

A photograph showing a group of four people in a meeting. A man in the center has his hand raised, and a woman on the right is gesturing with her hand. They are all smiling and appear to be in a collaborative discussion.

COMMUNITY-ENGAGED RESOURCE CENTER

Increasing the Rigor of Quantitative Research with Participatory and Community-Engaged Methods

A Participatory and Quantitative Methods Guidebook

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About This Guidebook

The experiences and insights of community members can strengthen quantitative research, but they are often locked out of the research domain. This guidebook describes the values and importance of participatory methods and offers tools and examples for how to incorporate these methods into research. Our aim is to equip quantitative researchers across multiple disciplines, including economics, demography, quantitative sociology, and data science, with a robust set of tangible strategies and theoretical considerations for using participatory methods in their work.

How does my quantitative research benefit the communities I am researching? Unfortunately, researchers do not ask this question enough to the appropriate stakeholders: community

In this guidebook, you will find:

- case studies and actionable participatory strategies for quantitative researchers to use during the five common stages of research projects
- “Defining the Community” worksheet, with guiding questions for quantitative researchers to consider when deciding which community members to collaborate with during research projects
- three theoretical considerations linking the goals and methods of quantitative and participatory research

members with lived expertise. Communities that have historically been excluded from collaborating on research design and implementation, especially communities of color and communities with low income, are searching for more equitable and inclusive research methods, approaches, and findings that can begin to repair past policy and research harms.

At the same time, quantitative researchers are increasingly concerned that standard research methods are unable to effectively engage communities, collect accurate data, and skillfully explore systemic inequities. Although participatory methods—or community-engaged processes that collaborate with community members in research—are often associated or conflated with qualitative research, their principles provide quantitative researchers with tangible tools and approaches to make sure research is more rigorous, equitable, and policy relevant. Using participatory methods is a way to ensure that quantitative research is ethically and equitably grounded, produces more robust data and findings, and is translated to equitable policy action.

We invite all quantitative researchers to envision a more equitable research paradigm and to pursue this vision together with the true experts in the policy fields of interest: community members with lived experience.

Positionality Statement

Our team includes one Boricua, one Black man, one cisgender Indian woman, and two cisgender White women. Our educational attainment spans from bachelor's to doctoral degrees. Our research draws on economics, education, public health, social work, psychology, public policy, sociological and anthropological methodologies. As a group, we bring lived experiences to our work, including gentrification and displacement, food insecurity, and immigration or diasporic experiences. Our advisors, mentors, and reviewers for this resource include community researchers Dung Ngo and Helen “Skip” Skipper, as well as Urban Institute colleagues Rita Ko, Rekha Balu, Margaret Simms, Alena Stern, Elsa Falkenburger, and Lauren Farrell. We work at a relatively well-resourced and predominately White research organization based in Washington, DC. We acknowledge the extensive history of intentional and unintended harm that research organizations have caused to structurally marginalized communities. As a team, we are committed to the values and lenses of meaningful community engagement, complex personhood, equity, and justice in creating and sharing our work. Ultimately, we value lived experiences as expertise and reject the notion that only technically trained researcher are experts.

Key Terms

Bias: In scientific research, bias refers to any flaw in the design of an experiment or analytic model that would influence the results. There are myriad ways this could occur, from selection bias to confounding variables to faulty measurement. This kind of bias is distinct from *objectivity* in that it is not a commentary on the researcher but on the nature of the experiment. However, bias is commonly used to refer to personal biases—such as those based on individual experiences, relationships, and perspectives—that can compromise a researcher’s objectivity.

Objectivity: A central principle of traditional scientific research, which asserts that research should be practiced independently of personal perspectives, emotions, or prejudices to reduce undue influences of personal biases in the research process. Bias is typically reduced by creating or adding distance between researchers’ preexisting beliefs/incentives and the new information (research) they are studying. While reducing bias through a measured and careful review of evidence is an important aspect of research, excising all biases generated from social and cultural context is not possible in a vacuum. Collaboration with community members is a helpful way to achieve stronger objectivity, which can highlight biases that may not be apparent to the researcher.

Participatory Methods: Methods that use the [leadership, input, and reflections from communities](#) that are directly impacted by or engaged with the issues being studied to guide analytic choices. Participatory methods allow for engagement with communities throughout all phases of a research project. By design, they recognize and center the valuable and unique perspectives, experiences, and input that communities bring to the research process.

Positionality: A person’s positionality is the intersection of all their identities and experiences. Who they are, how they are situated in society, the powers and privileges they hold, and their past experiences—all combine to shape the perspectives they bring to life and work. Examining the positionality of an individual (a team or an institution) is a common participatory research tool to understand and address imbalanced power dynamics between project teams and community partners.

As discussed in [Exploring Individual and Institutional Positionality](#), a researcher’s social and intersectional positionality can compromise *objectivity*.

Positivism: This term derives from natural science disciplines, such as physics, chemistry, and biology, and it has influenced the development of orthodox research paradigms in the social sciences. Positivism is a scientific paradigm that posits that the world operates under a collection of immutable natural laws, which can be observed and verified through independent, objective evidence. These observations are made by conducting experiments that are carefully controlled to remove observer influence and bias. Exporting the assumptions of positivism from the hard sciences to social sciences can create few challenges, including stripping key variables from consideration, obscuring how local context generates different outcomes, and preventing critical reflection of hypothesis generation.

Quantitative methods: Methods that describe, measure, predict, and explain a phenomenon through statistical and causal analysis. In contrast to qualitative methods, which use narrative tools like interviews and focus groups, quantitative methods use quantifiable data and models to test hypotheses and identify patterns. They encompass a wide range of analytic techniques, such as data collection approaches (surveys, primary vs. secondary data), measurement approaches (index measures vs. single indicators), modeling approaches (regressions), research designs (experiments), and data science (machine learning). They are also used across disciplines, including economics, demography, quantitative sociology, and data science. Quantitative researchers therefore have an expansive set of tools with which to support community-based research.

Researcher independence: This principle holds that individuals who conduct research should be free from undue influence that may hamper their ability to remain objective. Researchers therefore should be independent of political, economic, or relational pressures and should disclose any potential conflicts of interest when submitting their work.

Embedding Participatory Methods in Each Phase of the Research Cycle

Community-engaged or participatory quantitative research has been demonstrated to produce accurate, actionable, and collaborative quantitative research, which is representative of the aspirations and research goals of community members. When adapted purposefully, quantitative research is critically important to support the needs and goals of marginalized communities (Fine et al. 2000), and it is “well placed to chart the wider structures within which individuals live their everyday experiences, and to highlight the structural barriers and inequalities that differently racialized groups must navigate” (Gillborn, Warmington, and Demack 2018). However, quantitative researchers sometimes do not have access to the tools or infrastructure needed to incorporate robust community collaboration into their workflow.

The sections below provide an overview of some ways to embed participatory methods into all phases of the quantitative research process. We explore case studies and actionable participatory strategies quantitative researchers can use during the five common stages of research projects: (1) research and protocol design, (2) data collection, (3) data processing and analysis, (4) research and data interpretation, and (5) research dissemination and data access.

