and minority communities to access affordable health care (Luo & Wang, 2003; Sommers et al., 2012).

This analysis aims to contribute to existing literature on the measurement of the relationship between healthcare supply shocks and accessibility to healthcare services. Existing literature on urban healthcare supply shocks are limited in their ability to estimate the casual treatment effect of a certain decision due to limitations in data collection at the municipal level (Bondurant et al, 2018). This is also the case of existing analyses of the 2012 social service consolidation plan, wherein the majority of research consists of interviews and surveys conducted on Chicago mental healthcare patients and practitioners (Coen, 2019). This is undoubtedly related to the laborious nature of data collection on long-term healthcare service provision, which is often difficult to compare across regions and time periods without accounting for a number of extenuating variables (Lou & Wang, 2003). However, the use of the synthetic control approach in this analysis suggests that the application of advanced regression techniques can be accomplished when analyzing healthcare supply shocks at the municipal level. While this analysis fails to generate an accurate synthetic prediction of health-related outcomes for this specific supply shock, this failure is primarily attributed to limitations in publicly accessible data, indicating that the application of synthetic control methodology in other related analyses is entirely plausible.

This research will rely solely upon non-spatial factors in order to determine the effect of changes in healthcare accessibility on health-related indicators in the urban environment. The omission of spatial factors in my analysis is based on underlying assumptions associated with spatial factors that would likely skew the results specific to this research. First, measures of spatial accessibility assume that regions within an analysis are impermeable; that is, variable measurements are locked within the catchment area they are collected in (Luo & Wang, 2003). In the context of this research, it is entirely plausible to assume that citizens in healthcare catchment zones could potentially utilize clinics outside of their immediate vicinity for a number of reasons, including transit costs or work-related travel outside of their catchment zone. This suggests that spatial relation cannot accurately predict where a Chicago resident utilizes mental healthcare resources. Second, the relatively small area of analysis posits difficulty in isolating changes in accessibility. That is, the closure of a health clinic in a specific neighborhood is not likely to levy a significant change in spatial accessibility within a relatively small metropolitan region. This further supports the use of non-spatial factors, such as health- and crime-related outcomes, in isolating the treatment effect of the 2012 clinic closures.

Urban Mental Healthcare Accessibility

Existing literature on urban mental healthcare accessibility is significantly limited when compared to broader research on healthcare accessibility in the urban environment. Nonetheless, research under this topic area contains trends and findings that serve to strengthen my understanding of the literature I aim to contribute to. First, existing literature within this topic area focuses on the relationship between urban youth developmental outcomes and the provision of mental health services (Raval et al., 2019). Although results from these studies are varied, a growing number of studies have indicated that active participation in mental health programs have a significant positive effect on developmental outcomes among urban youth (Walter et al., 2019). Although not explicitly correlated to my topic of research, this relationship serves as a basis of understanding for the notion that urban social outcomes are positively linked to mental healthcare accessibility. Studies on the relationship between urban mental healthcare accessibility and racial and ethnic demographics indicate that the access and utilization of urban mental health resources is stratified along racial lines (Howell & McFeeters, 2008). These findings support conclusions within prior research that correlates race and other ethnic demographic indicators to urban healthcare accessibility and utilization (Kirby et al., 2006; Mahmoudi & Jensen, 2012). These conclusions support the notion that non-spatial factors, such as socioeconomic and demographic factors, are correlated to urban mental healthcare accessibility, which serves as a foundational component of my research.

Studies on urban mental healthcare primarily utilize surveys and interviews in order to determine the short and long-term effect of mental healthcare service provision on indicators of wellbeing and quality of life (Raval et al., 2019). While these studies have the potential to effectively define the social impact of urban mental healthcare provision, they are limited in their ability to depict causal relationships between access to healthcare services and social outcomes (Raval et al., 2019). In contrast, quantitatively based analyses of relationships between urban social outcomes and healthcare accessibility and utilization more succinctly depict causality between these variables (Cairney et al., 2014; Mahmoudi & Jensen, 2012). My research serves to address the underutilization of quantitative analyses in the study of mental healthcare accessibility in the urban environment.

Summary

After a detailed review of current literature, it is abundantly clear that a deficit of research exists on the potential relationship between reductions in access to mental healthcare and mental health-related social outcomes within the urban environment. Contemporary research on urban healthcare accessibility is limited in its ability to identify how changes in access to healthcare services in a given urban environment affects mental health-related social outcomes for urban residents. Similarly, a reliance on survey and interview data in existing literature on mental healthcare accessibility has limited the scope of such research in understanding the causal effect of mental healthcare service provision at the quantitative level. Finally, existing literature on substance abuse treatment care indicates a negative relationship between the provision of treatment care and drug-related mortality and crime at the county level, with more pronounced effects occurring in the urban context (Swenson, 2015). This suggests that significant shocks in access to healthcare resources, such as the 2012 clinic closures, could maintain an effect on health- and crime-related outcomes at the municipal level. This research aims to contribute to existing literature by quantifying the casual treatment effect of the 2012 clinic closures so as to provide a clear linkage between significant changes in healthcare accessibility and health-related outcomes at the municipal level.

