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Data Shop

Data Shop, a department of Cityscape, presents short articles or notes on the uses of data in housing and urban research. Through this department, the Office of Policy Development and Research introduces readers to new and overlooked data sources and to improved techniques in using well-known data. The emphasis is on sources and methods that analysts can use in their own work. Researchers often run into knotty data problems involving data interpretation or manipulation that must be solved before a project can proceed, but they seldom get to focus in detail on the solutions to such problems. If you have an idea for an applied, data-centric note of no more than 3,000 words, please send a one-paragraph abstract to david.a.vandenbroucke@hud.gov for consideration.

Law as Data: Using Policy Surveillance to Advance Housing Studies

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Abstract

Within the large body of literature evaluating the role of various demographic, geographic, and economic factors in housing-related outcomes, law is often neglected as an influential variable. The growing field of legal epidemiology is popularizing the use of law as data in quantitative analysis. As with any other dataset, it is imperative that legal data are accurate and meet high quality control standards. To that end, a method known as policy surveillance was developed to ensure the reliability and reproducibility of legal data and can be used to evaluate the impact of law. Policy surveillance is a type of scientific legal research that produces robust, scientific data for empirical research by mapping, or tracking, laws and policies and their characteristics across jurisdictions and over time.
Abstract (continued)

This article introduces readers to policy surveillance as a method to create empirical legal datasets, using two examples. The first is a cross-sectional state-level dataset covering fair housing protections in all 50 states and Washington, D.C., as of August 1, 2017. The second is a cross-sectional city-level dataset covering nuisance property ordinances in the 40 most populous cities in the U.S., as of August 1, 2017. These types of empirical legal datasets identify gaps and trends in policy and facilitate evaluation studies exploring the impact of law on housing outcomes.

Introduction

Social scientists have long investigated the variation in housing-related outcomes across time and space. The body of knowledge studying changes in racial segregation, poverty concentration, and displacement effects of gentrification is robust. Although housing studies generally use data from multiple sources to control, estimate, and proxy for various demographic characteristics, social conditions, and economic measures, law has largely been neglected as a causal variable that influences housing-related outcomes. The absence of law as an explanatory variable is peculiar given the abundance of legal regulation governing housing. One reason quantitative researchers omit law from their analyses is the challenge of translating law from text to data. Analysis of housing law remains largely confined to law review literature using legal analysis and qualitative methods.

Conducting a scientific study of law requires legal data that meet the quality standards of scientific peer-reviewed research. To address this need, a method to scope, collect, and code the law was established. The method, known as policy surveillance, allows for the “ongoing, systematic collection, analysis, interpretation and dissemination of information about a given body of public health law and policy” (Chriqui, O’Connor, and Chaloupka, 2011). Since its first use, the method has been revisited and standardized through trial and error, methodological scholarship, and a Delphi process (Presley, Reinstein, Webb-Barr, and Burris, 2015). The placement of studies using policy surveillance in top-tier journals is further evidence supporting the rigor of the method and the data that are produced.

The study of housing and housing-related outcomes is a prime example of a study that can benefit from the use of scientifically created legal data. Housing law is abundant and generally unstudied: a dearth of evaluation of laws such as state and local fair housing protections, impact of landlord-tenant law on housing stability, or the potential adverse effects of housing code enforcement on poor tenants exists (Gutman, Moran-McCabe, and Burris, forthcoming). Scholars at the Policy Surveillance Program at Temple University’s Center for Public Health Law Research created three
cross-sectional housing datasets in 2018: (1) state fair housing protections; (2) state landlord-tenant law; and (3) city-level nuisance property ordinances.

In this article, we review two of the three published datasets: state fair housing protections and city nuisance property ordinances. First, we provide an overview of the policy surveillance methodology, including quality control measures, then we provide a summary of the features of fair housing protections and city nuisance property ordinances. We end with the limitations of legal datasets and a call for the use of policy surveillance in the study of housing.

**Policy Surveillance: A Scientific Method to Create Legal Data**

Policy surveillance, a form of scientific legal mapping, is the ongoing, systematic collection, analysis, and dissemination of policies across jurisdictions and over time (Burris et al., 2016). This approach includes establishment of the legal framework and conceptual model, an iterative process of refining coding schemes and procedures, and rigorous quality control (Anderson et al., 2013). Creating a legal dataset requires different skills: legal research, a close understanding of the topic area, and ability to design variables in a way that will be conducive for quantitative analysis. Rarely will one person combine all these capacities; due to this rarity, a transdisciplinary team could be an ideal solution (Burris et al., 2016). The recommended number of team members is three, with at least one member being a lawyer or policy expert.