1. Research and Protocol Design

Engaging communities in research from the beginning—including during hypothesis generation and protocol design—is a way to make sure that the questions being asked and the variables being studied are relevant to the needs and preferences of the community. Although it is important to develop community collaborations along all phases of the research cycle, it is particularly impactful to do so at the very beginning of projects, because that is when community members have the greatest opportunity to influence the direction, purpose, and process of the research. Collaboration at this stage will lay the groundwork for achieving research and data justice, in which communities that bear the greatest burden from data collection also receive short- and long-term benefits from that research.

However, quantitative projects too often exclude community members’ perspectives and unique insights during the early task of hypothesizing key causal, nonlinear, time-delayed, or other systemic effects (Martin et al. 2020). Using participatory methods can highlight new causal relationships or confounding variables that could be included in the research project from the start. One way that community members can bring unique context, understanding, and lived experience to hypothesis generation is **by collaboratively helping to sketch out how causality will be included in the research questions.**

For example, in the Humber region of the United Kingdom, researchers used participatory modeling methodology known as “fuzzy cognitive” mapping to collaborate with community residents and subject matter experts. Together, they used this strategy to analyze the economic impact of locally fostering bio-based energy production. The co-construction of the local economic, social, and political system representation began with a series of workshops with key stakeholders who identified important grouped, linked, and weighted key factors. These workshops then allowed researchers to construct adjacency matrixes and linear/sigmoidal mappings, and, through an iterative process with key stakeholders, fine tune a cognitive model, which served as a solid basis for future modeling and estimation work (Penn et al. 2013). In the end, including community members in the design phase enabled researchers to inform causality and future research.

Another way that community members can improve the quality of quantitative research during the design phase is by **supporting the alignment of overall research questions with survey protocols**. For example, community members can work with researchers to develop survey length and order of items as well as question phrasing, vocabulary, or response options so that they align most strongly with the research goals initially set by both parties. By **aligning the research design with trauma-informed research approaches**, community members can also highlight how past research surveys have alienated or stigmatized them to make sure new studies and surveys do not repeat those mistakes—and, ideally, disrupt such harmful patterns.

Regardless of whether a research project is studying systems, such as employment, housing, or wealth inequality, community members can contribute in **creating an inventory of the positive or negative causal factors that drive outcomes** and/or contextual factors that may moderate or mediate the effect of those outcomes. This allows researchers to focus on salient drivers in their research questions and hypotheses, increase the rigor of research with more robust causal modeling, and more holistically examine complex research topics like intersectional equity or the study of how inequities related to various social identities can overlap.

EXAMPLES FROM THE FIELD

- **Participatory causal, causal loop, system or fuzzy cognitive mapping:** Researchers have used these strategies to compare and contrast how community members and researchers think about the causes of present-day inequities and to integrate this knowledge into the creation of research questions (Burns 2018; Lopes and Videira 2017; Penn et al. 2013). Typically, the process includes (1) convening researchers and community members, (2) establishing common assumptions about the system of interest using definitions and data, (3) breaking into small groups for people to list positive and negative factors influencing outcomes in the system, (4) bringing the full group together to map identified factors with nodes and then connecting the nodes with positive or negative arrows, and (5) reflecting on patterns worth exploring in the upcoming research project. With care, this process can be used to include community members with low income, low literacy, or disabilities in the mapping.
- **Community Advisory Boards (CABs):** A project-based CAB is a diverse group of community members selected, typically by a research team, to voice community perspectives as coleaders and/or advisers on a research project. This group can support all phases of research. The [Tools and Resources for Project-Based Community Advisory Boards](#) provides information about planning, forming, and operating a CAB (Arnos et al. 2021).

2. Data Collection

There are many just and equitable ways to approach data collection; the more equitable forms of data collection often correlate with more robust research. One early pioneer in this field was the sociologist W. E. B. Du Bois, who conducted quantitative and qualitative community-based studies focused on racial inequality and intersectionality of race and class in the post-Reconstruction era (Green and Smith 1983). His work—including his landmark study titled the *Philadelphia Negro* (Du Bois 1996) and his innovative work on data visualization at the 1900 Paris Exposition¹—required the respectful embedding and collaboration of local Black communities, and it led to groundbreaking and impactful research in emancipatory sociology.

This history of Du Bois's work shows the importance of community members co-leading and collaborating on a large swath of data collection activities. In the context of surveys, **community members can contribute to the creation of targeted**

sampling plans and test questions to reduce respondent error, ensure data collection measures are community/culturally competent, and build relationships with research participants to increase sample size. For example, in the Household Exposure Study, community organizers in Northern California requested the inclusion of key chemicals they had come across in their day-to-day work to the pollutant exposure analysis, showing the value of participatory methods in secondary data collection. The primary data collection was adjusted, and the project was able to demonstrate that chemicals from heavy oil combustion activities were detectable indoors in certain Richmond, California, neighborhoods, which informed a successful lawsuit showing that the city had violated state environmental law (Balazs and Morello-Frosch 2013).

Community collaboration can support secondary data or big data collection/compilation to effectively answer quantitative research questions. For example, **community members can collaborate on the selection of variables in a given dataset and on the time period and the priority geographies of interest in the data collected.** This collaboration can be especially important in aligning the final secondary dataset used in the analysis with the research questions developed or in surfacing novel local data sources.

One challenge researchers may experience is choosing between collecting variables validated in prior lab or survey and new variables suggested by community members. To address this challenge, researchers can share the justifications for why certain measures are traditionally used with community partners and transparently discuss the pros and cons of deviating from those measures. Also, researchers can use both measures and perform sensitivity analysis, then decide which measures work better—jointly with community members—during the analysis phase (see the next stage of research “Data Processing and Analysis”).

EXAMPLES FROM THE FIELD

- **Community-engaged surveys (primary data collection):** The *Community-Engaged Surveys* includes tips on how to test protocols, outreach, analysis, and dissemination of surveys (Harrison et al. 2021). Community members can help design sampling plans.
- **Crowdsourced data or citizen science projects (primary data collection):** These projects provide sensors, data portals, or other ways for residents to directly generate their own data; they are effectively used in the health, environmental, refugee resettlement, and housing fields^a (Naik 2016; Samulowska et al. 2021; Silvertown 2009; Smith et al. 2022; Tserstou et al. 2017). As evidenced by The Hive^b machine learning project, these projects can also provide community members with opportunities to surface community assets or new directions for research in large scale data projects (e.g., refugees identifying common meeting spaces for building new water/sanitation stations).
- **Collaborative neighborhood mapping (secondary data and big data collection):** Community-perceived neighborhood boundaries do not always line up with common block groups, zip codes, or PUMA boundaries; instead, they can vary across social groups (e.g., cultures, income, race/ethnicity, age, or historic usage). Participatory mapping can help surface these differences (Deng 2016) and disrupt harmful historical patterns of disempowerment (Parker 2006). New boundaries can be incorporated either by joining/aggregating preexisting geographic units or by creating brand new geocoded boundaries using [GeoJson.io](https://www.geojson.io/) (Catney, Frost, and Vaughn 2019; Coulton et al. 2001; Maman et al. 2009).