III. METHODOLOGY

When researching the causal relationship between an idiosyncratic policy decision and its related outcomes, researchers often face difficulty in isolating the effect of the policy from external factors that may skew time-series data. The city of Chicago, not unlike most large cities in the United States, experiences higher-than-average levels of crime and hospital utilization that are influenced by a plethora of social, economic and political factors. In order to separate the effect of the clinic closures from all other factors influencing arrest- and health-related outcomes in the city of Chicago, a counterfactual scenario in which the Chicago mental health clinics are *not* closed is created. The research utilizes a synthetic control approach to develop a synthetic counterfactual estimate of arrests and hospitalizations related to substance abuse in the city of Chicago, which is then compared to actual “treated” time-series outcomes to determine a causal relationship.

Synthetic control methodology was originally introduced in the seminal work of Abadie & Gardeazabal (2003) wherein the researchers utilized a case study on terrorism in Spain to determine the economic costs of conflict. The synthetic control methodology being used in this research was further conceptualized in Abadie et al. (2010) wherein the impact of Proposition 99 on tobacco use in California is assessed. Synthetic control methodology is commonly utilized in comparative case studies aiming to identify the causal effect of a specific policy decision on time-series outcomes related to the decision in the years following implementation.

A key element of comparative case studies is the development of an appropriate control group. In analyses using synthetic control methodology, the research is reliant on an idiosyncratic event of a relatively significant magnitude, as well as the presence of comparative units that can be measured and observed as independent from the analyzed treatment effect (Coffman & Noy, 2012). As previously discussed, the 2012 social service consolidation plan has been characterized as an incredibly significant policy decision by Chicago healthcare administrators and policymakers alike, thus qualifying the case study as an idiosyncratic event. Additionally, the city of Chicago has a number of comparable units that, with the benefit of synthetic control methodology, include states and mid- to large-size cities in the United States. These observable units are critical for this research in that they represent highly populated, strongly governed regions that are similar in nature to the city of Chicago and have not directly experienced the treatment effect being analyzed.

Although popular in research on the effects of federal and state policy implementation, synthetic control analyses are often underutilized due to the perceived opacity of the methodology (McClelland & Gault, 2017). In the context of my research, Synthetic control analysis posits itself as a reliable strategy for narrowing the undoubtedly broad social impact of the 2012 social service consolidation plan to determine the causal treatment effect on drug-induced mortality in the city of Chicago. Additionally, my research serves to contribute to growing, yet limited body of literature that utilizes synthetic control analysis to measure casual treatment effects of policies implemented at the municipal level of government (McClelland & Gault, 2017).

Model

The research utilizes the synthetic control approach first employed by Abadie et al. (2003) to conceptualize and define a set of weights on covariates from donor pool regressions to establish a synthetic prediction of variable outcomes for the city of Chicago. In the case of this analysis, $c = 0 \ldots C$ is used to index units of analysis. Suppose there exists a single treated unit, denoted as $c = 0$, and several untreated units denoted as $c > 0$. Additionally, let $t = 1 \ldots T$ index time periods, which are organized as years in this analysis. Assume that the treatment exposure, expressed as the 2012 clinic closures in this application, occurs in period $T_0 + 1$. Finally, establish $D_{ct} = 1[\mathrm{t} > T_0] \mathrm{X}\ 1[c = 0]$ as a binary variable equal to 1 if unit s is exposed to treatment in time period t.

Let $y(0)_{ct}$ and $y(1)_{ct}$ represent hypothetical outcomes that define the outcome of unit c in time period t under the effects of the treatment exposure. In this analysis, $y(0)_{ct}$ is the rate of mortality due to drug overdoses in city c during time period t prior to the clinic closures, and $y(1)_{ct}$ is the same rate in the same city after the clinic closure policy is instituted. The difference between the two notation is $\beta_{ct} = y(1)_{ct} - y(0)_{ct}$, which is the causal effect on unit c at time period t. The basic strategy of the synthetic control method is to determine values of $y(0)_{0t}$ in all post-treatment time periods in order to estimate the causal effect of the treatment. Given the estimation of these counterfactuals, it is feasible to estimate β_{ct} for all post-treatment periods.

Put simply, a synthetic control is a weighted average of outcomes compiled from a pool of untreated control units (Hollingsworth & Wing, 2020). Suppose that $x_t = (y_{1t},\ldots,y_{Ct})$ is the 1 X S vector for the compilation of outcomes that succeeded in each of the donor comparison units for time period t. Let $\omega = (\pi_1,\ldots, \pi_C)^T$ be a C X 1 vector of weights. A synthetic control group for the outcome of the treated unit is determined by the function:

$$y_t^* = \sum_{c=1}^{C} y_{ct}\pi_c$$

or

$$y_t^* = x_t\, \omega$$

The majority of comparative case studies which use the synthetic control approach rely upon the strategy as synthesized and applied in the seminal work of Abadie et al (2003). However, this methodology posits restrictions to the weights of donor predictors to non-negative values that summed to one, which inherently prevents extrapolation beyond which the convex hull of the donor pool (Hollingsworth & Wing, 2020). Additionally, the traditional synthetic control approach utilizes an OLS method for choosing synthetic control weights, which may over fit the pre-treatment data by highlighting idiosyncratic correlations that are not associated with the true data-generating process (Hollingsworth & Wing, 2020). As such, this analysis utilizes a method called Synthetic Control Using Lasso (SCUL) to establish donor weights. The SCUL approach allows for the creation of a higher dimensional donor pool than that which is provided under most other approaches to synthetic control. Put simply, the SCUL approach differs from other synthetic control methodologies by its use of a penalized regression method, such as lasso, to determine the synthetic control weights of the analysis. The lasso regression method chooses synthetic control weights to solve the function:

$$\widehat{\omega}_{lasso} = arg\ min_{\omega} \left(\sum_{t=1}^{T_0} (y_{0t} - x_t \omega) + \lambda |\omega|_1 \right)$$

The lasso regression method utilizes an identical squared prediction function as the traditional OLS method, however the SCUL method consists of an additional penalty that rises with the complexity of the vector of weights (Hollingsworth & Wing, 2020). With the addition of this penalty, coefficients that are large in an unconstrained OLS regression shrink toward zero, and small coefficients shrink down and approach zero (Hollingsworth & Wing, 2020). Given that some coefficients are set equal to zero, the lasso method is able to estimate coefficients that minimize the penalized sum of squares (Hollingsworth & Wing, 2020). Put simply, the SCUL methodology is an intuitive, straightforward approach to quantitatively analyzing the effect of a treatment on time-series data.

IV. DATA

The data collected for this analysis can be divided into two categories: treated and untreated outcomes. Treated data consists of annual drug mortality outcomes collected in the city of Chicago from 2000 to 2018 and serve as the time-series outcomes from which a "match" is to be established in the pre-treatment period. Treated time-series health outcomes from the city of Chicago consist of annual time-series outcomes in 18 time periods of drug-related mortality per 100,000 residents in Chicago. Treated variable outcomes were collected from the City of

Chicago Health Atlas (CCHA), a publicly accessible data portal that is annually audited by the CDPH. Variable data collected from the CCHA can be stratified by neighborhood, however, as previously mentioned, spatial factors were omitted in this analysis for the purpose of strengthening the application of the synthetic control method.

This analysis' untreated outcomes, or donor pool dataset, consists of 603 state- or city-specific annual time-series outcomes between 2000 and 2018 from a number of administrative data sources. City-specific variable data in this analysis consists of rates of arrest for drug-related crimes per 100,000 residents and is collected from a modified Universal Crime Reporting (UCR) dataset. Annual arrest outcomes were collected from 33 municipal police departments and were chosen based on arrest types that are consistent with existing research on crime and substance abuse care, such as aggravated assault and illicit drug possession. Cities were included in the analysis based on their relative population density, with all 33 cities chosen being within the most populated 50 cities in the country. This was done to ensure that city-specific data was comparable to treated outcomes collected in the city of Chicago. Additionally, the modified UCR dataset was utilized to collect annual state-specific rates of drug-related causes of death per 100,000 citizens. Cause-of-death outcomes were collected in all 50 states and included mortality rates for a number of drug-related causes, including suicide and drug overdose. The use of annual measurements for the collection of donor pool co-variates is due primarily to limitations in publicly accessible data on health- and crime-related drug use outcomes.

V. RESULTS AND DISCUSSION

This section outlines the procedural framework for the SCUL regression method, as well as presents estimates of the treatment effect analyzed in the SCUL procedure. The target unit analyzed is mortality related to drug overdose per 100,000 residents in the city of Chicago. The SCUL method is used to develop counterfactual estimates of drug-related mortality rates for each set of time-series outcomes using untreated outcomes on city- and state-specific covariates. Optimal weights were selected by use of a rolling-origin cross validation procedure, which allows donor weights to differ for each target product. The synthetic counterfactual is estimated by multiplying the cross-validated weights by the post-treatment values from the donor pool. Given that the Emmanuel administration's social service consolidation plan was fully implemented in April 2012, the initial time period in the post-treatment period for this analysis is designated as 2012. Although some community mental health clinic closures occurred in the latter half of 2011, it is unlikely that an observable treatment effect on mortality would be identified in the span of three months. Limitations in publicly accessible drug mortality outcomes in the city of Chicago prevent the use of the monthly periods for the treated variable, which would significantly increase the likelihood of the SCUL procedure identifying smaller treatment effects.