Although policy surveillance as a method was created with public health research in mind, the methods can be applied to any legal field and not health law per se. For example, a study published in the *American Journal of Public Health* used policy surveillance data on minimum wage laws by state and month from 1980 through 2011. The outcome variable in the study was infant mortality and birth weight, however, any other outcome variable—economic, social, demographic—would have been compatible for analysis with the legal data (Komro et al., 2016). Given the success of policy surveillance in illuminating the role of law in population level health, the time is right for the popularization of the method to other areas of inquiry in which law can be an important causal variable.

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The policy surveillance process begins with the conceptualization and scoping phase, which involves determining the topic and parameters of your scientific legal mapping study. An important consideration during this phase is whether a cross-sectional or longitudinal dataset is warranted, and if longitudinal, what the meaningful time period is. During the next phase, the team conducts background research and writes memoranda to analyze the legal landscape (that is, the jurisdictional unit of analysis—federal, state, or local law—and the important features of the law—such as prohibited conduct, exemptions, and penalties). Additional memoranda are written that explore the law in detail within a sample of jurisdictions. By studying the sample of jurisdictions researchers may get a sense of the variation in the law and the feasibility of continuing the study. With respect to state fair housing protections, for example, key points of variation included which protected classes were regulated under the law, what types of actions are regulated under the law, and what exemptions exist in the law, among others.

If the initial project scoping and memoranda drafting phase deems the project viable, the researchers then develop search strings and conduct keyword searches using legal research databases (such as Westlaw or LexisNexis) to identify and record citations of relevant statutes, regulations, and ordinances. For example, search terms from the nuisance ordinance dataset included chronic nuisance, abatement, and disorderly house. Using the recorded citations, the researchers collect a sample of relevant legal text from the state legislatures’ and local cities’ websites.
Based on a review of a sample of relevant laws, a list of important features is developed to fully capture the landscape of the chosen topic based on the project's predetermined scope. These important features, or constructs, are then used to develop coding questions. The questions are constructed in a form that makes them easily translatable to data: binary, multinomial, or numerical. To code the law, the researchers answer the coding questions with the relevant legal text that was collected. Importantly, the goal of coding is to identify the observable features in the law, not to interpret the law.

Quality control is the keystone of the policy surveillance process. To ensure data quality, each step of the research process—identification of laws, inclusion of relevant citations, and coding—is implemented redundantly. Two researchers independently research and code the relevant laws to identify and resolve divergences. Error rates are calculated by comparing all differences in coding among researchers, and divergences are resolved through group consensus. Redundant coding is checked by a research supervisor, and error rates are recorded in a research protocol. As a final quality check, statistical quality control (SQC) is implemented to provide a population parameter estimate for the overall error rate of the datasets. SQC is conducted by taking a random sample of the data for an additional round of redundant coding.Datasets should aim to guarantee with 95 percent confidence that the overall dataset error rate is 5 percent or below.

Using the policy surveillance method, a research team of four lawyers conducted in-depth, cross-sectional legal assessments of state fair housing protections in the 50 U.S. states and Washington, D.C. and city nuisance ordinances in the 40 most populous U.S. cities. We discuss these datasets in the following sections as examples of the opportunity for legal data in housing.5

Policy Surveillance and Housing Law: Two Datasets

State Fair Housing Protections

One housing outcome that is especially of interest for social scientists is the distribution of race and income across areas. What are the contributing factors to the persistence of racial segregation and the increase in income segregation in U.S. cities? The historical and qualitative account of the role of law in the creation and maintenance of segregation is compelling (Rothstein, 2017), however, there is almost no quantitative evaluation of the legal mechanism that was put in place to combat housing discrimination—fair housing law. What we do know is that housing discrimination persists one-half of a century after the enactment of the federal Fair Housing Act (FHA) (Gutman, Moran-McCabe, and Burris, forthcoming).

The FHA, signed into law in 1968, prohibits discrimination in housing-related transactions for individuals who are members of a protected class—these include race, color, national origin, religion, sex, familial status, and disability. The FHA provides protections to certain individuals seeking to rent or purchase a home from discriminatory actions such as refusing to rent or sell, discriminatory advertising, and refusal to make or allow reasonable accommodations.

5 Both datasets could be found on LawAtlas.org, a depository of policy surveillance datasets.
The FHA, however, only provides the minimum floor of protection for renters and buyers. Many states have chosen to adopt their own fair housing policies, some of which provide more expansive protections than the federal law. As of August 1, 2017, Mississippi was the only state that did not have a fair housing law.

**Exhibit 2**

Effective 1 August 2017, 22 states and the District of Columbia included sexual orientation as a protected class in their fair housing law.