^a Camille Braswell, “Ending Environmental Harm for Healthy Communities,” *Medium* (blog), January 25, 2023, <https://medium.com/local-data-for-e-quitale-recovery/ending-environmental-harm-for-healthy-communities-5111c67d6b4e>; “Hacking into History,” Zooniverse, accessed September 15, 2023, <https://www.zooniverse.org/projects/tim-maps/hacking-into-history/about/research>; and Erik Wallenberg, “The Young Lords’ Fight for Environmental Justice in NYC,” *Edge Effects*, July 29, 2021, <https://edgeeffects.net/young-lords/>.

^b Charles Beames, “One Giant Leap For Mankind: Managing The Global Refugee Crisis From Space,” *Forbes*, June 18, 2019, <https://www.forbes.com/sites/charlesbeames/2019/06/18/one-giant-leap-for-mankind-managing-the-global-refugee-crisis-from-space/?sh=497292e632b7>.

3. Data Processing and Analysis

This phase of the research life cycle (e.g., model selection, sensitivity analysis, etc.) is where it is less common to include participatory methods. This is in part because of an assumed lack of community members' competence—especially young people, people with disabilities, or people with limited schooling—to engage with the theoretical aspects of data processing and analysis (Nind 2011). This deficit-based notion can be challenged when researchers think of this phase as an iterative feedback loop, instead of a discrete “mechanical application of a method” (Thomas and O’Kane 2006).

As a first step, it is important to evaluate the data acquired during data collection for “missingness” within key variables—that is, absence of key variables. **A community conversation can help inform how to deal with missing values (e.g., zeros, imputation, or deletion) and the selection of proxies for key topics of interest. It can also help researchers think through whether the acquired data are fit to answer specific questions about key communities or subgroups of interest,** and it provides a natural stop to a potentially harmful research process if they are not (e.g., the data are not representative of key populations of interest). It can assist researchers prepare data so that iterative analysis can be conducted more easily in partnership with community members. As shown in the “Examples from the Field” below, data processing strategies can include disaggregating preliminary statistics or decomposing preliminary regression outputs to better demonstrate disparate effects across groups of interest. Data processing creates the space for both researchers and community residents to test assumptions made initially in research design, related to what data are available, what is measurable, and what equity impact certain data (or lack of data) can have.

This work has been done successfully in a few projects. One example is the Healthy Neighborhood Research Consortium and Moving Mapper project, where researchers collaborated with Boston community members to map and evaluate residential moves in local neighborhoods with big data—specifically the Federal Reserve Bank of New York/Equifax Consumer Credit Panel, which contains quarterly observations on numerous financial variables for more than 13 million individuals. In addition to supporting the selection of research questions, data, and neighborhood boundaries, community members helped adjust the mapping visualization to better stratify the data by socioeconomic status using credit scores (an imperfect proxy chosen through team discussions about socioeconomic status) (Daepf et al. 2022). Community collaboration helped inform a more effective gentrification measure with visualized neighborhood-level moving rates and a network detection methodology to identify pairs of communities people were likely to move between.

There are two areas with space for innovation within participatory data processing and analysis. First, involve communities in discussing and testing the assumptions made in the model selection process. For example, in checking for model misspecification, **community members can help assess whether there are new variables or interaction terms needed; whether there are any omitted, irrelevant, or confounding variables; or whether there is functional form misspecification.** Even if they lack the terminology, community members can narrate whether there is a parametric relationship. Second, **community members can provide feedback during sensitivity analysis** by commenting on the chosen weights given to various parametric values in a model (which are informed by a priori assumptions) or by reflecting on the comparison between parametric and nonparametric models. This step will require researchers to carefully explain the limitations of chosen variables and models to community collaborators, including bias or generalizability.

Machine learning algorithm is an area of quantitative research that is growing rapidly, and for this reason, it is imperative that researchers provide greater transparency in analysis. This can be seen in the health care industry, where machine learning algorithms are used to prioritize resources for the sickest patients. These measures have been shown to exhibit racial bias by under-identifying sick Black patients as eligible for programs and resources reserved for “high health risk” patients (Obermeyer et al. 2019). Black patients go to the hospital less during serious medical emergencies and are less likely to be referred for further treatment (Odonkor et al. 2021). This is, in part, because structural factors—such as racial income disparities, differential access to health care, differential treatment by health providers, and historical mistreatment—have created differences in quality of care. In this example, participatory methods engaging Black and white patients could have revealed the inadequacy of metrics, such as “hospital utilization rates” or “projected future health costs,” by highlighting differential community experiences with the health care system and helped identify alternative proxy variables or outcome metrics to be included in the prediction algorithms and modeling. With the advent and pervasiveness of machine learning and artificial intelligence in people’s daily lives, participatory methods are key to mitigating bias and ensuring data justice.

Lastly, researchers must aim to make sure that timelines are feasible to collaborate in a meaningful way. This requires holding space and time for orienting community members to the research process, including concepts, methods, and terminology, as well as discussing potential trade-offs of certain analytical decisions.

EXAMPLES FROM THE FIELD

- **Disaggregated data (primary and secondary data):** Given existing data constraints, distinguishing between groups in an analysis can be crucial in answering key questions of interest for the community. When considering which groups of people to aggregate, it can be helpful to incorporate community member context and sense of shared history.³
- **Imputation (secondary or big data):** Some data limitations that prevent disaggregation (e.g., lack of race and ethnicity data) can be addressed with imputation. The Urban Institute’s *Ethics and Empathy in Using Imputation to Disaggregate Data for Racial Equity* uses a nationally representative sample of credit bureau data to highlight examples of “ethics checkpoints” researchers should consider when inputting race/ethnicity in research (Stern et al. 2021).
- **Decomposing effects (primary, secondary, or big data):** Researchers can use statistical strategies, such as the Kitagawa-Oaxaca-Blinder decomposition, multilevel analysis, multilevel regression with poststratification, or quantile regressions, to isolate sources of inequality (Evans et al. 2018; Kröger and Hartmann 2021; Rahimi and Hashemi Nazari 2021; Sevak et al. 2022). These strategies create space for both researchers and community residents to test and adjust assumptions made in the research design, which can lead to more accurate selection of parameters or weights and ultimately to more stable subgroup estimates.

³Jonathan Schwabish and Alice Feng, “Considerations for Ensuring Data Aggregation Is as Inclusive as Possible,” *Urban Wire* (blog), February 15, 2022, <https://www.urban.org/urban-wire/considerations-ensuring-data-aggregation-inclusive-possible>.

4. Research and Data Interpretation

Without community perspectives, bias and error in modeling can generate harmful research conclusions. One example of this is the *Moynihan Report*, drafted by Daniel Patrick Moynihan, assistant secretary of labor in 1965. The report originally intended to advocate for the expansion of Civil Rights Act–related racial equality policies. However, its focus on the interpretations of research, which asserted that “broken families” were driving Black unemployment,

pathologized Black families and shaped the treatment of Black families by federal agencies.² Importantly, the primary issues with the psychological and sociological research cited in the report arose in this fourth research phase.