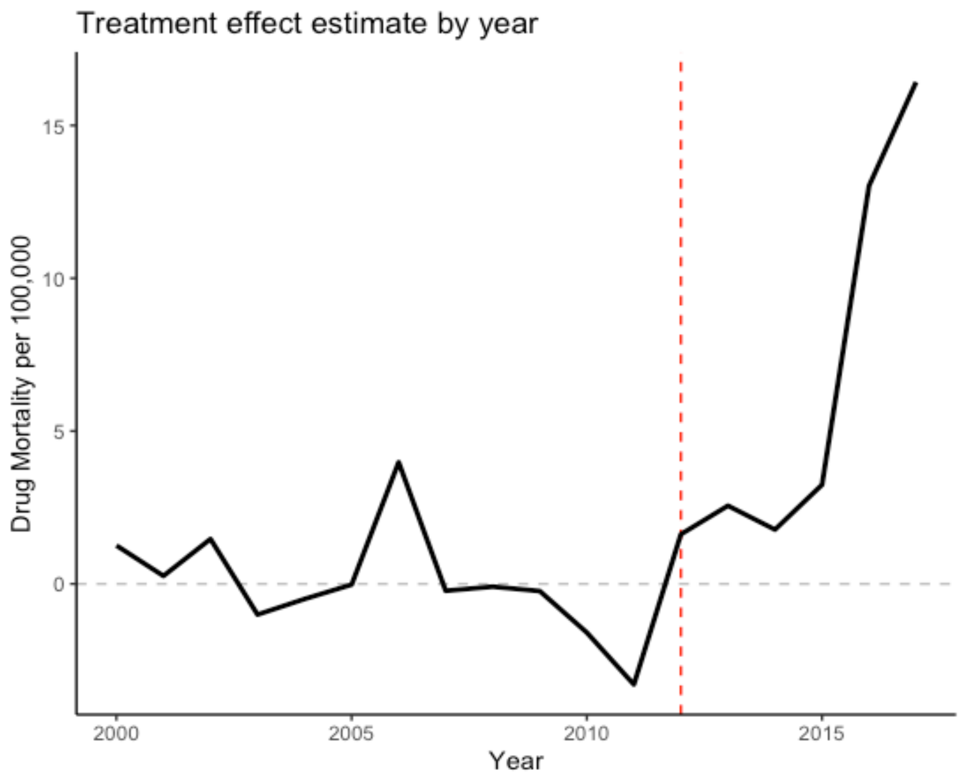
Choosing Synthetic Control Weights

Figure 1 depicts observed annual drug mortality rates in the city of Chicago between 2000 and 2018. Figure one simply serves as a visualization of the treated variable over time, with a delineation in 2013 dividing the pre- and post-treatment periods. A number of observations can be made from this visualization. Figure 1 depicts a clear and obvious increase in the rate of drug overdose mortality in the city of Chicago in the post-treatment period. The treated data series additionally indicates an immense, yet steady rise in the rate of drug overdose mortality between the years 2015 and 2018. This further supports the hypothesis that the 2012 health clinic closures maintained a significant treatment effect on Chicago residents, as mortality outcomes are typically lagging in nature and require several post-treatment periods in order to observe a significant effect.

Interestingly, the treated data series exhibits a significant rise in the treatment variable in 2011, the year immediately preceding the observed treatment effect. This rise in drug mortality rate immediately preceding the post-treatment period could potentially be linked to the initial shock in access to the community health clinics following the adoption of the social service consolidation plan. While the last health clinic slated in the consolidation plan was officially closed in April of 2012, the city began shutting down clinics in underserved communities as early as August 2011 (Corley, 2012). This reduction in accessibility to services, coupled with the closure of more health clinics throughout the last several months of 2011, may explain the slight increase in Chicago drug-related mortality as small treatment effect. This is, however, not an entirely sound assumption for a number of reasons. Although immediate reductions in service were made in the latter months of 2011, it is highly unlikely that they led directly to an increase in drug abuse mortalities. Further, although this data exhibits a significant shift in the dependent variable of this analysis, it does not serve as evidential towards proving an explicit treatment effect. This data simply serves to suggest that given the hypothesized increase in the rate of

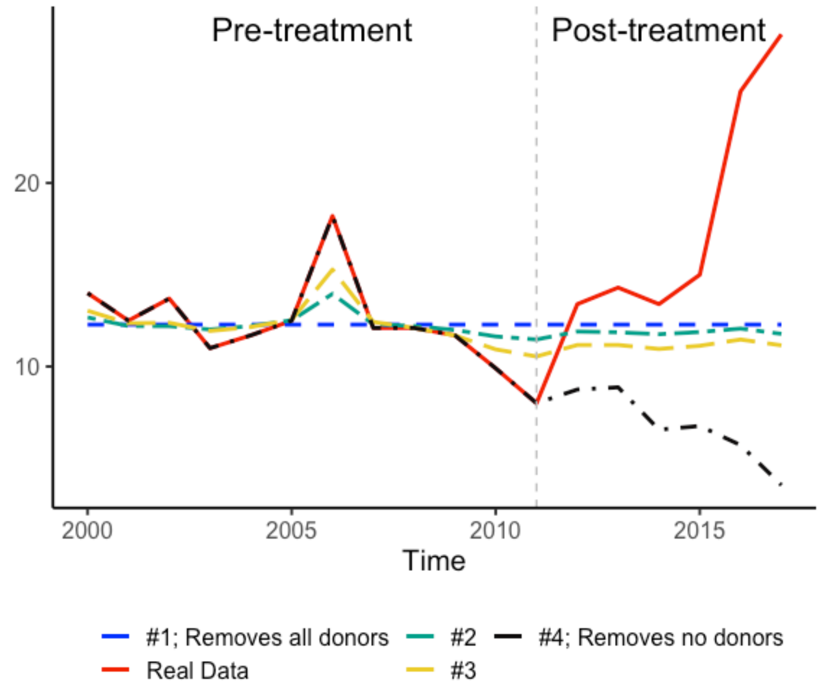
Chicago drug overdose mortality immediately following the 2012 mental health clinic closures, it is plausible that an observable treatment can be identified through further analysis.