State laws vary on which protected classes are included, the types of discriminatory actions that are prohibited, and when discrimination is exempt under the law. For example, some states include sexual orientation (23 jurisdictions—see exhibit 2) and gender identity (19 jurisdictions) as protected categories. Fourteen states include source of income as a protected class, which research suggests could address discrimination against voucher holders (Tighe, Hatch, and Mead, 2016). However, not all those states include housing vouchers under that protection. Eleven states include housing vouchers under the source of income protection, whereas three explicitly exclude housing vouchers. Texas law does not include source of income and furthermore, preempts local jurisdictions within the state from enacting such protections.
Exhibit 3
Count of number of states that include a certain protected class in their law effective 1 August 2017.

The findings from this dataset (exhibit 3) raise important questions, such as whether adding new categories of protected classes is effective at battling discrimination for covered individuals. Further, the variation in exemptions—the situations in which the fair housing protections do not apply—begs questions that can only be answered with more data on the operation of landlords, such as how many landlords and sellers fall under the different exemptions provided under the law.

City Nuisance Property Ordinances

Eviction is a housing-related outcome that is of growing interest in the literature. One legal mechanism Desmond (2016) exposed that potentially contributes to the epidemic of evictions is city nuisance property ordinances (NPO). NPOs (exhibit 4) require landlords to regulate the conduct of their tenants, sometimes through eviction, and often penalize them when they fail to do so. Although these laws were initially enacted to target drug use, many ordinances now include a wide range of actions that the city deems to be a nuisance (Desmond and Valdez, 2012). NPOs can have consequences with a significant impact on public health. For example, some ordinances consider calls to law enforcement to be nuisance activities, thus discouraging tenants from calling the police when necessary. These laws, which may force tenants to choose between calling the police in an emergency and being threatened with eviction, can have a disproportionate effect on domestic violence survivors and people with disabilities, who may have to call the police for help more often than others (Werth, 2013).
Effective 1 August 2017 in 28 of the 40 most populous cities of the U.S. disturbance is considered a nuisance activity.

The main concern about NPOs that arises from the literature is the impact on the housing stability of victims of domestic violence who seek emergency assistance. Indeed, five of the cities studied explicitly consider 911 calls for emergency service as nuisance activities—although exceptions apply. Twenty-eight cities deem a disturbance, breach of peace, disorderly conduct, or similar behavior to be a nuisance. With such a broad concept of nuisance activity, it would not be hard for a tenant, particularly one who is a domestic violence survivor, to be accused of creating a nuisance. Although domestic violence-related incidents are exempt from being considered a nuisance in 6 of the 40 largest cities, 30 of these jurisdictions do not exempt any conduct from their definition of nuisance. In addition, 20 of the cities with NPOs specifically include eviction as a possible way to abate the nuisance, which may contribute to the problems that these ordinances can cause. The most common penalty that may be imposed for failure to abate a nuisance in the cities studied is a fine—which could be capped by law at $100, $200,000, or not capped at all.

Having an empirical legal dataset of NPOs is the first step to evaluate the impact of various elements of the ordinances on eviction and their disparate impact on victims of domestic violence. Such research will allow advocates to call for specific changes to ordinances to ensure that they achieve their intended consequences. Further, by focusing on the 40 most populous cities, the dataset provides a baseline of how these ordinances look on average in the largest U.S. cities.
Legal Data: Limitations and Opportunities

Policy surveillance is a valuable tool for housing researchers. Robust legal data can help both illuminate questions about the law and its impact and provide data for analysis to find answers. However, every legal dataset has at least two limitations.

The first is the gap between law on the books and the enforcement on the ground. Fair housing law is a prime example. Despite the protections provided under federal and state law, research has identified large gaps between the prevalence of discrimination and instances of enforcement (Abedin et al., 2017). Legal data only provides information about the law and not the actual enforcement, compliance, or adherence to it. The second limitation is that datasets do not often cover all the layers of law that operate in a certain geographical area. For example, although Philadelphia’s NPO does not include an exemption for victims of domestic violence, Pennsylvania state law preempts the enforcement of any municipal ordinance that penalizes people for contact made for emergency assistance by or on behalf of victims of abuse, victims of crime, or individuals in an emergency (53 PA. CONS. STAT. § 304). To be able to capture exactly the laws that govern the lives of people in a certain jurisdiction, Federal, state, and local law needs to be taken into consideration.

The fact that housing law has been relatively unstudied does not mean that it doesn’t have an impact on every aspect of housing—it just means that we do not know the severity, degree, or direction of the impact. Proliferation of housing-related legal data will enrich the literature and offer new and novel avenues of investigation.

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