Collaborations with community members can help increase the rigor of interpretation of analysis, especially in projects that focus on the conditions, experiences, or outcomes of people of color. In the Tribal Core Capacity Program, a participatory research project in partnership with the Ramah Navajo Tribe, community members identified the importance of modifying a federal assessment tool of health services based on their interpretations of survey data. This led to better tools for assessing gaps in tribal health services, something that would not have been achieved without the perspective of community members (Cashman et al. 2008). Community members also can help researchers identify what research means in the community context. For example, communities may have insight into why results show up in specific ways, how well results reflect lived experience, and what other factors or variables not previously accounted for could be driving results.

When including community members in the participatory interpretation of research results, it is important that researchers provide data in a plain, digestible, and tangible format. Clearly labeled data visualizations and nontechnical summaries can support community members without statistical or technical background.

A potential tension can arise during this research phase when the interpretations of findings by community members differ from that of researchers. At such times, researchers should be careful not to leverage power dynamics and deprioritize community member interpretations, either because they do not align with researcher perspectives or because researchers do not fully grasp what community members are communicating; doing so can harm relationships and create mistrust of researchers and their motives. Instead, researchers should endeavor to create space to discuss discrepant interpretations and aim to collaboratively reach a conclusion, or at least be willing to include multiple interpretations of the same data in the final report. Once the project has concluded, researchers should inform communities on how their feedback and interpretations will be used in final reporting and dissemination.

EXAMPLES FROM THE FIELD

- **Data notebooks (primary data interpretation):** After the first phase of survey collection, data notebooks—scalable forms of survey follow-up with community members (1,000–1,500 respondents)—are compiled. Data notebooks involve creating a booklet with visualizations of primary and secondary data, which is used to systematically collect open-ended interpretations of the research by community members. Their responses are then aggregated and synthesized using survey methods (Martí 2016).
- **Data interactives or data chats (primary, secondary, and big data interpretation):** Data interactives or chats provide a facilitated space for community members to share observations and conclusions about research findings. While data sharing like this can be used across the research process to engage communities, in this phase it can help ensure a more robust interpretation of quantitative data that may inspire collective action by community and policymakers alike (Cohen et al. 2022; Murray, Falkenburger, and Saxena 2015). Additionally, the process of planning for a data interactives or chats is a useful exercise for making data more accessible at all phases of research.

5. Research Dissemination and Data Access

In traditional scientific research, it is standard practice to widely disseminate the results in academic publications and limit data access to researchers—and to not return data back to community members. The reasoning for this practice includes a need to reduce re-identification risks for individuals involved in the data as well as an assumption that community members would have no use for the data. Although data security and privacy are crucial aspects of all quantitative projects, it is important to balance these concerns with creative approaches to research dissemination and data access.

To disseminate research results in more participatory ways, **it is important that researchers accept community members as valued audience and decisionmakers.** This could mean creating additional products tailored for a community member audience or not publishing certain products in traditional venues like academic journals at the request of a community. **Community members should be directly involved in the dissemination process by contributing to the final written products, developing appropriate formats for products, and forming effective community-engaged dissemination plans, including using social media, local news, and community meetings.** Community members have access to different social identities and networks, and they may be able to more effectively share results through both formal and informal networks that researchers outside the community would not have access (McLean and Campbell 2003). Across settings, community members should be partners in disseminating and presenting information.

Additionally, community members are important stakeholders in determining future use for their data (if any), but they are frequently excluded from these decisions. **Community members and researchers jointly should be able to decline access to researchers seeking to use data beyond the scope of what the community consented to as well as to create new ideas for research.** Simply anonymizing data before integrating them with other datasets (even if individual respondents have consented to the integration) is not enough to prevent harmful data uses or harmful narratives being formed at the community-level (Hendey and Pettit 2021). Privacy is a key concern, and the consent of communities of color and low-income communities is the most likely to be violated or undermined through re-identification because of small sample sizes.³ Thus, determining to whom, how, and when data from a research study will be accessible is an important step in sharing data ownership with community members.⁴

In the absence of community-based processes for making decisions about dissemination and data access, gross ethical and equity violations can take place—even in projects that on paper have robust data security and privacy practices. For example, in 1989, to counter high rates of diabetes in their community, the Havasupai Tribe allowed academic researchers to collect blood samples. However, without Havasupai's consent, researchers shared access to the study samples with unaffiliated researchers for unrelated genetic research. They also denied Havasupai access to their samples and used the data to disseminate erroneous narratives about the tribe's origins (Couzin-Frankel 2010; Kunesh and Root 2022). It was not until Havasupai sued that members were able to receive \$70,000 in damages, an amount much lower than they had originally requested. Because Institutional Review Boards, which are based in a variety of different regional and institutional contexts, have different guidelines for re-consenting research participants in new data uses, violations of consent in dissemination and data access are more likely in projects that are not community-based. While the Havasupai Tribe example may be

considered extreme, it is a common practice that collected data stay with researchers, sometimes for indefinite or very long periods of time, rather than returned to or shared with community members at the close of a project. When community members are excluded from the list of potential “changemakers” or “data users,” it is more likely that their consent over data access will be violated, and that research will not be disseminated in a way that can produce long-lasting policy change through collective action.

EXAMPLES FROM THE FIELD

- **Neighborhood portraits (dissemination):** Data You Can Use, a data intermediary in Milwaukee, Wisconsin, created “neighborhood portraits” with the input from community organizers. These portraits include short explanations for how to interpret certain tables or results and short, pithy takeaways about various Milwaukee neighborhoods. For this project, local community members are centered as the primary audience.
- **Bottom-up data trusts or data governance councils (data access):** These trusts or councils, which can exist within or adjacently to CABs, provide a formal infrastructure for community members to have collective/public management and oversight over the collection and use of personal data. This strategy allows community members and researchers to jointly make decisions on how data will be anonymized, aggregated, protected, used, and shared (Delacroix and Lawrence 2019; Sharp et al. 2022).

Determining Who to Engage: Defining the Community in a Quantitative Research Project

The aim of defining the community in quantitative research is to foster and value diverse forms of knowledge and knowledge creation in order to strengthen community ownership, validity, and relevance in the research process and outcomes. Determining who to engage in a community is an important task for researchers seeking to incorporate participatory methods into their work, and it should be considered necessary pre-work in all phases of the research cycle. This exercise serves as an important starting point for aligning research priorities with the priorities of the identified community collaborators in a few ways. First, it helps move researchers away from thinking of community residents as “research subjects” to thinking of them as fellow collaborators with lived expertise. Second, it helps researchers connect the equitable priorities in their research to tangible action. Given that participatory work will not be able to reach every single person in a dataset or everyone affected by a research topic, community members who have been most marginalized through policy action or most excluded from research decisionmaking should be prioritized.

Not only is determining who to engage in the community an exceedingly important task, it also happens to be one of the biggest challenges quantitative researchers encounter when first delving into participatory methods. It can be overwhelming or impossible to conceptualize the communities behind data points in a data frame, especially in large, anonymized datasets. These concerns show up in slightly different ways, depending on whether a researcher is working with primary data, secondary data, big data (including third-party data), or a combination of these. Below are some of the challenges, strategies, and questions researchers should ask themselves before engaging with community members and a tool to put these concepts into practice.