Figure 1: Actual Treatment Outcomes Across Time



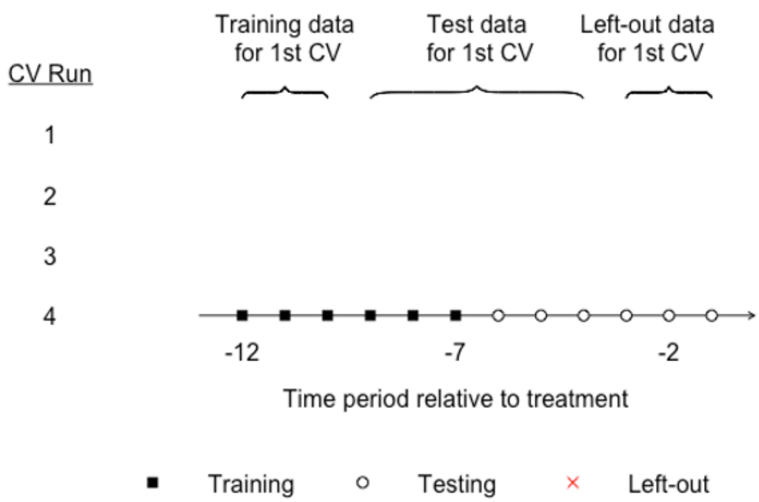
Under the guidelines of SCUL methodology, synthetic control weights are selected using a penalized regression method, such as the lasso. We begin the SCUL procedure by choosing the penalty parameter, denoted as γ in the above equations. In order to determine the penalty parameter, four lasso regressions are run to determine which γ value best matches the pre-treatment data. Figure 2 compares four lasso regressions to the pre-treatment data to determine which penalty parameter is to be used to determine the synthetic control weights. In general, the SCUL prediction chosen for the analysis is one that most effectively captures the underlying pre-treatment outcomes, as this prediction is eventually used to predict a counterfactual estimate of the treatment data had the effect never occurred. Figure 2 identifies lasso regression #3, wherein some coefficients were removed, as the most effective at predicting the pre-treatment outcomes of the analysis. Still, however, lasso prediction #3 does not strongly match the pre-treatment outcomes, suggesting an insignificant level of correlation between the pre-treatment outcomes and the donor pool. More analysis is necessary to determine the degree to which coefficients in the donor pool can be matched using the selected lambda penalty.

Figure 2: Actual Data Vs. SCUL Predictions for Different Lambda Penalties



The next element of the SCUL procedure includes running a rolling forecasting origin cross validation. Cross validation is a relatively simple procedure wherein a dataset is partitioned into two subsets, training data and test data, where the optimal analysis is determined through the use of the test data. Essentially, cross-validation is a strategic procedure for determining which synthetic control weights best match the underlying factors in the pre-treatment observations *and* develop a suitable post-treatment prediction. The primary justification of these procedural elements is to ensure that predictions for treated values across all post-treatment time periods is determined accurately, thus model optimization is critical. The application of rolling-origin cross validation in this analysis ensures that post-treatment observations are not used to make predictions of pre-treatment outcomes. Figure 3 serves as a visual representation of the cross-validation procedure with the use of pre-treatment data. The square icons represent the training data, the circle icons represent the test data, and the X icons represent data unused in this specific cross-validation run. Figure 3 indicates that one cross validation was run, with the maximum amount of training time periods being determined to as 6. Ideally, the number of cross-validation procedures would exceed four, with the number of training time periods increasing until the maximum level. The value of the maximum number of training time periods in this analysis is relatively low for the SCUL procedure, further indicating the presence of an insignificant relationship between the donor pool and the treatment data. The cross validation does not suggest that the SCUL method is flawed in its ability to predict the treatment effect, but rather that the relatively small size of the donor pool leaves little room to cross-validate and remove coefficients.

Figure 3: Cross-Validation Procedure for Pre-Treatment Observations



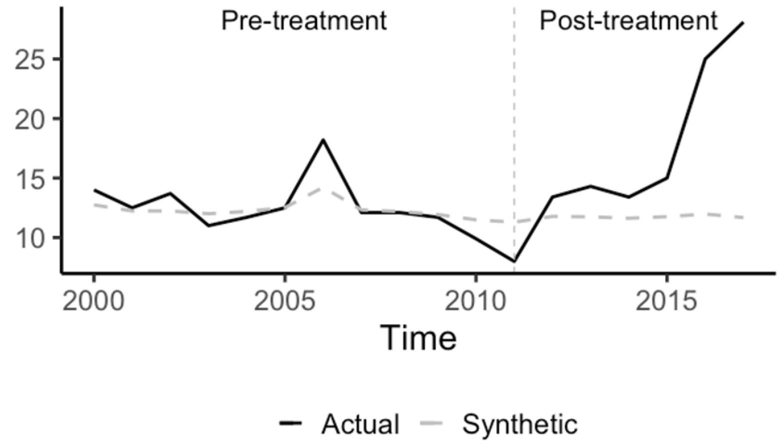
Creating the Synthetic Control Group Using SCUL