Primary Data

Primary data is defined as data that the research team collects directly, whether in the form of researcher-conducted surveys, grantee data, or programmatic data at the individual or household level. When working with primary data, researchers have the benefit of being able to directly connect with study participants. In these cases, defining the community can be a matter of forming connections and trust with potential collaborators in the community by attending networking opportunities, conducting “listening” sessions, or reaching out and investing time to build relationships with trusted organizations, individuals, and facilitators to discuss what they consider are the important geographic, social, and experiential characteristics that distinguish their community. If data has not been collected yet, it is especially important to have conversations not just about what data will be collected but also about intersecting priorities, how to create consent language that clearly indicates that researchers hope to connect with participants again for community-based activities, and any additional data-sharing provisions.

Before determining who to engage in the community, following are some questions quantitative researchers working with primary data should consider when assessing the gaps in research that community members with lived experience can help fill in:

- What are the various identities, experiences, and geographies that comprise this community?
- How has this community been studied in the past? Which of these groups has been underrepresented in research?
- Has this community been engaged in research in the past? Have certain subsets of this community been excluded in past research?
- What processes can researchers adopt to ensure that proper context and language choices are included in data collection protocols and tools?

Secondary Data or Big Data (or Third-Party Data)

Secondary data is defined as data collected by a party other than the one conducting the research, such as a federal agency or a private entity. Frequently, secondary data cannot be connected back to individual community members without prior informed consent and Institutional Review Board approval—at least not without egregious violations of privacy—either because the data are reported at an individual or household level in an anonymized way with no personally identifying information or because the data are reported in an aggregate level, such as ZIP code, city, county, or state level. With big data, including third-party data, the anonymity and quality assurance challenges are magnified, because the data are frequently obtained from a variety of unknown sources whose data definitions and practices may be unclear or unknown. Many of these datasets exist at such a scale or format that they either cannot be connected back to community members or would be unmanageable or unethical to do so. For both secondary and big data, researchers would not be able to directly reach out to study participants.

It may be helpful to form partnerships with different types of institutions that serve communities, such as unions, community-based organizations, practitioners, and academic partners, to get a variety of perspectives on the harm and opportunities that may arise from researchers’ engagement (see more details in the worksheet below). Geographic (city or county level) or identity-based (race/ethnicity, disability, etc.) case studies also can be helpful when collaborating with community members.

Before determining who to engage in the community, following are some questions quantitative researchers working with secondary or big data should consider when assessing the gaps in research that community members with lived experience can help fill in:

- What is the geographic level or scale of the available data (e.g., census tract, ZIP code, county, etc.)?
- Does the research question already limit the scope of analysis to a sub-list of geographies, such as a specific region? If not, which sub-list of geographies (e.g., state, city, county, or district) may provide meaningful and feasible categorizations of representative lived experience?
- How representative is the current dataset? Who are researchers leaving out of the analysis because of data limitations?
- Who could be a key partner in interpreting or framing the data?
- Which communities might be differentially affected because of the included or excluded datasets and variables or by the research overall?
- What variables can serve as creative proxies in place of missing variables? When there are missing values for existing variables, how well can imputation of values ethically fill some of the missing data?

Combination of Two or More of the Above

Using a combination of primary, secondary, or big data frequently requires linking, integrating, or merging of datasets to obtain research insights. Unique concerns can arise when linking datasets, including re-identifying individuals in a way that violates privacy, incorrectly connecting data of different individuals with similar names (and thus creating negative consequences, such as poor credit scores, past criminal history, etc.), and using data beyond what individuals consented to (Saba et al. 2017).

In addition to the tips, considerations, and questions above, following are some questions quantitative researchers working with a combination of primary, secondary, or big data should consider:

- How did data collection occur for each of the datasets and what practices may impact data quality?
- What new opportunities exist to meet and define community priorities based on the linking or merging of multiple data sources?
- What risks arise from the process of data integration? What contexts or biases get lost in the process of merging or linking datasets?
- After quantitative researchers have wrestled with some of the specific challenges and limitations of implementing participatory methods, given the characteristics of data, they can move to the next step in defining the community: considering the different ways to delineate a group. The worksheet below can help with this task. It can be used to begin the brainstorming process of selecting community members to collaborate with.

“DEFINING THE COMMUNITY” WORKSHEET

In quantitative research projects, determining which community to include in the decisionmaking process and defining the community are often the hardest barriers researchers face when starting community collaborations for the first time, especially for projects that have a national geographic scope or that do not have contact with the people in the dataset. This worksheet provides some guiding questions and resources for researchers aiming to overcome these barriers.

PREPARATORY REFLECTIONS BEFORE DETERMINING WHO TO ENGAGE

How can researchers and community members address questions of interest to communities?

Has the community of focus been harmed by policies, research, or programs in the past?

How can collaboration with community members help promote more equitable research with historically and contemporarily marginalized individuals?

PRE-WORK CHECKLIST

- Assess current level of community engagement or collaboration.
- Inventory existing partnerships that could provide a foundation for the research.
- Consider individual and the team’s positionality in the work and how those positionalities might generate certain unchecked biases.
- Consider power dynamics between external researchers and researchers who are based in the community and how those dynamics can be acknowledged and addressed.
- Reflect on the harms and structural inequities that have been perpetuated by historical and contemporary policymaking in the topic of interest.
- Conduct a literature review or environmental scan of how quantitative research in the topic of interest has violated privacy and consent, denied democratic data access, or perpetuated erroneous and harmful stereotypes.
- Inventory existing data pipelines or data sources to assess data gaps that community members can contribute to filling in or help enhance understanding.

DETERMINING WHO TO ENGAGE AT THE BEGINNING OF A RESEARCH PROJECT^a

Based on the reflections in this section, which of the following categories feel like the best way to enter conversations with the community and propose an initial set of questions?

- Demographic:** Does the community define itself by one or more salient demographics (e.g., race, ethnicity, gender, sexual orientation, disability, class, immigration status, etc.)?

- **Geographic:** Does the community define itself in a place-based way (e.g., neighborhood, city, county, or some other creative geocoded set of boundaries informed by community members' lived experience)?
- **Topical:** Does the community define itself through individuals or groups of people who have specific expertise about the topic or subject (e.g., experiences with homelessness or with the criminal-legal system)?
- **Aspirational:** Does the community define itself by common motivations between researchers and community members to address mutual policy interests (e.g., ending child hunger)?
- **Generative:** Does the community define itself organically through established networks or in a snowball manner? This approach works well when community members have established networks to spread the word.
- **Combination/Intersection:** Does the community define itself using a combination of the methods above?

STARTING POINT RESOURCES FOR HOW TO EFFECTIVELY ENGAGE COMMUNITY MEMBERS

- **Chicago Beyond:** *Why Am I Always Being Researched: Guidebook for Community Organizations, Researchers, and Funders to Help Us Get from Insufficient Understanding to More Authentic Truth*
- **Community Research Collaborative:** *In It Together: Community-Based Research Guidelines for Communities and Higher Education* [PDF]
- **Southern California Clinical and Translational Science Institute:** *Toolkit for Developing Community Partnerships* [PDF]
- **March of Dimes:** *Making Community Partnerships Work: A Toolkit* [PDF]
- **Urban Institute:** "Community-Engaged Methods Guidebook" project page.

FRAMING TIPS

- **Combining equitable selection and community-engaged methods:** When timeline or budget requires limiting community collaboration to a subset of community members, it is important to prioritize community members who have been most marginalized through policy action or most excluded from research decisionmaking.
- **Intersectionality:** It can be advantageous to delineate the community in a combination of the categories outlined in this box. For example, a hypothetical evaluation of a new guaranteed-income pilot in San Francisco can collaborate with Asian American and Pacific Islander immigrants who have an interest in addressing income insecurity in their community. The combination approach can welcome solidarity and push understanding of the challenges that arise from the intersectional reality of group members, such as the intersections of income and race. Intersectionality may also apply to members of the research team who identify as members of the community. It is essential to remember that lived experience/identity and professional experience/identity are not mutually exclusive.

^a The categories are adapted from geography studies literature to incorporate the fluid nature of neighborhood identity. They were selected to act as a departure from the traditional and potentially disempowering ways of categorizing individuals (Catney, Frost, and Vaughn 2019).

The Promising Overlap between Quantitative and Participatory Methods

As shown in the sections above, there are many practical and tangible ways to incorporate participatory methods within quantitative research projects. However, along with these practical considerations, it is important to reflect on the theoretical underpinnings of why participatory quantitative methods produce less extractive or harmful research than some traditional forms of quantitative research.

Questioning and learning from the history and failures of past research are vital to conducting ethical, responsible research. Doing so can enable researchers to identify opportunities to strengthen quantitative research. Participatory methods can improve traditional quantitative social science research by engaging in thoughtful consideration of researcher positionality, challenging damaging stereotypes that get encoded in hypotheses and data, and creating opportunities to deepen understanding of social phenomena in order to model them more accurately. They provide researchers with more ways to independently make informed and equitable research decisions in all phases of the research process. For example, participatory methods help close the forced distance traditional standards of “objectivity” require and provide a much stronger and better-documented objectivity, which ensures that research is responsive to community needs and is accurately contextualized. Participatory methods, by increasing collaboration with key stakeholders affected by issues of interest, can also offer a more nuanced understanding of causal mechanisms and processes to ensure proper knowledge of how variables are related to one another and what contributes to those relationships. Finally, participatory methods provide a framework for reflecting on how researcher positionality might surface biases and potential threats to validity in their work. These benefits of collaborating with community members as research partners and fellow experts require both an understanding and an examination of traditional quantitative methods as well as an openness to using new approaches and tools.

We conclude this guidebook with three key theoretical considerations that underpin the potential value community-engaged methods bring to quantitative researchers:

1

Recognize the limitations of positivism and encourage the practice of considering researcher positionality

2

Balance researcher objectivity and independence with researcher responsibility to the community

3

Expand community participation in research to include community members as collaborators and experts rather than only as research subjects

Recognize the Limitations of Positivism and Encourage the Practice of Considering Researcher Positionality

Normative Foundations of Quantitative Research

Much empirical social science practice can be traced back to historical roots in positivism, a paradigm of scientific research that is rooted in the ideas of natural sciences, such as chemistry, physics, or mathematics. Positivism holds that there is a singular, observable reality—or truth—driven by “immutable” laws like gravity (Guba and Lincoln 1994). This perspective in the social sciences would assert the validity of one singular observable, fundamental truth about why outcomes differ across different communities. To study this truth under a positivistic framework, academic researchers must objectively observe phenomena without influencing them or being influenced by them (Maxwell 2013).

Implications

When seeking to understand social phenomena, positivism can pose problems for developing appropriate research questions and hypotheses. This is primarily because positivism assumes an immutable and singular mechanism for the phenomena—such as race, gender, immigration status, poverty, education completion, and others—when instead they are influenced by historical and sociopolitical process. In an attempt to emulate the conditions of a controlled scientific lab or mathematical lemma, positivism in the social sciences can omit key factors from consideration (e.g., new creative variables that can better account for historical context and influence outcomes), obscure how local contexts can generate different outcomes from one central hypothesis, and exclude necessary analysis of how researcher drafting the hypothesis can be influenced by the very constructs that are being studied (Guba and Lincoln 1994).

Table 1 compares how a social issue like race in the US would be conceptualized using a positivistic perspective compared to other more critical paradigms, such as those commonly used in participatory approaches. The table is organized from

TABLE 1

Race and Its Measurement, as Conceptualized by Different Research Paradigms

Positivism	Post-positivism	Critical theory	Constructivism
Races is real, discrete category into which all humans classify. It is inherent to an individual regardless of the observer. It can be measured with appropriate tools, and its impacts on outcomes can be isolated from other variables using statistical techniques. Replicated findings can be considered true.	Race is real and everyone has one, though it is likely impossible to perfectly assign one race to everyone. Greater emphasis is placed on determining the meaning of race within a setting and getting insider perspectives. While observer perspectives may impact measurement, researcher can measure the impact of race as well as regulate and referee findings for bias. Replicated findings are viewed as likely but not absolutely true.	Race is not real, but it has crystallized into a series of structures through centuries of social, political, cultural, and economic embedding. These structures are understood as real. Truth can be ascertained only dialectally, so that researcher misapprehensions can be transformed into informed consciousness. Findings are both researcher and context dependent. Researcher can measure disaggregated data by race/ethnicity, gender, class, disability status, citizenship status, and so on to observe how differences in access to resources create structural differences in outcomes.	Race is not real. It is understandable only as a socially based mental construction and depends entirely on the individuals or groups holding the construction. Mental constructions of race can vary from more or less informed to nuanced and can be changed critically. While these constructions can be shared broadly, their impacts are local and specific. Researcher can measure how they show up in the world and in their research by using open-ended research questions. Findings are “literally created” as research proceeds.

Source: Adapted from Egon G. Guba and Yvonna S. Lincoln, “Competing Paradigms in Qualitative Research,” in *Handbook of Qualitative Research*, 2nd ed., edited by Norman K. Denzin and Yvonna S. Lincoln (Thousand Oaks, CA: Sage, 1994).

The conceptualization of race as a true, natural phenomenon has real-world implications. One striking example comes from the medical community, where race was included as a predictor variable in a Modification of Diet in Renal Disease (MDRD) study that was developing an equation for kidney function. While there was no hypothesis provided for why race was included (or why Black vs. non-Black was the appropriate racial classification) during the specification of the functional form or hypothesis question, researchers suggested post hoc that race acts as a proxy for muscle mass differences. The original studies cited for this assumption did not explore alternative social explanations, and the data from the MDRD study indicated that Black participants differed on many strong predictors of kidney function. This study served as the basis for the inclusion of race adjustments in other studies and measures of kidney function, and it popularized the idea of racial adjustment in medical tests. The differences in testing results for patients in the US led to approximately 3 million Black Americans going untreated or undertreated for kidney disease (Tsai et al. 2021).