The main results of the analysis appear in Figure 4, where the synthetic prediction for the rate of mortality due to drug overdose in the city of Chicago is plotted against the treatment data series. Based on the results indicated in Figure 4, it is clear that an accurate synthetic prediction was not able to be made from the donor pool, indicating that an accurate match between the pre-treatment donor coefficients and the treated data series was unable to be made. While the SCUL prediction relatively matches the pre-treatment outcomes in the years 2006 and 2007, the weighted coefficients generally fail to match the treated time series outcomes in the pre-treatment period.

A number of explanations can be offered concerning the failure to create an accurate prediction of drug overdose mortality outcomes using the SCUL procedure. First, the donor pool co-variates, which included 603 annual city- and state-specific rates for arrests and mortality related to drug abuse, are simply ineffective as predictors of the actual pre-treatment outcomes in the city of Chicago. Put differently, the trends observed in the donor pool data could not serve as a match to the actual time series data, thus nullifying the capacity for the SCUL procedure to accurately predict a counterfactual estimate of the treated time series in the post-treatment period. This conclusion does not necessarily undermine the casual relationship between healthcare accessibility and drug-related mortality and crime outcomes, as existing literature indicates that these variables maintain a significant relationship (Swenson, 2015; Bondurant et al., 2018). Rather, such variables prove insufficient to matching the target series data in the specific context of this analysis.

A second explanation for the inconclusive results presented in this analysis considers the 2012 mental health clinic closures as an idiosyncratic event. This notion expresses that the analyzed treatment data series is simply too unique to generate a match between the donor pool co-variates, resulting in a null prediction of actual outcomes in the post-treatment period. The observed rise in the rate of drug overdose mortality can thus be described as a unique event to which other variables fail to match. A third explanation supports this claim in the assertion that the treated data series in the pre-treatment period is too volatile to form a significant match with the co-variates selected from the donor pool. In order to develop an accurate counterfactual estimate in the post-treatment period, donor pool co-variates must not only match the variation of the treated series in the pre-treatment period but match the variation specific to each unit of analysis as well. Figure 1 depicts significant variation in the treated data series during the pre-treatment period, which decreases the likelihood of an effective match between donor pool co-variates, resulting in a null prediction of actual outcomes in the post-treatment period. This effect could undoubtedly be remedied by the use of monthly or quarterly outcomes for the treated data series, which would reduce variation and increase the likelihood of an accurate match between the donor pool co-variates.

Figure 4: Actual Time-Series Data vs. Synthetic Counterfactual Prediction



Evaluation of Synthetic Control Fit

An evaluation is made on the relative "fit" of the synthetic control weights in matching the pre-treatment treated data series. In the case of any lasso regression, there is no assurance that the method will select a combination of weighted donor units that resembles the treated units during the pre-treatment time period. An adapted version of the Cohen's D threshold is applied in this analysis in order to measure the pre-period fit of the donor pool data. Table 1 shows pre-period fit and treatment effect estimates for several synthetic control predictors. The Cohen's D statistic in Table 1 serves as the average annual difference between the observed values for each unit and the synthetic prediction, measured in standard deviation units. This SCUL procedure utilizes a pre-specified Cohen's D threshold of 0.25 to measure pre-period fit. Each prediction in Table 1 has a Cohen's D value over the threshold, indicating that each lasso prediction poorly predicts the treated data series in the pre-treatment period. The closest regression to the Cohen's D threshold is lasso regression 3 with a value of 0.36.

Table 1: Pre-Period Fit and Treatment Effect for Different Lambda Predictions

Method	Penalty parameter	Cohens D (pre-period fit)	ATE estimate
SCUL procedure using:			
Cross-validation for determining penalty	1.27	0.47	6.44
SCUL using naive guesses for penalty			
Naive guess 1: Max penalty (remove all donors)	1.87	0.64	5.92
Naive guess 2: Random penalty	1.35	0.50	6.32
Naive guess 3: Random penalty	0.93	0.36	7.02
Naive guess 4: No penalty (include all donors)	0.00	0.00	11.50