As positivistic perspectives, which emphasize experimental and quantitative approaches without critical perspective, become institutionalized in how researchers define rigor and evidence, there is a growing risk that researchers will not be able to overcome the idea that these approaches are the only ways to finding the “truth.” For example, the Evidence-Based Policymaking Act of 2018 shapes the categorization of rigorous research for US government–led and funded research projects, and it places experimental quantitative approaches as the most rigorous way to generate evidence on the effectiveness of policies and programs (Newcomer and Hart 2021).

Value of Community-Engaged Methods of Positionality Reflection

Participatory methods, derived from the popular education movement and Latin American critical education methodologies (Freire 1970), are not rooted in the traditional positivistic thinking. They are more aligned with critical theory, which considers the social context and history that shape phenomena and encourages researchers to consider truth in context, as opposed to rigid truth or natural law (Guba and Lincoln 1994; Orłowski 2019). Critical approaches to quantitative research incorporate the concept that the world is often very much shaped by perspectives and experiences of people living within structures that confer benefits and burdens onto different groups. Accordingly, participatory methods explicitly acknowledge the influence researchers have on the world (and vice versa) and promote researcher reflexivity around how this may impact their work. These methods often rely on researchers exploring their own positionality within a research project, and how their personal experiences may create biases or blind spots when analyzing certain topics. Reflecting on positionality can enable researchers to surface biases and potential threats to validity in their work, strengthening research studies. When researchers reflect on their access to personal and institutional power, it becomes more likely that their collaboration with community members can include frank discussions about identities, experiences, worldviews, and power dynamics. As researchers become more transparent about their own positionality, they are able to articulate a clearer conception of the implicit purpose, function, and ideal end goal of their research (Secules et al. 2021), ultimately leading to a more thoughtful and impactful long-term research agenda.

Balance Researcher Objectivity and Independence with Researcher Responsibility to the Community

Objectivity and Researcher Independence

The concept of objectivity—the idea that research can be practiced independently of personal perspectives, emotions, or prejudices—is a valuable goal insofar as it attempts to reduce researcher bias in the research process. Objectivity

is typically achieved by creating distance between researchers' preexisting beliefs and the new information (research) they are studying. Reducing bias through a measured and careful review of evidence has been shown to be an important aspect of social science research. An example can be shown in the impartial analysis conducted by the Congressional Budget Office, which provides invaluable nonpartisan economic projections that cut through political biases and inform the congressional budget process.

However, it is not possible for researchers to be entirely objective when engaging in social science research, because they have biases that cannot be excised simply by expanding the distance between themselves and the communities affected by their research (or limiting interactions between the two). Academic researchers do not sit in a vacuum removed from the world; they carry their worldviews and histories with them into research, and this can shape research decisions from start to finish (Fine et al. 2000; Van Heertum 2005). These biases, which are too often unaccounted for, unknowingly influence all aspects of the research process. The questions researchers ask, the populations they define, the models they design, and the variables they include or exclude are all decisions informed in some way by their perspective, experience, training, and expertise. By erasing or ignoring the assumptions, weaknesses, and biases they bring to the research process, researchers accept and promote results as "truthful" reflections of the world, when in fact they are perspectives greatly influenced by the individuals observing them (Berger 2015). In a guide for conducting research, the University of Minnesota explains:

Data (even quantitative data) is not neutral, objective, or free of bias. Humans are involved in all aspects of data creation—we decide what data gets collected and from whom, how that data is combined and analyzed, and where and how that data is presented or shared.... While the individual measurement of something may return an objective data point ... the process of collecting, combining, analyzing, reporting, and using of data imbues a seemingly objective dataset with biases.⁵

As with objectivity, the concept of researcher independence has merit, as it aims to conduct research free from political or financial interference. Traditionally, the concept is used to protect researchers from asymmetrical power dynamics with funders, federal lawmakers, or military contractors that overly limit the research scope or publication of findings (Bammer 2008). One of the primary benefits of researcher independence is that it maintains a more objective, balanced, and evidence-based approach to research, which increases the use of research in changing and improving public policy (Haynes et al. 2011). It is important for research, including community-based research, to maintain a level of independence, so that research findings remain based in evidence and trusted by policymakers and key stakeholders.

However, researcher independence has on occasion been used to exclude nonacademic community members from the research process, under the assumption that they are less likely to be objective than academic researchers. This line of thinking is often used to justify dismissing participatory methods and treating collaboration with community members as impossible or problematic. This is at odds with the traditional reasoning behind research independence, which is to protect research findings from powerful influence. Community members are typically outside the sphere of influence that can unduly pressure research findings in a certain nonevidence-based way. In fact, the successful integration of diverse knowledge, perspectives, and skills from all key stakeholders, including community collaborators, can be a way to shore up evidence for findings that are unpalatable to powerful, political, or monied interests—and maintain researcher independence (Bammer 2008).

Implications

At times researchers overvalue objectivity and researcher independence in an attempt to devalue community member expertise. For example, in the welfare policy space, surveillance of people with low income has been rooted in racist narratives about the “undeserving poor” (Jain Family Institute 2021), which have created a continuous cycle of over-surveying to justify improving means tests for eligibility requirements. Furthermore, the perception of people with low income as being responsible for their own economic precarity has similar roots as the perception that welfare recipients have clouded, emotional, or biased views about research related to them. Both can result in community members being perceived by researchers, as well as policymakers and other key stakeholders, as uninformed and unknowledgeable about the topic at hand, such as welfare policy.

Prioritizing objectivity or researcher independence and excluding community members from research perpetuates biased and less rigorous research practices (Balazs and Morello-Frosch 2013; Gläser et al. 2022). For example, academic researchers may justify not collaborating with community members in identifying research questions, because they believe such engagement infringes on their independence. Similarly, quantitative researchers may publish findings framed in a way that perpetuates harmful stereotypes (based in individual biases) by claiming “it’s just what the data says,” rather than engaging the community in data interpretation, which may likely surface and remove individual biases from data interpretation. As discussed in the sections above, these practices would result in a less rigorous research design or data interpretation process.

The drive for researcher independence may also be rooted in the drive to publish individual research, amplified by the “publish or perish” mentality. For example, pressure to publish may lead to researchers focusing on the flashiest topics or methods most likely to get published, rather than on topics that center community needs or interests. Moreover, these topic selections are often reinforced through peer-review and editorial decisionmaking processes, which tend to prioritize research that does not have direct or immediate benefit to communities. The result is that researchers may unwittingly pursue excessive and burdensome data collection that furthers their own professional interests but does not benefit (or might outright harm) the community. Inclusion of community perspectives throughout the research process can help guide (but not direct) the selection of important and impactful research.

Value of Community-Engaged Methods

Objectivity and researcher independence are valuable concepts and practices, but they need to be adapted, so that they do not exclude community collaboration and unintentionally allow biased, nonrigorous research to be published. Quantitative researchers can reframe away from a “weak” objectivity that claims neutrality to a “strong” objectivity that incorporates multiple types of evidence, including the lived experience, positionality, and critical examination of social structures (Harding 1995). This reframing creates objectivity and researcher independence that is inclusive.