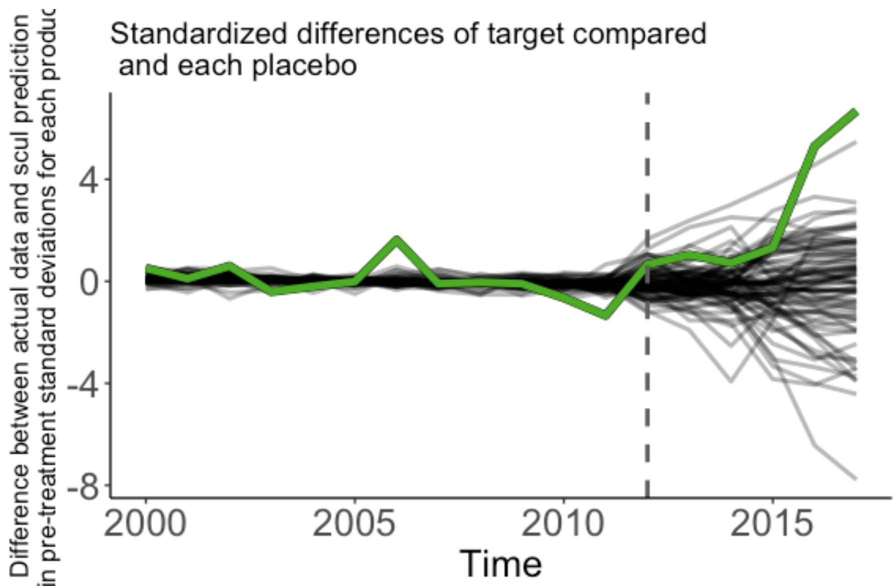
Statistical Inference of SCUL Estimation

In order to determine whether the observed treatment effect estimates are statistically significant, the estimates are compared against pseudo-treatment effects that were estimated for many of the untreated donor units. Placebo units are characterized as city- and state-specific annual rates of arrest and mortality related to drug abuse in 33 large cities and all 50 states. The distribution of pseudo-treatment effect estimates represents the null distribution of no treatment effect. The placebo analysis serves to illustrate how the fit of the SCUL counterfactual prediction deteriorates over time. In order to be considered statistically significant, the synthetic prediction must be large enough to overcome this deteriorating fit.

Figure 5 depicts the difference between the treated data series for Chicago drug-related mortality outcomes and the synthetic prediction in green. The pre-treatment difference between the two data series is relatively small, with values remaining relatively close to zero with the exception of small spikes in 2006 and 2011. In Figure 5, the gray lines represent the pseudo differences between each donor pool variable and its synthetic prediction. The graph only includes estimates that pass the pre-specified Cohen's D threshold of 0.25, The placebo lines in the graph are given transparency so as to allow areas with a greater density of placebo units to appear darker. The shading observed in Figure 5 highlights the deterioration of the counterfactual fit across time.

Provided that statistical inference essentially functions to compare the magnitude of the treatment effect estimate to the cloud of placebo estimates, placebo units that depict poor model fit will increase the spread of the null distribution. To mitigate the spread of the null distribution, placebo units with poor pre-treatment fit are removed by use of the pre-specified Cohen's D threshold of 0.25. However, post-treatment fit worsens with time even for those placebo units with satisfactory pre-treatment fit. This deterioration implies that statistical power will worsen as time from initial treatment increases. In other words, as the placebo distribution grows wider, the minimum effect size needed to be considered significant at a given level also rises.

Figure 5: Estimation of Standardized Differences for Each Placebo Estimation



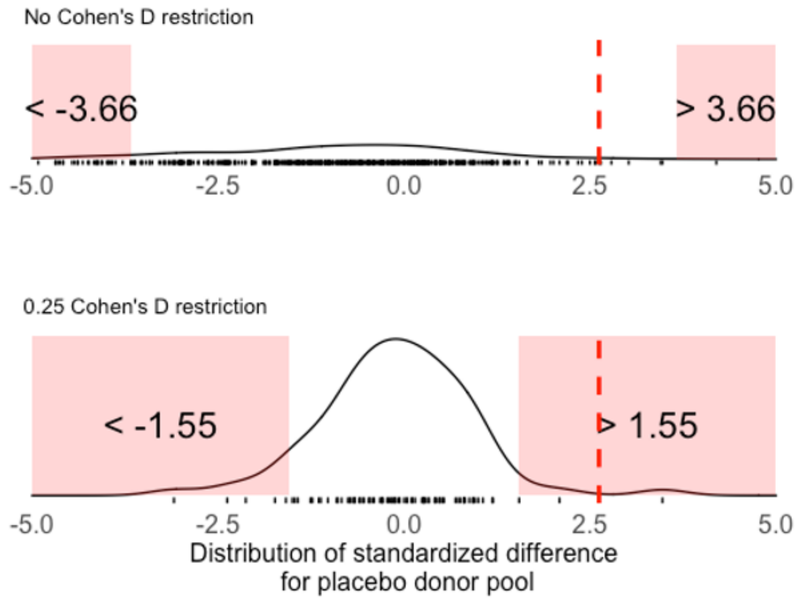
The weights from the SCUL procedure are not representative of the share of the synthetic prediction composed by each donor series. Provided this, it is critical to understand the relative share that each weight maintains on the synthetic prediction over time. Figure 6 expresses the relevant contribution and the lasso coefficient for each donor unit in the synthetic prediction. Given that relative contribution can change over time, the measurement is reported for both the first and last time period. Of the nearly 600 donor pool co-variates analyzed only four within the lasso regressions effectively match the pre-treatment actual outcomes. Further, the weighted average of donor pool data series only accounts for 28% of the share of the synthetic prediction, signaling that the donor pool variable selection accounts for the insignificant results of the analysis. Ideally, the synthetic prediction would be composed of several of the donor pool variable data. However, given that the donor pool includes only 19 time periods, with a pre-treatment timeframe of only 12, it is not entirely surprising that the average synthetic prediction was only comprised of four variables. Figure 6 effectively diagnoses the factors that contribute to the failure to create an accurate counterfactual prediction of the treated data series in the post-treatment period.