If quantitative researchers want to achieve the goals of objectivity—unbiased, truthful research—they must include people who directly experience the topic of research as partners and decisionmakers using participatory and community-engaged methods. Participatory methods help to close the forced distance traditional standards of objectivity creates and to make sure that research is more accurately contextualized. This allows for a more effective consideration of how individual values and interests influence the assumptions being made in the research process. From this standpoint, researchers and community members alike should seek to iteratively minimize the influence of biases and to champion the diversity of thought and democratic dialogue. We argue that, ultimately, this is achieved when researchers involve community members at all stages of research.

Expand Community Participation in Research to Include Community Members as Collaborators and Experts Rather than Only as Research Subjects

Distributing Decisionmaking Power

Traditionally, in social science research community members are engaged flatly as research subjects. This paradigm of engaging community members only as research participants and not as collaborators in the research process results in multiple inequities, including not providing community members information about the purpose of the research; access to decisionmaking processes about what questions are being asked, how the research is being conducted, and what actions to implement after the completion of research; and the benefits that come from successful research publication (e.g., authorship, acknowledgment as experts, and compensation) (Chicago Beyond 2018).

Additionally, although individual consent is a common, accepted (if imperfect) practice in social science research, gaining consent from marginalized communities on the use of their data and discussing the conclusions drawn from the research with community members is less common, resulting in researchers having disproportionate amount of power in deciding the future of a community. The consent process most often occurs only at the time of initial data collection and does not typically extend to administrative, secondary, or big data; it also does not establish limits on how research can be used or disseminated after data collection. Projects like Our Data Bodies have demonstrated that data collection riddled with power imbalances in decisionmaking, such as some led by government offices or private companies, can disproportionately result in surveillance and “diversion from public benefits, insecure housing, loss of job opportunities, and the policing and criminalization” for communities of color (Saba et al. 2017). Addressing these collective inequities in traditional research process and distributing some of the decisionmaking power to marginalized community members can lead to more equitable research and policymaking.

The process of reimagining and redistributing decisionmaking power in research does not have to begin from scratch. In addition to the myriad participatory quantitative examples provided above, there are multiple examples that have originated outside the academy and within communities of color. For example, knowledge systems in Indigenous communities have conveyed social observations and findings via social encounters, oral traditions, and ritual practices for thousands of years (Bruchac 2014). These practices of data generation and ownership have been successfully institutionalized, as evidenced by the creation of the Navajo Nation Human Research Review Board in 1996, which has led the regulation, monitoring, and overseeing of research about the tribe. The board has required that all data be returned to the Navajo Nation at the end of each project (Carroll, Rodriguez-Lonebear, and Martinez 2019). Relatedly, the Young Lords’ Lead Offensive, a 1960s example of community-led data collection by Puerto Rican activists, is an example of how a community-centered quantitative research effort can translate into policy action: it resulted in new laws requiring landlords to remove lead in Harlem buildings.⁶ All examples given in this guidebook highlight the competence and expertise that already exist within communities—and the opportunities researchers have to improve their research and its impact when decisionmaking power is distributed more equitably.

The distribution of decisionmaking power can occur at all stages of the quantitative research process. Although some quantitative research has begun incorporating collaboration with communities at the interpretation and dissemination stages, many decisions about the selection of research questions, goals, or models (e.g., selection of covariates, interrelationships between variables of interest, target populations, and sampling) are still only subject to researcher discretion. Better distribution of the decisionmaking power can be achieved when there is inclusive space for community members to contribute and embed their insights at all stages of research. Such distribution can contribute to the collection of the gold standard for data—firsthand, self-identified, ground-truth data directly from people with lived experience—that can be incorporated into larger quantitative projects, with the ultimate goal of improving the

quality and relevance of the research overall as well as the lives of community members and community conditions. Additionally, the processes started by the open science movement—which encourages researchers to share variables, datasets, statistical models, and programming codes with other researchers—can be extended. Researchers should go even further to include meaningful and active consent processes and level-setting processes around both researcher and community member expectations and goals.

Implications and Value of Community-Engaged Methods

At times, researchers are not members of the community they study and have no shared identities, meaning that the way they approach research and their understanding of the relevant context are incomplete when not informed by community members' lived experiences (Fine et al. 2000). Members of the community can provide valuable insight, giving validity or counterpoints to many of the assumptions mathematical models make about the world. Without community members' perspectives, there is the risk that quantitative models will not reflect important factors relevant to the phenomena under study and will fail to generate valid results that would improve the use of study findings (Patton and Campbell-Patton 2021). This has been demonstrated by the Household Exposure Study, which summarized how community organizers in Northern California were able to advance an effective environmental justice campaign by requesting the broadening of research questions and data collection (Balazs and Morello-Frosch 2013). Without robust community collaboration, quantitative research can undermine its internal validity or its ability to accurately model factors relevant to the phenomena, which would render research insights less useful.

Placing decisionmaking power in marginalized communities through participatory approaches can play an important role in building on and extending quantitative knowledge. Some quantitative methods and research designs are well-suited for developing causal relationships between interventions and outcomes, but they often fail to generate causal explanations for the mechanisms, processes, and conditions that generate causal impacts (Shadish, Cook, and Campbell 2002). By leveraging community perspectives to understand why and under what conditions these relationships hold, participatory approaches have the unique value of being able to offer insight into causal mechanisms and processes. For example, quantitative researchers can use participatory modeling methodology known as “fuzzy cognitive” mapping to provide researchers, community residents, and subject matter experts a venue to co-develop a weighted and directed graph that can produce more complete models, simulations, or regression analysis (Burns 2018; Lopes and Videira 2017; Penn et al. 2013). This strengthens the rigor, usability, and external validity of quantitative findings by not only revealing how variables are related to one another but also the mechanisms underpinning these relationships and how the results generalize (or not) to other contexts.

Finally, participatory approaches can provide strategies for holding complex and somewhat paradoxical insights simultaneously, such as acknowledging structural oppression and its damage at the same time highlighting community resilience and strength (Fine et al. 2000). While quantitative research frequently assumes discrete groups of communities make for neater categories, these categories can restrict the differential outcomes that can arise from intersectional experiences. Collaborating with community members moves researchers away from isolating groups to tapping into the relational and dynamic nature of groups, which allows them to focus on structural dynamics (Sandwick, Hahn, and Ayoub 2018). By holding and eliciting rich and complex lived experiences that illuminate structural realities of communities, participatory research lends particularly well to deepening and nuancing research about complex policy topics.

Overall, we encourage researchers to reflect on these three theoretical considerations when conducting quantitative research that aims to incorporate community-engaged methodologies.

Conclusion

We are heartened and excited by the interest of our fellow quantitative researchers to use the power of quantitative methods to foster equitable collaborations with the communities most affected by research. We humbly share this guidebook to further disseminate practical strategies and theoretical considerations our team is actively exploring, and as an open call to fellow quantitative researchers and community members interested in participatory quantitative research to join us in reimagining more equitable research processes. We hope this guidebook is only the start of much deeper and longer-term participatory quantitative initiatives at Urban and beyond. Ultimately, we are excited to see more rigorous and robust quantitative research that has better processes for collaborating and highlighting community expertise.

Notes

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