Figure 6: Share of Synthetic Prediction by Accepted Donor Coefficients

	Share for First Prediction	Share for Most Recent Prediction	Coefficient
Intercept	0.76	0.72	13.14
georgia_cod_total_suicide_crude_rate	0.16	0.18	-0.23
pennsylvania_cod_drugs_all_other_crude_rate	0.06	0.06	1.38
newjersey_cod_drugs_all_other_crude_rate	0.01	0.02	0.38
kansascitypd_arrests_agg_assault_tot_arrests_rate	0.01	0.02	0.00

Finally, Figure 7 depicts the distribution of average treatment effect for the post-treatment time period. This is achieved with the production of two distributions: one with no Cohen's D restriction on the placebo pool, and one with a Cohen's D restriction of 0.25. The treatment effect estimate is added to each distribution and designated as a red dashed line. Generally, more compact distributions are desired on the theoretical basis that wider distributions are less able to distinguish smaller treatment effects. As evidenced by Figure 7, the placebo distributions for this analysis were significantly wide, indicating that the overall treatment effect in the post-treatment time periods was unable to be effectively determined. Additionally, Figure 7 outlines the average treatment effect as immensely higher than what would be considered plausible, thus proving that SCUL procedure was ineffective in producing an accurate synthetic prediction.

Figure 7: Placebo Distribution and ATE Estimate in Pre-Period Standard Deviations



VI. CONCLUDING REMARKS

Rahm Emanuel’s 2012 social service consolidation plan can easily be interpreted as the most consequential decision of his tenure as the city’s mayor. In the nine years that have followed the policy decision, patients and practitioners of the now closed Chicago community mental health clinics have displayed unrelenting public outcry against the decision’s long-term effect on the quality of life and social wellbeing experienced by Chicago residents. Despite this, however, limited research has been conducted on how the Mayor’s decision impacted mental health-related outcomes in the years that followed the 2012 decision. This research aims to answer this gap in understanding through the application of synthetic control methodology as a strategy for understanding the decision’s impact on mental health-related outcomes in Chicago. This analysis utilizes a synthetic control methodology to develop a counterfactual estimate of health-related outcomes in Chicago following the clinic closures in 2012. Although the applied synthetic control method was unable to create an accurate counterfactual prediction, the findings do not disqualify the notion that the policy decision levied adverse effects on mental health outcomes for Chicagoans. Further, the inconclusive results of this analysis highlight the importance of stronger data collection on health outcomes at the municipal level, as meaningful analysis of causal outcomes related to changes in healthcare accessibility is futile until this is achieved.

This research primarily serves to contribute to a limited but growing body of research in applied synthetic control methodology as a strategy for predicting causal treatment effects at the municipal level. The analysis compares annual time-series outcomes for deaths related to drug overdose per 100,000 residents in the city of Chicago against a synthetic prediction for the same variable. The synthetic prediction consists of a weighted average of annual health- and mortality-related donor variables from all 50 states and 38 large U.S. cities that serve to "match" the trends expressed in the actual time-series outcomes. Several conclusions can be drawn from the analysis that serve to strengthen future research using synthetic control methodology on outcomes at the municipal level.

First, the potential for meaningful causal inference from the results of this analysis is limited by the relatively small size of the donor pool series. The application of the synthetic control approach requires a relatively high volume of time-series data in order for accurately estimate the synthetic prediction of post-treatment outcomes. Donor pool units in this analysis come from a number of administrative data sources and include 756 state- or city-specific covariates over the period of 2000 to 2018. However, a significant proportion of these covariates were unused in the lasso regressions due to the presence of missing values, as well as the existence of treatment effects that would have skewed the relationship between the average synthetic prediction and the actual post-treatment outcomes. Future research may benefit from the inclusion of consistent, untreated donor pool datasets that span over a significant period of time. The presence of such data is dependent on the strong collection of observations at the municipal level, which varies significantly by data type.

Second, the relatively small volume of observable outcomes for the treatment data contributes to a low likelihood of a sustainable match occurring between the average weighted counterfactual and the actual outcomes. The SCUL methodology is more accurately able to estimate a synthetic counterfactual prediction as the number of time periods for the actual time series outcomes increases. As such, the publicly accessible data on mortality due to drug overdose in the city of Chicago, which served as the treatment variable, is limited to annual observations collected since the year 2000. When this data is compared against the year of the hypothesized treatment effect, a clear and significant rise during the post-treatment time periods can be observed. However, the number of actual time series observations in this analysis is simply too minimal to provide a significant match with any number of coefficients in the donor pool. Further research could likely more accurately develop a counterfactual synthetic prediction with the use of health-related indicators organized by biannual, quarterly, or monthly observations that extend beyond the scope of two decades. The use of such data sources in this analysis was limited to the time and resource constraints of the researcher, however further analyses can be conducted to identify treatment variables that could provide meaningful causal inferences on the treatment effect of Emmanuel's 2012 social service consolidation plan.

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